DEPARTMENT OF TRANSPORTATION

Performance Evaluation of Different Detection Technologies for Signalized Intersections in Minnesota

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April 2024

Research Project
Final Report 2024-10

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Technical Report Documentation Page

1. Report No.	2.	3. Recipients Accession No.
MN 2024-10		

4. Title and Subtitle	5. Report Date
Performance Evaluation of Different Detection Technologies for Signalized Intersections in Minnesota	April 2024
	6.
7. Author(s)	8. Performing Organization Report No.
Malcolm Grossman, Yuankun Jiao, Haoji Hu, John Hourdos, Yao-Yi Chiang	2021050
9. Performing Organization Name and Address	10. Project/Task/Work Unit No.
Department of Computer Science & Engineering University of Minnesota 200 Union St. SE Minneapolis, Minnesota 55455	11. Contract (C) or Grant (G) No. (c) 1036342 (wo) 18
12. Sponsoring Organization Name and Address	13. Type of Report and Period Covered
Minnesota Department of Transportation Office of Research & Innovation 395 John Ireland Boulevard, MS 330 St. Paul, Minnesota 55155-1899	Project Final Report, 3/19/2021-5/31/2024
	14. Sponsoring Agency Code

15. Supplementary Notes
http://mdl.mndot.gov/

16. Abstract (Limit: 250 words)
This research evaluates the performance of non-intrusive detection technologies (NITs) for traffic signals in Minnesota. Prior work shows that while no single NIT device performs best in all situations, under specific circumstances, some NIT devices consistently outperform others. Our goal in this research is to find which NIT devices perform better in conditions specific to Minnesota and provide cost estimations and maintenance recommendations for operating these devices year-round. Our research has two main components: 1) synthesizing national and local experiences procuring, deploying, and maintaining NITs, and 2) evaluating real-world NIT deployments in Minnesota across different weather conditions. Our results and analysis combine the results from these steps to make recommendations informed by research and real-world experience operating NIT devices. Through interviews with Minnesota traffic signal operators, the research finds that environmental factors like wind, snow, and rain cause most NIT failures, requiring costly on-site maintenance. Operators emphasize the need for central monitoring systems, sun shields, and heated lenses to maintain performance. The research then analyzes NIT video, signal actuation, and weather data at six Twin Cities intersections using Iteris and Autoscope Vision technologies. No single NIT performs best, aligning with previous findings, but Autoscope Vision is less prone to lens blockages requiring on-site service. Our analysis also finds some intersections have more failures, indicating location and geometry impact performance. Key recommendations are based on the relative performance of a NIT in different weather conditions and accounting for local weather conditions when selecting a NIT at an intersection. We also recommend using central monitoring systems to troubleshoot remotely, installing heat shields to prevent snow/rain accumulation, and routine annual checks and checks after major storms.

17. Document Analysis/Descriptors	18. Availability Statement
Signalized intersections, Detection and identification technologies, Data analysis, Time series, Geographic information systems	No restrictions. Document available from: National Technical Information Services, Alexandria, Virginia 22312

19. Security Class (this report)	20. Security Class (this page)	21. No. of Pages	22. Price
		230	

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Final Report

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April 2024

Published by:

Minnesota Department of Transportation
Office of Research & Innovation
395 John Ireland Boulevard, MS 330
St. Paul, Minnesota 55155-1899

Acknowledgments

Thank you to the members of the 24.7 lab who helped with revisions and editing: Min Namgung and Yijun Lin. Thank you as well to the members of this project's Technical Advisory Panel: Michael Fairbanks, Paul Ackerley, Nik Costello, Ben Hao, Allan Klugman, Derek Lehrke, Steven Misgen, and Nicklaus Ollrich. And finally, thank you to Jakin Koll for providing the weather data.

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List of Abbreviations

Non-Intrusive Detection Technology (NIT)

Comma-separated values (CSV)

Minnesota Department of Transportation (MnDOT)

Local Road Research Board (LRRB)

Executive Summary

Modern intersection control primarily relies on actuated systems that respond to traffic at the intersection. MnDOT and many local Minnesota agencies have traditionally used embedded loop detectors in the pavement for detecting vehicles. Although the performance of a well-placed loop detector has yet to be matched by any other method, changes in the vehicle fleet (higher use of non-ferrous material), as well as increased need for more comprehensive detection (vulnerable road users, all lanes individual advance and stop-line detection), has resulted in the increased use of non-intrusive technologies (NIT).

There are studies evaluating the performance of NIT detection. Still, all have been racing against obsolescence given the rapid developments in the market, and more importantly, all of them have focused on the comparative evaluation of different detection technologies. This report 1) synthesizes national and local experience in procuring, deploying, and maintaining NITs for signal operations and 2) reports the results of year-round observation and recording of the performance of selected real deployments of all major products used in Minnesota. In achieving the first objective, this research conducts a market search on currently employed NITs, synthesizes current research on the performance of NITs, and surveys local signal operators on their use and experiences operating different NIT devices. In achieving the second objective, we select several sites within the Twin Cities metropolitan area and analyze their performance when subjected to different environmental conditions.

The market search results and prior research synthesis show that many NITs used for detection employ video, radar, or a combination of the two for detecting cars. Even though these detection systems employ various technologies, prior research shows that no single system outperforms others in every condition. Different NIT devices perform better than others depending on environmental factors, such as the time of day, location, and weather. The interviews with signal operators reinforce these results as signal operators in St. Paul and Hennepin County show no preference for one detection technology over the others. Both interviews describe the difficulty of operating multiple types of detection technology and strongly suggest a single type for any municipality. Still, they make no statements on the performance of different NITs used for detection. However, the interviews indicate that certain weather conditions, namely severe storms involving high wind, are more detrimental to NIT performance and increase budgeted costs. Signal operators report that the most significant factors in maintaining NIT performance are using a central monitoring system for active NIT devices, properly installing sun shields, and using heated lenses. Properly installing sun shields ensures that glare is minimized, reducing potential failures. Employing a central monitoring system helps operators minimize some NIT failures by adjusting camera angles and zooming remotely. In addition, the interviews describe how a primary motivation for switching from loop detectors to NIT is cost. MnDOT provides the research team with cost estimates for each detection technology, and we find that loop detector installations can cost 1.5 times as much as a NIT installation.

Our work builds off prior research and focuses on weather specific to Minnesota, namely storms involving high winds, cold temperatures, and heavy snow, and evaluating the performance of NITs on those conditions. The research results reinforce those of prior works that no single (camera-based) NIT outperforms others in all conditions. However, when observing the performance of both Iteris and Vision detection technologies under intense winter storms, we find that the Vision detection technology is less susceptible to long-term failures that require on-site maintenance (e.g., snow, dirt, rain, etc., blocking the camera lens). The interviews with signal operators report that most of the cost of maintaining NITs comes from on-site maintenance. Therefore, our analysis and recommendations focus on these types of NIT failures.

Our studies with selected road intersections recommend that MnDOT take into account weather conditions local to a specific intersection when determining which NIT to choose as performance varies between the different NITs when exposed to different weather conditions. We also recommend installing glare protection and heated shields as recommended by signal operators and using a central monitoring system for NIT devices that allows operators to adjust detection areas in the field of view and adjust the tilt and zoom of the cameras to reduce the need for on-site maintenance. The results also indicate further analysis needs to be done on the effects of glare and intersection geometry, as glare has a minor effect on NIT performance, causing late or early car detections. Finally, our results show different failure rates between locations with the same detection technology, indicating that intersection geometry or other local factors impact NIT performance.

Introduction

1.1 Objectives

Intersection control can be pre-timed, or vehicle actuated. Modern controllers implement natively only actuated control with pre-timed implemented as the case of actuated, termed vehicle recall. Actuated signals respond to the traffic present at the intersection so that the pattern of the signal (the length and order phases) depends on the traffic and can be different at every cycle. In all versions of actuated control, the cornerstone of the system is vehicle detection. MnDOT and many local Minnesota agencies have traditionally used embedded loop detectors in the pavement for detecting vehicles. Although the performance of a well-placed loop detector has yet to be matched by any other method, changes in the vehicle fleet (higher use of non-ferrous material), as well as increased need for more comprehensive detection (vulnerable road users, all lanes individual advance and stop line detection), has resulted in the increased use of non-Intrusive technologies (NIT) for detection. There are studies evaluating the performance of NIT detection. Still, all have been racing against obsolescence given the rapid developments in the market, and more importantly, all have focused on the comparative evaluation of different detection technologies. Unfortunately, very few studies have identified the long-term true costs of operating and maintaining such intersection control systems. In this project, we guide MnDOT and Local Road Research Board (LRRB) members in selecting the most appropriate technology for a given location and evaluating the expertise, effort, and material cost of maintaining each of these systems year-round in Minnesota. Achieving this goal involves two parallel but separate efforts.

The first effort synthesizes national and local experience in procuring, deploying, and maintaining NITs for signal operations. On the national level, the project establishes a baseline on the currently available detection technologies and the products in the market that employ them. It also composes a synthesis of current research on the performance of NITs. On the local level, we survey signal operation and maintenance offices in St. Paul and Hennepin County on their use and experiences with NITs for signal control to collect practitioner experiences in operating and maintaining the different detection products.

The second effort involves year-round observation and recording of the performance of selected real deployments of all major products used in Minnesota. We select sites based on varying geometry and demand characteristics. At these sites, field or remotely placed hardware records all control signals (actuations and phase changes) coming in and out of the controller while recording the detection system's available raw data and video from additional Minnesota Traffic Observatory (MTO) cameras separately. We produce records of system errors affecting actuated control from these records and correlate the event records with weather measurements of wind and temperature and environmental conditions like snow, rain, pavement conditions, time of day (lighting), etc. Please refer to Appendix A for more information about the overall project goals.

1.2 Prior Work

Most prior work in evaluating NITs is based on product evaluation and compares the accuracy of a system or systems to the accuracy of loop detectors. Many agencies have been employing video detection at intersections for over two decades, and some states, such as Texas, have developed manuals for implementation [1]. Cal Poly's 1990 evaluation of 10 video-based detection systems yielded vehicle count and speed errors of less than 20% over a mix of low-, moderate-, and high-traffic densities. However, transitional light conditions, occlusion, and slow-moving, high-density traffic conditions reduced the accuracy of these systems [2]. Over the past two decades, video detection research has indicated that lighting conditions are the main cause of detection errors. Systems usually have more problems at night due to headlight glare [3, 4, 5]. During the day, the sun can create stationary or moving shadows that confuse the detector, and glare can reduce camera visibility [3]. Work done in the late 1990s [6] and early 2000s [3, 7, 8] on commercially available systems indicates that lighting conditions and shadows have the most significant effect on NIT performance and that loop detectors perform better in the majority of cases when compared to NIT.

It is challenging to compare the performance of two or more NIT products at installations located at different intersections or points in time. Setups using side-by-side comparisons can provide an advantage over other installations, as the video-based detection (VID) systems process the same image using their own cameras. The National Institute for Advanced Transportation Technology (NIATT) at the University of Idaho conducted the most recent study [9] with funding from the Idaho Transportation Department. NIATT researchers evaluated four video, two radar, one thermal, and two hybrid detection systems, and the results proved inconclusive. Based on the results of this study, no single system universally performed better than all other systems. Depending on the time of day or weather conditions, many system types tested could claim their technology outperformed all others.

1.3 Research Goals and Approach

The expected benefits from this research encompass several categories. **Table 1.1** provides an overview of these benefits.

The cost of the vehicle detection instrumentation for a fully actuated control can go as high as $40,000 per intersection, and several of the currently operational intersections owned by MnDOT had to be put on recall mode in the winter of 2021, one of the coldest winters in recent records [11], due to failures of the detection system, further increasing costs. Such events represent safety hazards until they are discovered and can generate long delays to road users and dramatically increase maintenance costs. This project identifies the most common forms of failure, develops and proposes early detection of performance reductions, and provides guidelines on the required periodic maintenance and replacement (possibly half-life of the entire system) actions that can minimize signal control times.

These results will benefit life-cycle cost estimation, leading to higher returns on investment and minimizing user costs in traffic delays and crashes.

Table 1.1 Expected Research Benefits

Benefit Category	Are the benefits quantifiable (Yes/No)	How these key benefits will be quantified?
Climate Change & Environment	Yes	Cumulative time vehicles spent idling on red due to NIT miss detection. Separately for main and side road approaches.
Improved Safety	Yes	% reduction of time period intersection is placed on all phase recall. % of time bad detection resulted in insufficient yellow clearance interval.
Operation and Maintenance	Yes	Newer detection technology for traffic signals may perform better at same or reduced costs. Determine which technology has the lowest long term costs for the life of the signal system.

In addition to the technology reports and synthesis documents we deliver, the final goal is to guide MnDOT and LRRB members not only in selecting the most appropriate technology for a given location but also onthe expected expertise, effort, and cost involved in maintaining each of these systems year-round in Minnesota for the life of the signal system.

The overall approach combines the information gathered from the technology reports, synthesis documents, interviews, and research to provide a decision-making tool to guide signal design by MnDOT and other public works entities in Minnesota. This decision-making tool takes the form of a flowchart describing a system for evaluating the performance of NIT in various conditions. The technology reports, synthesis documents, and interviews inform the results of the system to provide domain expertise and help decide the optimal NIT technology for Minnesota weather.

The scope of this research is limited to NIT devices used by MnDOT and to weather patterns and locations in Minnesota.

1.4 Report Organization

The report is structured as follows. Chapter 2 overviews the process and results of the survey of intersection owners and operators. Chapter 3 discusses the market search for different types of detection technologies. Chapter 4 discusses the data used in our research approach. Chapter 5 discusses the research approach, implementation, and results. Finally, Chapter 6 discusses the analysis of the overall results of the project, conclusions, recommendations for implementation, and further testing.

Chapter 2: Summary of Interviews with intersection owners/operators

2.1 Introduction

This study collects and compiles real-world experience working with and maintaining NIT vehicle detection installations in this task. To achieve this goal, the study collects survey results from Hennepin County and the City of St. Paul and provides a summary below. The original report for task 2, containing the motivation, survey, and results, is in Appendix B.

2.2 Summary of Interviews

The Hennepin County interview took place on June 17th, 2022, in Median, MN with Mr. Ben Hao and several other county employees at the Hennepin County Traffic Management Center, and the City of St. Paul interview took place on October 17th, 2022 over email and teleconference with Mr. Mike Klobucar at the City of St. Paul Traffic & Light Division in the Department of Public Works. Hennepin County reports that they “operate[s] 450 signals”. When prompted on the types of signals and technologies deployed, they said, “all signals are semi or fully actuated” and “vehicle detection utilizes video NITs. No loops remain in use”. In comparison, the City of St. Paul reports that they “operate[s] 390 signals” with “approximately 90% of these signals are actuated” and “approximately 70% of the signals still use loops for vehicle detection while a couple of locations use Wavetronix radar”. Both municipalities use Vision and Terra products for NIT detection and are testing GridSmart products. Hennepin County also deploys Encore by Econolite and has been testing Iteris Next. While Hennepin County has switched from loop detectors to NIT, the City of St. Paul is still phasing out loop detectors, saying the “current plan is to move towards video by replacing loops with video when [the] road is resurfaced”. Still, both municipalities are committed to making the switch. The change is primarily motivated by the flexibility of NIT when compared to loop detectors, as operators can easily reconfigure detection zones in NIT. The City of St. Paul also states that their “main reason for switching to video is to adequately cover the bike lanes”. Hennepin County instead points to cost-saving measures as its primary motivating factor, saying “video is cheaper to maintain due to mill and overlay (from ops or construction budget)”. Both entities find that environmental factors play the most significant role in NIT failures, with Hennepin County specifying that “sun glare also causes contrast failure” and that “It is important to take the horizon into consideration when install[ing] the camera”.

In contrast, the City of St. Paul says the “main cause of down time [is] due to storms such as lighting, strong winds, heavy snow fall, knocked down poles due to accidents and camera failures”. Both entities use a central signal system for monitoring NIT device alerts and downtimes, which they report as incredibly helpful in resolving NIT failures. These central systems allow operators to remotely adjust NIT camera views and detection zones to help mitigate NIT failures and the need for operators to go on-site to diagnose problems. Hennepin County also reports that "camera housing with heated lens is absolutely necessary" and properly installed sun shields are vital for optimal performance.

Regarding overall maintenance schedules, both entities report that remote adjustments through the central monitoring system are made as needed and cost the time for adjustment. Hennepin County reports that it performs annual lens cleanings for 450 intersections with costs from 188k to 218k including the labor and non-labor costs.[1] The City of St. Paul also performs annual cleanings on all cameras but conducts additional cleanings as needed after significant winter storms. They also report that "all systems are reviewed every three weeks as well as after major events involving strong winds". Both entities state no issue with system providers or helpdesk responsiveness and costs and find no need for stockpiling inventory due to the rarity of physical device failures and the fact that systems are replaced/discontinued by the manufacturer every 10-15 years. A primary concern of both Hennepin County and the City of St. Paul is reducing the number of different systems used. They both report that relying on one system for the entire municipality reduces the burden on technicians/operators as they only need to learn how to perform maintenance on that one product. Additionally, neither entity reported that any of the NIT products deployed provided better functionality/ease of programming than the others.

[1] "The accounting department filtered the labor and non-labor costs for lens cleaning and the summary shows the annual cost ranged from 188K to 218K."

Chapter 3: NIT Products Description

3.1 Introduction

This section overviews the most commonly used NIT detection products MnDOT employs. These include the Gridsmart Cubic system, the Autoscope Vision system, and the Iteris Vantage Next System. More information on the companies and products currently on the market can be found in Appendix C. For cost comparison, we list the prices of loop detector contracts in Table 3.1. These prices are provided by MnDOT.

Table 3.1 Contract prices for loop detectors as of March 2024

Item	Cost
EDI 4 CH detector card	$332.00
6x6 loop	$1300
1 ft homerun/lead in cable	$1.25

3.2 Autoscope – Vision

GENERAL DESCRIPTION OF EQUIPMENT: Autoscope Vision® is an integrated camera-processor sensor that provides high-performance stop bar vehicle detection, bicycle detection and differentiation, advanced vehicle detection, traffic data collection, and High-Definition video surveillance. Autoscope Vision is capable of concurrently satisfying multiple transportation management objectives:

- Stop bar vehicle detection
- Bicycle detection and differentiation
- Advanced vehicle detection up to 600 feet from Vision sensor
- Traffic data collection
- HD video surveillance

TECHNOLOGY USED: Machine Vision using high-definition (720p) camera

SENSOR INSTALLATION: Autoscope Vision installs on existing signal poles, mast arms, and luminaire standards.

INSTALLATION REQUIREMENTS: The camera and sensor are integrated into one unit. Camera mounting over the center of monitored lanes provides optimum performance. The minimum camera mounting height is 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: Six to seven

NUMBER OF DEVICES PER INTERSECTION: one per intersection leg (a four-lane intersection will have cameras).

COST (MnDOT contract prices as of March 2024):

- $6915.00 per camera
- $4450.00 per camera control unit (CCU)
- $1595.00 per 1400ft of cable
- $150.00 per camera bracket

3.3 Iteris – Vantage Next

GENERAL DESCRIPTION OF EQUIPMENT: Vantage Next® is Iteris' second-generation vehicle detection platform that capitalizes on the latest technology. Vantage Next uses a powerful processor that enables future functional growth while maintaining proven Iteris video detection performance and reliability. One significant difference to the Edge2 product family is that the camera sensor is now a POE IP camera connected to the system through a CAT5 network cable. The platform also supports different sensors like the video and radar hybrid (Vantage Vector) and radar only (Vantage Radius).

TECHNOLOGY USED: Machine vision using high-definition (720p) camera and radar

SENSOR INSTALLATION: Camera installs on existing signal poles, mast arms, and luminaire standards.

INSTALLATION REQUIREMENTS: Camera mounting over the center of monitored lanes is ideal, with a minimum height of 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: Up to 4 sensors

NUMBER OF DEVICES PER INTERSECTION: camera+radar for each mainline leg and one camera for each minor leg.

COST (MnDOT contract prices as of March 2024):

- $2010.00 per standard camera
- $5999.00 per camera-radar hybrid
- $13345.00 per camera control unit (CCU) supporting 4 cameras/camera-radar hybrids
- $2000 per 1000ft of cable
- $150 per camera bracket

Chapter 4: Research Data

4.1 Introduction

This research uses several data sources to evaluate the performance of NIT products. This chapter provides an overview of the data sets we use in the research pipeline (Chapter 5). This chapter discusses the Traffic Camera, Signal Controller, and Weather Data and summarizes these data sets in the following sections. Further details can be found in Appendices D, E, and F.

4.2 Traffic Camera Data

The Traffic Camera Data is video data we collect from traffic cameras around the Twin Cities Metropolitan Area. MnDOT provides the data which contains the video recordings from traffic cameras in *.mp4 format. Of the 39 original cameras from MnDOT, we are able to identify the locations of 31 of these cameras. In our approach, we evaluate 6 cameras shown in **Figure 4.1**. Of these cameras, 4 use the Autoscope Vision detection technology, and 2 use the Iteris Vantage Next Detection Technology. We choose to exclude the Gridsmart NIT because it is not widely deployed in the study area. We select cameras using these detection technologies because they are the most widely used systems within the Twin Cities Metropolitan area. Video data is collected from 11/22/2021-05/20/2023 and 08/09/2023-10/07/2023.

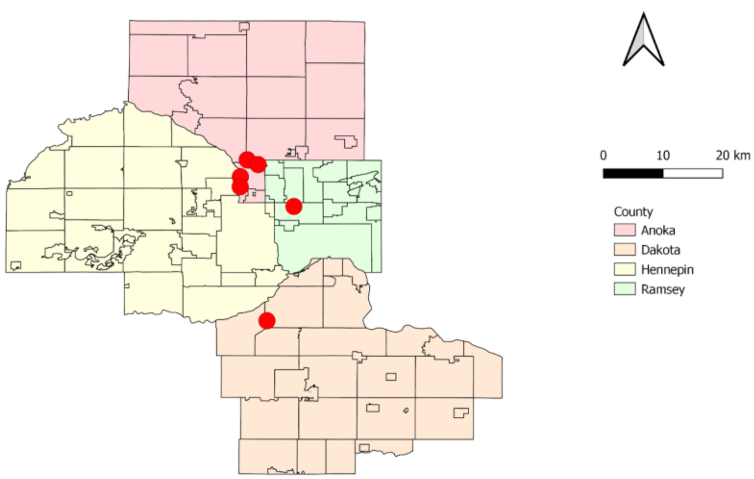

Figure 4.1: The locations of the six cameras we study overlaid on the county map of the Twin Cities Metropolitan Area.

Our manual evaluation of portions of the video data shows that most failures in the NIT systems employed by MnDOT are due to bad weather conditions, such as heavy snow/rain, high wind speeds, and low temperatures. We also find that particles of snow, rain, or dirt accumulating on the camera lens cause more long-lasting failures. Our approach determines when these types of failures occur using the video data. More details on this analysis are provided in Appendix E.

4.3 Signal Controller Data

We collect the Signal Controller Data from intersections with cameras MnDOT provides in *.CSV format as a downloadable link and download all records from the MnDOT website. The Signal Controller Data contains temporal event data on signal changes, maintenance, and traffic passing through the intersection. We use this data as our primary means of evaluating the performance of NIT in detecting traffic moving through an intersection. We collect Signal Controller Data from the 6 sites in section 4.2 between 12/20/2022 and 01/10/2023. Each event specifies a Time (Year, Month, Day, Hour, Minute, Second, Millisecond), Camera ID, Event Code, and Event Parameter. Event Codes are specific values that indicate the type of event based on a pre-defined schema [10]. In our approach, all Event Codes that are not 81/82 are excluded because they do not directly correspond to vehicle counts based on detector activation.

The Signal Controller Data provides traffic detection data for both NIT and baseline detectors in the intersection. These baseline detectors can be loop detectors, radar detectors, or other types previously used by MnDOT. There is no good way of determining which type of baseline detector MnDOT previously deployed at a specific location, so we lump all of these devices into a single baseline detector category. In our evaluation of NIT performance, we separate these baseline detectors from the NIT detectors based on the Event Parameter. The Event Parameter is a numerical value MnDOT assigns to a detection volume at an intersection (See **Figure 4.2).** MnDOT provides a rule that Event Parameters 1-4 correspond to the baseline detectors, and all other Event Parameters correspond to NIT devices. A more detailed analysis of the Signal Controller Data can be found in Appendix E.

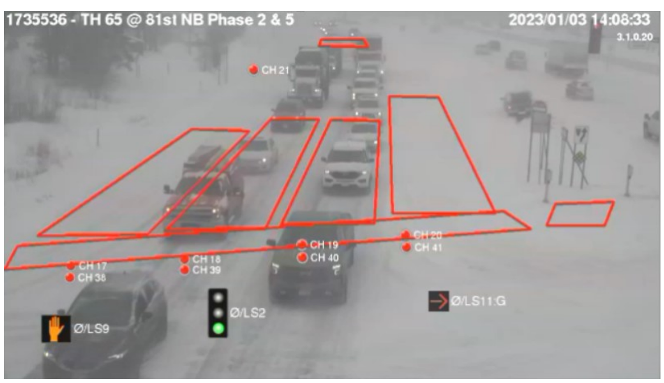

Figure 4.2: A snippet from a NIT device showing Event Parameter values. All Detection Volumes (outlined in red) in the image have two associated Event Parameter except for the two bottommost and the topmost volumes.

4.4 Weather Data

Weather Data is directly collected from weather stations around Minnesota, and we download the records from MDSS (www.webmdss.com), which reports weather data every 5 minutes as a *.CSV document. It contains metrics describing temperature, humidity, visibility, etc. We collect Weather Data from December 2022 and January 2023 to cover the same period as the Signal Controller Data from several weather stations within the Twin Cities Metropolitan Area (See **Figure 4.3**). The results of both the operator interviews (Appendix B) and our analysis of the Video Data (Appendix E) indicate that weather conditions are the primary cause of NIT failures. As a result, we choose to make the Weather Data a core part of our NIT performance analysis. A more detailed analysis of the Weather Data is provided in Appendix E.

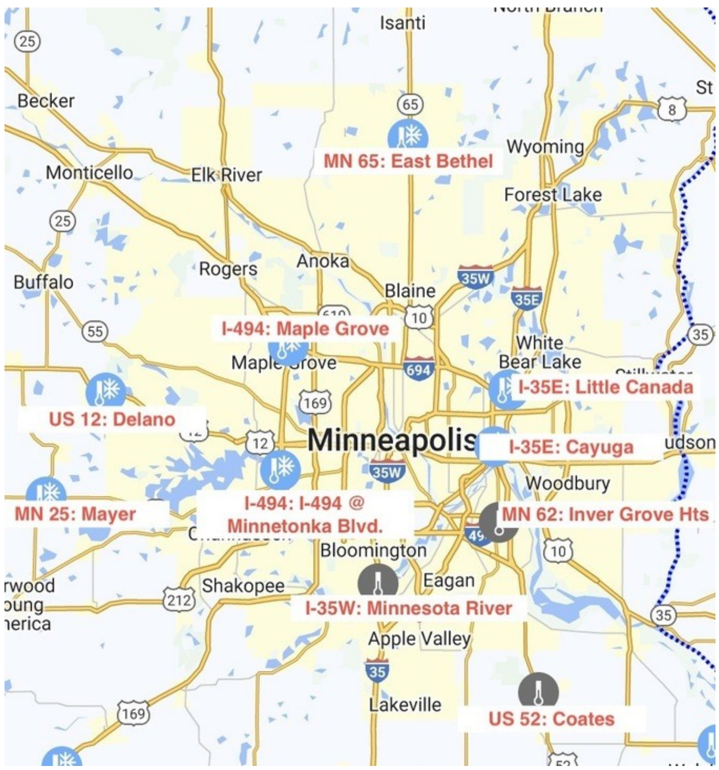

Figure 4.3: The weather stations within the research study area

Chapter 5: Research Approach/Implementation

5.1 Introduction

Our research approach is motivated by the results of the interviews with intersection owners/operators (Chapter 2) and our data analysis (Chapter 4). The results of the interviews indicate that while analyzing overall NIT failures is essential, most of the cost of maintaining NIT comes from routine maintenance and cleaning. Both the interviews and our data analysis indicate that snow, rain, and dirt can accumulate on camera lenses, rendering them inoperable for long periods. Additionally, the interviews and our data analysis indicate that severe weather conditions cause most NIT failures. As a result, our research approach focuses primarily on determining the underlying weather conditions that cause different NIT devices to fail and under what conditions snow, rain, and dirt tend to accumulate on the lens. Using the results of our approach, we provide analysis for failure rates of different detection technologies and specifics on what weather conditions primarily contribute to NIT failure. More details on our research approach, implementation, and results can be found in Appendix G.

5.2 Approach

This study uses the Signal Controller, Weather, and Video Data described in Chapter 4 to detect, categorize, and perform a correlation analysis of malfunctions of NIT detection technologies. In **Figure 5.1**, we show an overview of the methodology through a flow chart with color-coordinated sections for each sub-task in evaluating NIT performance.

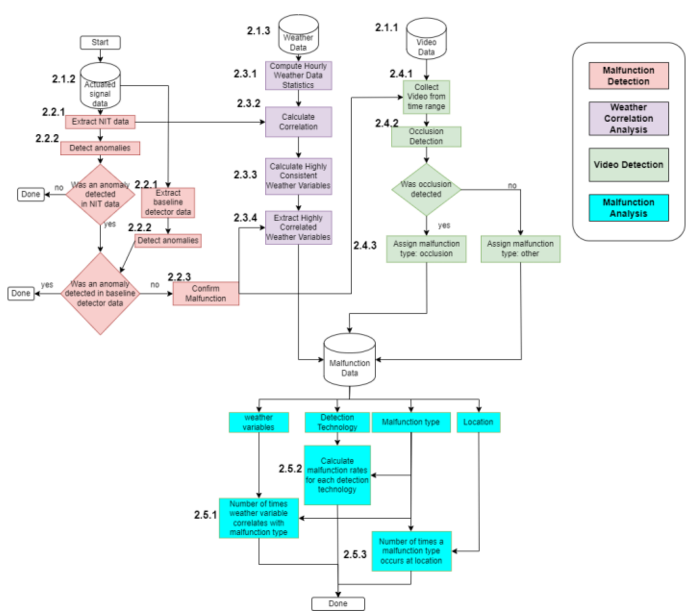

Figure 5.1: The flowchart of our proposed methodology broken down into color-coordinated sections.

In the Malfunction Detection section, colored red on the flowchart, we use the Signal Controller Data to determine when a NIT device is experiencing a malfunction. We perform a pre-processing step on the Signal Controller Data and calculate the number of detected cars passing through an intersection, the average amount of time cars were in detection volumes, and the total amount of time cars were in detection volumes. We then compare these statistics to historical averages using Pearson Correlation, a statistical measure that quantifies the degree and direction of a linear relationship between two continuous variables, to obtain anomalous periods in the NIT and baseline detectors. Using the baseline detectors as our ground truth, we extract the anomalous periods in the NIT devices that are not anomalous in the baseline detectors. Extracting only anomalous behavior in NIT devices ensures that we only evaluate conditions that cause NIT devices to fail.

In the Weather Correlation Analysis section, colored purple on the flowchart, we use the Weather Data and the periods when NIT devices fail from the Malfunction Detection section to determine which weather conditions caused the NIT failure. This process extracts weather variables highly correlated to NIT failures and labels them as a cause of the NIT failure. Through this, we gather statistics on what weather conditions cause failures in NIT.

In the Video Detection section, colored green on the flowchart, we use the Video Data and the periods when NIT devices fail from the Malfunction Detection section to determine if there is snow, rain, dirt, etc., blocking the camera lens. This method categorizes NIT failures depending on whether there is a blockage. We distinguish between NIT failures requiring on-site maintenance and those that do not.

In the Malfunction Analysis section, colored teal on the flowchart, we use the results from the three prior sections to compile statistics on NIT failures. We analyze weather effects on each NIT device in the study area and the different malfunction types (defined by the Video Detection section). We also compile overall NIT device performance information to determine which technology performs better. Finally, we look at which locations experience more NIT failures than others to help guide future NIT placement.

5.3 Research Results

This study analyzes the effects of weather, different detection technologies, and location on NIT performance. In our analysis of the effects of weather on different detection technologies, the study finds evidence supporting the claim made in prior research (See Chapter 1.2) that no single NIT product outperforms others in all cases. While the Iteris detection technology is more susceptible to malfunctions caused by weather conditions, NIT devices with the Iteris detection technology experience fewer overall malfunctions than the NIT devices using the Vision detection technology. We also find that devices using the Iteris detection technology are more susceptible to failures caused by snow, rain, or dirt occluding the lens. These results indicate that cameras using the Iteris detection technology require more on-site maintenance to function correctly. In looking at the locations where NIT products are employed, we find that some locations experience more NIT failures than others. In particular, the NIT device at the intersection of 81st Ave NE and Highway 65 NE experience the most overall NIT failures. The results of our analysis are discussed in more detail in Appendix G.

Chapter 6: Conclusions and Recommendations

6.1 Conclusions

This chapter combines the results from the previous chapters and gives recommendations for implementing the results and what MnDOT can do to continue evaluating NIT products. We primarily use prior work, interviews with the intersection owners/operators in Hennepin County and St. Paul, as well as the results from the research approach.

The initial results from the prior analysis and interviews with intersection owners/operators indicate that adverse weather conditions, primarily those with high winds and rain or snow, negatively affect the performance of NIT products. In addition, we find that NIT failures caused by these adverse weather conditions often require on-site maintenance to resolve as snow, rain, dirt, etc., accumulate on the lens. From interviews with intersection operators/owners, on-site maintenance is the primary expense when maintaining NIT as most other failures can be resolved off-site. Our research confirms that these weather conditions cause many NIT failures and that we can predict them by observing wind speeds and reported visibility. The interviews with intersection owners/operators support this conclusion, as intersection owners/operators have already taken steps to address this by monitoring and cleaning NIT products after storms involving high winds.

Using the contract cost estimates for recent NIT and loop detector installations and an example “T” intersection provided by MnDOT (Figure 6.1), we can compare the installation cost of the different NIT products and the loop detectors. For loop detectors, we require 36 6x6 loops, 26 lead-in cables, and 9 EDI 4 CH detector cards, which sums to $49,820.50 for this intersection, not including extra costs for conduits and handholds. For an Autoscope Vision installation, we require 3 cameras and camera brackets, 1 camera control unit, and around 1 loop of 1400 ft cable (we estimate ~1000 ft of cable for an average intersection), which sums to $34,305.00. For an Iteris Next installation, we require 2 camera-radar hybrid cameras, 1 standard camera, 3 camera brackets, 1 camera control unit, and 1 loop of 1000 ft cable, which sums to $29,803.00. Using these figures, we estimate that loop detector installation can cost around 1.5 times the amount of an Autoscope Vision or Iteris Next installation. Moreover, Iteris Next generally costs less than an Autoscope Vision installation with a $916 difference between the Iteris Next hybrid camera and the Autoscope Vision camera in this example.

When comparing NIT devices, our research supports the results in prior work that no one NIT system outperforms all others in all weather conditions. However, the performance of different NIT products diverges when subjected to different weather conditions and factors like snow, rain, dirt, etc. contribute to lens blockage on some NIT products more than others. In addition, we find that specific locations experienced more NIT failures than others.

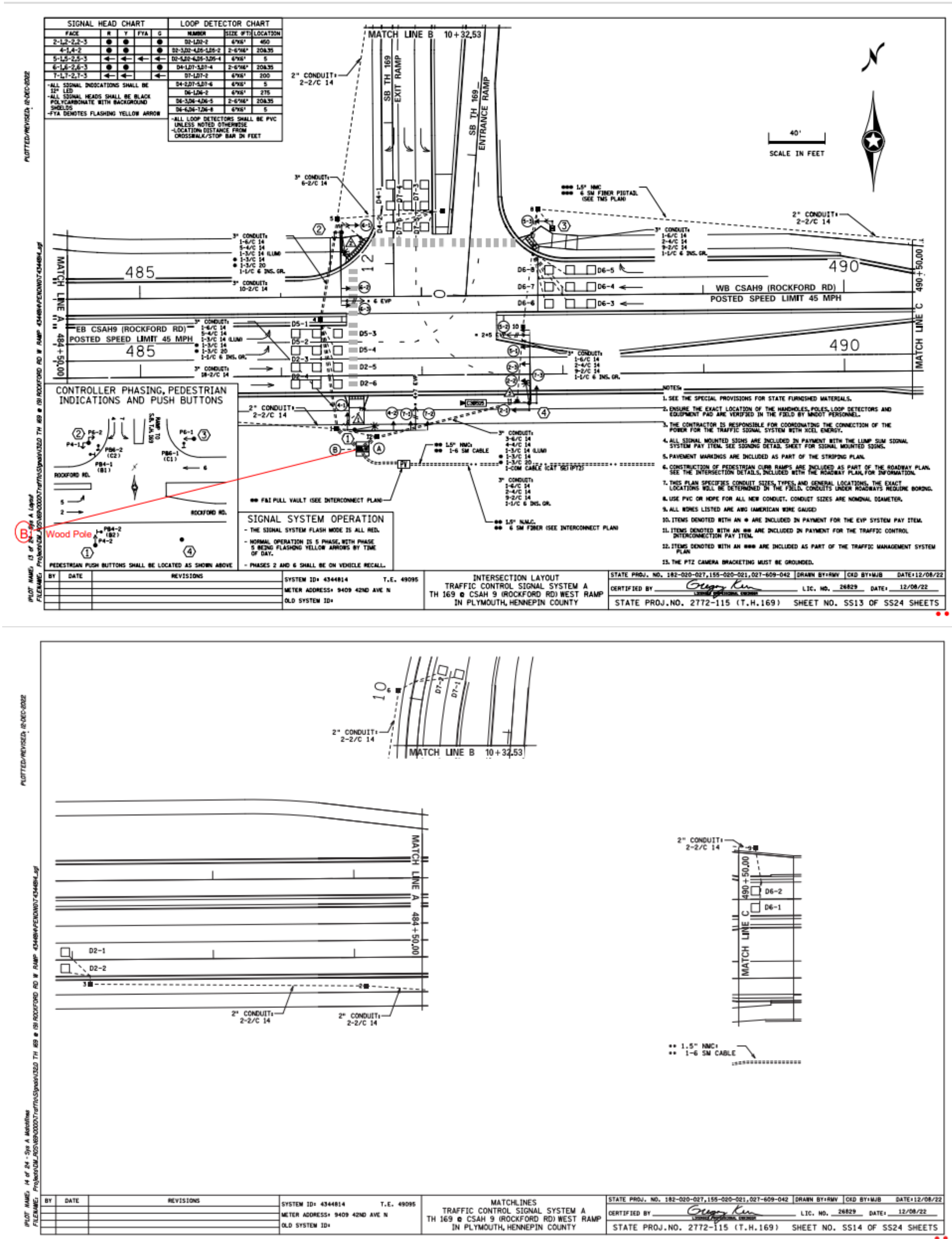

Figure 6.1: An example intersection for NIT and loop detector installation (a) the top figure depicts an example intersection installed by MnDOT (b) the bottom figure depicts the lead-in rows to (a).

6.2 Recommendations

From the interviews with intersection owners/operators, we know that glare from external light sources causes many NIT failures. From operator interviews, we recommend angling cameras at intersections to reduce this by adjusting the angle below the horizon line and installing glare shields on the sides of the camera to reduce glare. We also note that a significant glare source can come from the sun reflecting off snow when a large amount accumulates on the road. As such, we recommend installing filters on affected cameras to reduce glare and continue making periodic adjustments to camera positioning when necessary. Moreover, both Hennepin County and St. Paul signal operators employ a tactic to put all NIT devices on a central monitoring system. Adding devices to a remote access network helps operators diagnose failures remotely and reduces the need for on-site maintenance, potentially reducing costs for operators. This does not take into account potential externalities from the cost to the traveling public. Employing a central monitoring system could also reduce the need for on-site maintenance and allow operators to diagnose problems in NIT devices more quickly, reducing overall costs.

The results of our research show that while NIT products tend to have similar overall performance, under specific weather conditions performance diverges. Using the results from our research and the prior reports we compile our recommendations in the form of a flow chart (Figure 6.2). We recommend considering local weather conditions and the relative performance of different NIT products when selecting a NIT product for an intersection. Furthermore, we provide examples of accessories that can be installed on the camera to prevent failures as well as maintenance schedules and windows that operators should consider when reviewing intersections. We recommend routinely checking the NIT devices through the central monitoring system after severe storms, especially those involving low visibility and high wind speeds. Furthermore, we recommend installing heat shields on all NIT devices to reduce the need for on-site maintenance to clear snow and rain.

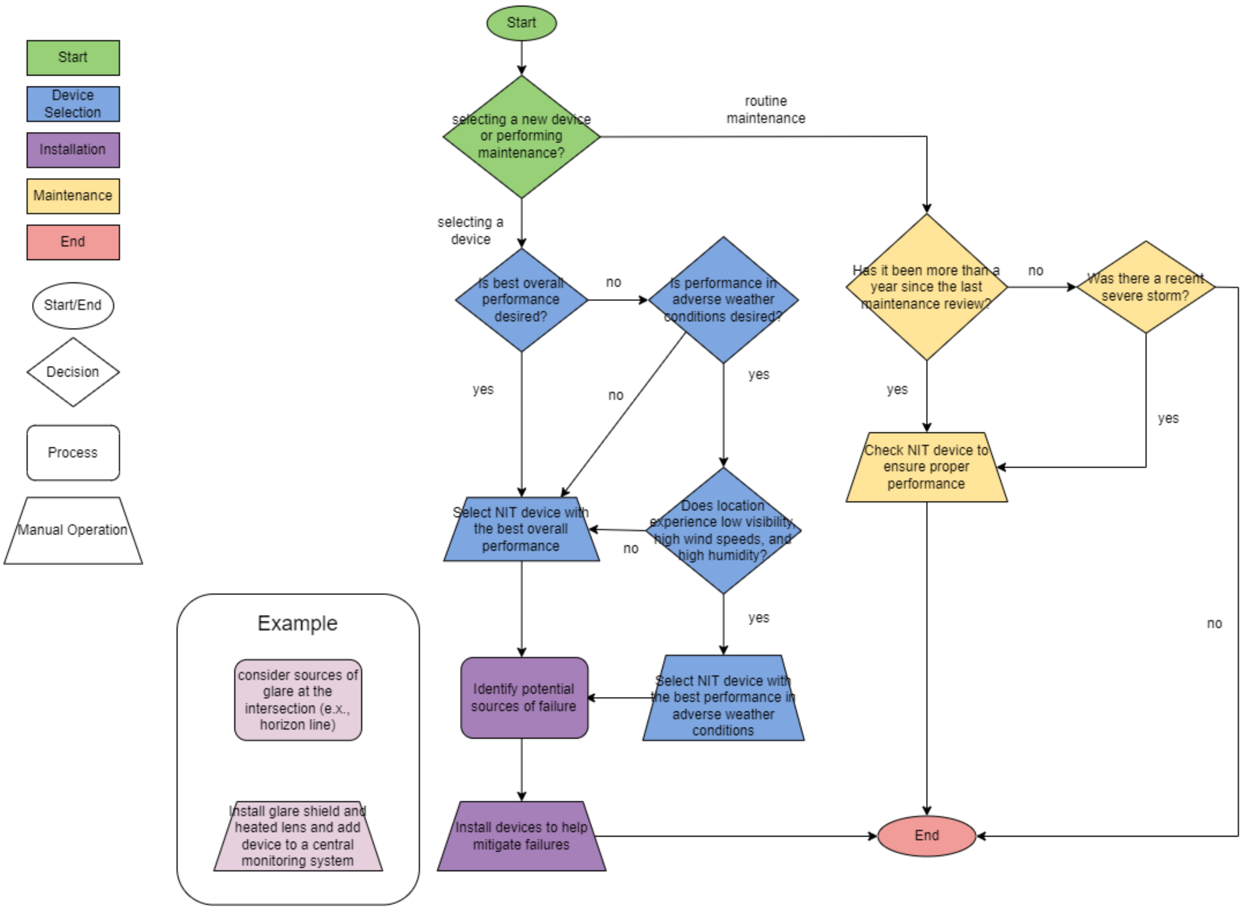

Figure 6.2: Recommendations for installation and maintenance of intersections. Users are asked to consider local weather features before selecting NIT devices and installing proper accessories to help prevent failures. We also include recommended maintenance schedules and windows.

6.3 Future Work

In summary, performance evaluation of different detection technologies for signalized intersections is important, especially for NIT devices because they rely on what a camera can visually see. Any time a camera is used in a NIT device (e.g., for vehicle detection), there will be affects and limitations to the continual successful operation, maintenance, and costs to the signal system. In the future, we would like to conduct a more in-depth analysis of sources of glare-reducing NIT performance. Our research shows that glare is a factor in causing NIT failures, but we do not differentiate between glare from the sun, glare caused by headlights, and glare caused by reflections from the road. We would also like to conduct further studies on a wider variety of NIT products to compare performance and cost. Finally, we would like to perform a more in-depth analysis of how intersection geometry and geographical context affect camera performance. We find a high discrepancy between the number of NIT failures at different locations, and determining the underlying cause of this would allow better deployment of NIT devices to reduce overall costs and improve efficiency.

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Appendix A: Task 1 Deliverable

Performance Evaluation of Different Detection Technologies for Signalized Intersections in Minnesota

MnDOT Contract No. 1036342 Work Order No. 18

Task 1: Initial Memorandum on Research Benefits and Implementation Steps

Intersection control can be pre-timed or vehicle actuated. Modern controllers implement natively only actuated control with pre-timed implemented as the special case of actuated, termed vehicle Recall. Actuated signals respond to the traffic present at the intersection, so that the pattern of the signal (the length and order phases) depends on the traffic and can be different at every cycle. In all versions of actuated control, the cornerstone of the system is vehicle detection. MnDOT and many local MN agencies have traditionally used embedded loop detectors in the pavement for detecting vehicles. Although the performance of a well-placed loop detector has yet to be matched by any other method, changes in the vehicle fleet (higher use of non-ferrous material) as well as increased need for more comprehensive detection (vulnerable road users, all lanes individual advance and stop line detection) has resulted in the increased use of Non-Intrusive detection Technologies (NIT). As stated in the NS, testing of these newer technologies on MN intersections has not been conducted in a comprehensive way. Although there are studies evaluating the performance of NIT detection, all have been racing against obsolescence given the rapid developments in the market, and more importantly all of them have focused in the comparative evaluation of different detection technologies. Unfortunately, there has been very few studies identifying the long term true costs of operating and maintaining such intersection control systems. The goal of this project is to provide guidance to MnDOT and LRRB members on selecting the most appropriate technology for a given location as well as on the expertise, effort, and material cost involved in maintaining each of these systems year round in Minnesota. Achieving this goal involves two parallel but separate efforts.

The first effort aims in synthesizing national and local experience procuring, deploying, and maintaining NIT for signal operations. On the national level, the project will establish a baseline on the currently available detection technologies and the products in the market that employ them as well as compose a synthesis of current research on the performance of NITs. On the local level, a survey of signal operation and maintenance offices covering the entire state of Minnesota and neighboring states, on their use and experiences with NITs for signal control, will be followed by a series of interviews to collect practitioner experiences in operating and maintaining the different detection products.

The second effort involves a year round observation and recording of performance of selected real deployments of all major products used in Minnesota. Sites will be selected based on varying geometry and demand characteristics. At these sites, field or remotely placed hardware will record all control signals (actuations and phase changes) coming in and out of the controller while separately recording of the detection system available raw data and/or video from additional Minnesota Traffic Observatory

(MTO) cameras. Where possible already deployed infrastructure will be used. Analysis of these records will produce year round records of detection system errors affecting actuated control such as False Calls, Missed Calls, Stuck-on Calls, and Dropped Calls. The produced event records will be correlated with weather measurements of wind and temperature, as well as environmental conditions like snow, rain, pavement condition, time of day (lighting), etc.

TABLE 1. EXPECTED RESEARCH BENEFITS

Benefit Category	Are the benefits quantifiable (Yes/No)	How these key benefits will be quantified?
Climate Change & Environment	Yes	Cumulative time vehicles spent idling on red due to NIT miss detection. Separately for main and side road approaches.
Improved Safety	Yes	% reduction of time period intersection is placed on all phase recall. % of time bad detection resulted in insufficient yellow clearance interval.
Operation and Maintenance	Yes	Newer detection technology for traffic signals may perform better at same or reduced costs. Determine which technology has the lowest long term costs for the life of the signal system.

Benefits

The expected benefits from this research encompass several categories. **Table 1** provides an overview of these benefits.

The cost of the vehicle detection instrumentation for a fully actuated control can go as high as $40,000 per intersection and although manufacturers always claim that their systems require minimum maintenance, as pointed by the NS champions, several of the currently operational intersections owned by MnDOT had to be put on Recall mode last winter due to failures of the detection system. Such events, not only represent safety hazards until they are discovered, they can generate long delays to road users and dramatically increase maintenance costs. The proposed project will identify the most common forms of failure, develop and propose early detection of performance reductions, as well as provide guidelines on the required periodic maintenance and replacement (possibly half-life of entire system) actions that can minimize signal control down times. These will result in benefits from better estimating life cycle costs leading to higher return on investment as well as minimize road user costs in the form of traffic delays and crashes.

Implementation

In addition to the technology reports and synthesis documents delivered during the project, the final goal is to provide guidance to MnDOT and LRRB members, not only on selecting the most appropriate technology for a given location, but also on the expected expertise, effort, and cost involved in maintaining each of these systems year round in Minnesota for the life of the signal system. The final product delivered will be a decision tool to guide signal design by MnDOT and other public works entities in Minnesota. Although the precise form this decision tool will have is not yet clear, on request of the TAP, it will include regular loop detectors as a baseline for comparison. Information regarding life cycle costs of loop installations will be based on information collected during the interviews as well as from relevant literature.

Appendix B: Task 2 Deliverable

Performance Evaluation of Different Detection Technologies for Signalized Intersections in Minnesota

TASK 2 DELIVERABLE:

Survey of and interviews with intersection owners/operators

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November 2022

Introduction

The goal of Task 2 was to collect and compile real world experience in working and maintaining NIT vehicle detection installations. Towards that goal we have communicated and attempted to survey all major NIT owners/operators in Minnesota. Specifically, we contacted the following organizations:

1. Hennepin County
2. Washington County
3. Dakota County
4. City of Minneapolis
5. City of St. Paul
6. All MnDOT District offices

Indirectly we have also collected information from MnDOT Metro since the information sought was identified along with project liaisons in the office of signal operations. Unfortunately, a minority of the aforementioned entities replied to our call for information. Specifically, from the ones that indeed own NIT detection systems, only Hennepin County and the City of St Paul responded back. Therefore, this report is based on the information received them and from MnDOT Metro.

In this task report we will first describe the survey content and information sought during the in-person interviews, followed by a compilation of the information collected.

Developing the Survey

As already mentioned the goal of the interviews will be to collect practitioner experiences in operating and maintaining the different NIT based detection products. The following is a copy of the email send to the entities mentioned in the previous section.

> As part of a MnDOT-sponsored project, the University of Minnesota is investigating the performance of different non-intrusive vehicle detection technologies for signalized intersection control. The main objective of the project is to collect information regarding the full life cycle cost of such systems to inform current and future signal owners. The project has selected a large number of MnDOT operated signals utilizing such detection systems and is conducting a year round observation of their performance.
>
> On a separate task we would like to meet and discuss with owners, operators, and maintainers of such vehicle detection systems around the state. The following is an incomplete list of the types of information we seek to accumulate.
>
> - Frequency of down-times per intersection/detection system

- How do you monitor this?
- Frequency of system operational parameter adjustment in order to maintain desired performance.
- Average effort and/or estimated annual expenditures to keep the system running
    - Cleaning, upgrading, adjusting cameras, etc.
- Effort in monitoring, identifying that something is wrong, and taking action.
- Need for stockpiling of replacement equipment
    - What components fail more often (per OEM)
    - Labor of maintenance is a cost even if the replacement part is free.
- Firmware upgrades
    - Free for life, requiring subscription, or a maintenance plan?
- Helpdesk service cost?
    - On-site help available? Cost?
- Learning curve per system.
    - Who's learning curve?
        - Technician, Engineer, Operator?
- Responsiveness of system providers.

You are receiving this email because you have been identified by the project Technical Advisory Panel (TAP) as a first point of contact because you can provide the relevant information and/or you can forward this email request to other people in your organization who can benefit this research. We would appreciate if you can assist us in organizing one or more information gathering meetings with the relevant persons in your organization.

If you have any questions regarding the project, please feel free to communicate with me (info at the end of the message) or the MnDOT technical liaison Mr. Steven Misgen.

Prior to the interviews, a more extended questionnaire was communicated to assist in the conversation.

This questionnaire was the following:

Introduction to the project

Although the performance of a well-placed loop detector has yet to be matched by any other method, changes in the vehicle fleet (higher use of non-ferrous material) as well as increased need for more comprehensive detection (vulnerable road users, all lanes individual advance and stop line detection) has resulted in the increased use of Non-Intrusive detection Technologies (NIT). **Video is less than half of the price of a loop installation.**

There has been very few studies identifying the **true costs of operating and maintaining** such intersection control systems. This proposal aims in providing guidance to MnDOT and LRRB members on selecting the most appropriate technology for a given location as well as on the expertise, effort, and material cost involved in maintaining each of these systems year round in Minnesota.

The goal of the interviews is to collect practitioner experiences in operating and maintaining the different detection products.

Trying to understand and estimate the Full Life Cycle Costs.

Discussion Questions:

1. Approximately how many signalized intersections do you own and/or operate?

2. How many of those utilize vehicle detection?
    a. How many use NITs?
3. What prompted you to transition to NITs?
    a. How long have you been using NITs?
4. Do you use one type of product or manufacturer or have several different ones?
    a. Any products that involve subscription?

5. (Multiple Systems or Single OEM)
    a. What is the Learning curve per system?
        i. Who's job is to learn the system? Technician, Engineer, Operator?
        ii. How much of this effort do you outsource?
        iii. Is a similar cost involved in loop installation and operation?
6. How often do you inspect/adjust the system operational parameter to maintain desired performance?
7. What is the effort in monitoring, identifying that something is wrong, and taking action?
8. On average what is the frequency of down-times per intersection/detection system
    a. How do you monitor this?
9. Average effort and/or estimated annual expenditures to keep the system running
    a. Cleaning, upgrading, adjusting cameras, etc.
10. Do you see a need to stockpile replacement equipment/parts?
    a. What components fail more often (per OEM)?
    b. Labor of maintenance is a cost even if the replacement part is free.
11. Firmware upgrades
    a. Free for life, requiring subscription, or a maintenance plan?
12. Helpdesk service cost?
    a. On-site help available? Cost?
13. Responsiveness of system providers.
14. What is the construction/reconstruction related differences between loops and NIT?
    a. Loops are often changed with someone else paying for the cost (road surface maintenance project). Maintenance projects now drop the cost to the signal operator unless signal poles are affected.

Interview with Hennepin County

The interview with Hennepin County took place on June 17th 2022 at the traffic operations center in Medina, MN. Ben Hao, the director of signal operations organized the meeting and invited several other county employees from the signals and maintenance departments. Prior to the meeting, Mr Hao had solicited the input from all relevant stakeholders. The following section is composed mainly by the minutes of the meeting as provided by Mr Hao.

1. Hennepin County operates 450 signals
    - All signals are semi or fully actuated.
    - Vehicle detection utilizes video NITs. No loops remain in use.
2. The products used through the system are primarily Vision, Terra, and Encore by Econolite
    - Currently the group is testing one Iteris Next and one GridSmart products.
3. Why moved from loops to video?
    - Video is cheaper to maintain due to mill and overlay (from ops or construction budget).
    - The cost for maintenance is due to the cause of the replacement.
    - $10K to replace one loop, resulting to $200K for an intersection
    - Video is easy and flexible to configure the zones
4. Tech support is free by TCC.
    - When asked regarding preferential treatment to big customers, the group replied that to their knowledge TCC does not charge for tech support regardless of the size of the system.
5. What should users know to move from loops to video
    - Vision: TCC provides all training and helps with turn-ons
    - Contrast failures are by nature the limitations for video so good understanding of the camera view in relation to external light sources (sun, luminaires, etc.) is important.
    - Field techs need to have developed enough experience working with each system. This is the reason why Hennepin avoids having a large variety of products.
    - Connecting the intersections to the network allows access and management of the system. The majority of issues that arise can be worked on remotely by changing the zone configuration.
6. How do NIT systems cope with Minnesota weather?
    - Winter impacts the lens clarity.
    - Camera housing with heated lens is absolutely necessary.
    - Snowstorms cause failures of detection due to contrast failures.
    - Sun glare also causes contrast failure. It is important to take the horizon into consideration when install the camera.
    - Usual issues involve inappropriately installed Sun shields.

Glare from the road can be also an issue. There can be a difference between concrete and asphalt pavements and wet surface may have more impact than dry pavement.

7. Frequency of down-times per intersection/detection system
    - How do you monitor this?
    - Complete system failures are extremely rare.
    - The ATMS software (MaxView[2]) provides alarms for detection malfunction on a daily basis.
        - In rare cases issue detection comes from citizen comments.
    - Would like to have some external auditing application monitoring the systems. The county is currently considering acquiring such applications. Currix. TraffOps (ATSPM and AI).

    - Effort in monitoring, identifying that something is wrong, and taking action.
        - Adjust detection configuration, cleaning, cycle the power.
        - Put min recall for contrast failures
        - ATMS software would generate alarms for contrast failures
        - Loops can also have intermittent failures
8. Frequency of system operational parameter adjustment in order to maintain desired performance.
    - Dependent on when the detectors are down, generate false calls, or have contrast failures.
    - Most issues are dealt by adjusting zoom, scope, and virtual detection zone dimensions.
        - Latest Visions firmware allows for user adjustment of the contrast failure threshold.
9. Average effort and/or estimated annual expenditures to keep the system running
    - Cleaning, upgrading, adjusting cameras, etc.
    - Annual cleaning takes several months to complete.
        - One staff member does it for three months
        - Estimated cost of $10K for cleaning/year for all 450 intersections.
    - Upgrading the firmware is easy and can be done remotely. Can do multiple cameras at one time.
10. Need for stockpiling of replacement equipment
    - Not a lot of inventory is necessary.
    - Once or twice per year a camera may be hit by lightning.

[2] Note that MaxView is now Kinetic® Signals as of April 2024.

- Only once lighting fried all interface cards that connect to the cabinet.

- Vision systems installed in 2017. It has been 5 years and no hardware issues have been reported. Very reliable.

11. Firmware upgrades
    - Free for life.
    - Do not require subscription

12. Helpdesk service cost?
    - TCC is under county contract

13. Learning curve per system.
    - Switching from Terra to Vision is easy. It is user friendly.
    - Power Over Ethernet system (POE) connects camera to cabinet Vision in the field.
    - Tech can access and configure in the field with the one cable.
    - Initial install: County staff do it.
        - TCC may provide tech support if needed.
        - Contractor may pay TCC to do the initial setup for construction projects.
    - County does all the maintenance.
    - Signal shop technicians and TMC engineers
    - TCC provides training

14. Responsiveness of system providers.
    - TCC is responsive.
    - Comes out in the field the same day or the next day.

Interview with City of St. Paul

The interview with the City of St Paul took place on October 17th 2022. Initially Mr Mike Klobucar, director of the Traffic & Lighting Division in the Department of Public Works had solicited answers to the introductory questions communicated with the original survey email. The follow up meeting over teleconference helped to drill down to additional details. The following is a compilation from both information sources.

1. The City of St Paul operates 390 signals.
    - Approximately 90% of these signals are actuated.

- Approximately 70% of the signals still use loops for vehicle detection while a couple of locations use Wavetronix radar.
- Current plan is to move towards video by replacing loops with video when road is resurfaced.
- Main reason for switching to video is to adequately cover the bike lanes. Loops have not been successful in that regard.

2. The video based NIT detection products use are mainly Vision with some older Terra by Econolite.
    - There are approximately 4 sites that currently use GridSmart.
3. Frequency of down-times per intersection/detection system:
    - Very minimal down times. Main cause of down time due to storms such as lighting, strong winds, heavy snow fall, knocked down poles due to accidents and camera failures.
    - How do you monitor this?
        - City monitors signal detection systems by setting up alerts through the central signal system (Centracs). They are able to review the individual alert, troubleshoot and/or make necessary adjustments to resolve the issue.
        - For unresolved issues and off network detection systems, a request is submitted for the city electrician to investigate and perform field troubleshooting.
4. Frequency of system operational parameter adjustment in order to maintain desired performance.
    - As needed to maintain optimal performance when alerts are reported by Centracs.
    - There is a review of all on network detection systems monthly to make sure desired performance is met.
    - For off network detection systems when issues are reported they perform field trouble shooting.
5. Average effort and/or estimated annual expenditures to keep the system running
    - Upgrades & adjustments are fairly low effort. City tries to proactively monitor.
    - Once a year all cameras are cleaned with additional rare cases after some major winter storms.
    - All systems are reviewed every three weeks as well as after major events involving strong winds.
6. Effort in monitoring, identifying that something is wrong, and taking action.
    - Review the detector alert, observe and investigate if there is an actual problem when the alert is reported by Centracs and/or citizen. If a problem is discovered, trouble shoot, make adjustments, and/or restarting detector system. If cannot be resolved, inform and have electrician investigate in the field and repair/replace equipment as needed.
7. Need for stockpiling of replacement equipment
    - There haven't been a lot of failures. A couple of detector cards failed, and a few issues involved manufacturer defect.
    - City does its own maintenance.

8. Firmware upgrades
    - Free firmware upgrade when available and/or to resolve issues for purchased systems.
9. Helpdesk service cost?
    - On-site help available? Cost? Depends on the vendor. Typically no cost if all other troubleshooting options are exhausted.
10. Learning curve per system.
    - Technicians/operators probably have the largest learning curve, with the need to use multiple applications if multiple camera systems are in use.
    - City's electricians don't seem to have issues with installation in most cases.
11. Responsiveness of system providers.
    - Same day or the day after reported to providers. Provides tech support in resolving the problem/issue and assist in other trouble shooting methods.
12. General comments:
    - Most important reason for switching to video based detection is to cover bike lanes.
    - The Green LRT line is where the bulk of the video based detection is. System is 8 years old and has encountered very few issues.
    - In difference to MnDOT and the counties, the city intersections are much smaller in size resulting in smaller cost difference between NIT and loops.
    - Radar has been used in cases where video could not be used due to site limitations.
    - It is wise to avoid dealing with multiple products. Goal for the City is to eventually switch to only one product, if possible.

Appendix C: Task 3 Deliverable

Performance Evaluation of Different Detection Technologies for Signalized Intersections in Minnesota

TASK 3 DELIVERABLE:

Synthesis of Non-Intrusive detection technologies and products

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March 2021

Introduction

Vehicle detection began in the late 1920’s in Baltimore, Maryland. A railroad signal engineer named Charles Adler, Jr. developed a horn-activated sensor that consisted of a microphone in a small box mounted to a nearby pole. It was installed at a Baltimore intersection in 1928 and enabled operation of the first semi-actuated signal. Around the same time, a pressure-sensitive pavement device was introduced that proved to function better and was more popular. The sensor used two metal plates that acted as contacts when pushed together under the weight of a vehicle. The device was the primary means of vehicle detection at actuated intersections for more than 30 years (1)

Mechanical problems with the plate sensor led to the introduction of electro-pneumatic sensors. Although these sensors were used for a short time, they were costly to install, capable only of passage (motion) detection, and had poor counting accuracy. By the early 1960’s, Inductive Loop Detection (ILD) systems were being implemented for traffic signal operations and have since become widely used vehicle detection technology. However, problems such as the cost of installation and maintenance and the need for closures during maintenance created the demand for alternative systems (1).

In the late 1980’s, video imaging detection systems appeared in United States (US) and international markets, warranting the need for research to determine the viability as a replacement to ILDs. In 1990, California Polytechnic State University (Cal Poly) began testing 10 video detection systems that were either prototypes or commercially available in the US. Since the 1990’s, several more NIT detection system types have been introduced including microwave radar, infrared sensors, and hybrid systems, warranting the need for extensive research (2,3).

This project focuses only on Non-Intrusive Technologies (NIT) for the detection of vehicles, specifically for the operation of actuated signals intersection control. Further on, following current guidance from the Technical Advisory Panel, given that the main focus of the research is the long term performance of NIT detection under various environmental conditions, the majority of the effort is spent in the discussion of video imaging detection system. Regardless, other NITs are mentioned in this document for generality and comparisons.

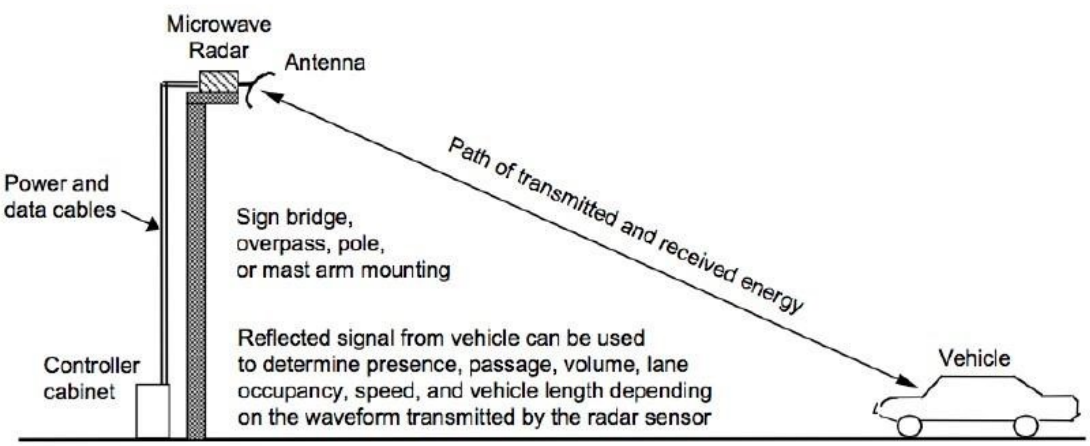
The first part of this report covers the basics of vehicle detection and discusses the different varieties of sensor families. It ends with a short literature review on past sensor evaluation studies. The second part of the document presents a synthesis of mostly video based vehicle detection systems from the manufacturers that have the greatest market share in the USA.

Basics of Non-Intrusive Technologies for Vehicle Detection (NIT)

Over the years, a large number of sensors have been developed and commercialized. Today still, the inductive-loop detector is, by far, the most widely used sensor in modern traffic control systems. These and sensors like magnetometers and magnetic sensors are all belonging to the intrusive technologies, or in-pavement category. NIT or Over the Pavement sensor category includes video image processors, microwave and laser radar sensors, ultrasonic, acoustic, and passive infrared sensors a lot of which are produced commercially and used for various traffic management applications. From these Video, Radar, and Thermal are currently the dominant products available in the market. As it can be seen from the following sections, they share a lot of operating principles.

Radar, Laser, and LiDAR Detection

Radar, Laser, and LiDAR detectors transmit energy toward an area of roadway from an antenna/light emmitter that is mounted overhead. When a vehicle passes through the beam of energy, a portion of the energy is reflected back to the antenna and detection is made. These detectors can sense the presence of stationary vehicles and multiple zones through their range finding ability (4). This concept is illustrated in the following figure (5).



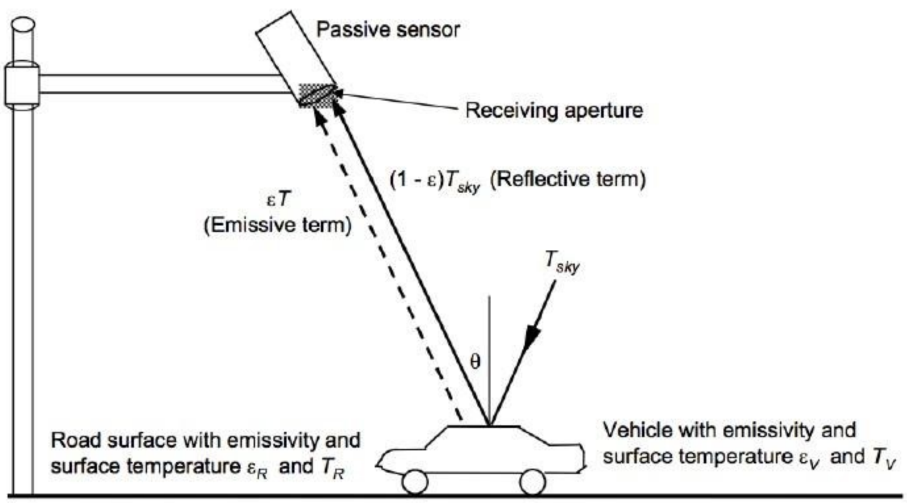
In more detail, there are two types of these detectors, the time-of-flight and the Doppler principle based. Their differences are in many ways critical to the application. Radar Time-of-Flight (TOF) sensors share the same principle with Laser/LiDAR sensors in that they base their detection to the measurement of the signal travel time between the antenna and the target. Essentially, they measure distances. Similar “echos” from consecutive scanning intervals that produce different distances are identified as targets and their presence and/or track is recorded. If information is given to the sensor regarding the echo image of an empty road, then even stopped targets can be detected. This is the major difference with sensors that exploit the Doppler principle. These sensors do not send out pulses of microwaves or light but a continuous microwave signal of known frequency. The Doppler principle indicates that if a wave is reflected over a moving target, the return wave will have its frequency shifted by an amount that depends on the speed of the target. Doppler radar sensors are much cheaper to develop and can cover much greater fields of view but they can only detect moving objects.

In the case of a vehicle, if the vehicle stops moving then it becomes invisible to the sensor until such time as it starts moving again. Most of the Commercially available sensors in the market cope with this huge limitation through post-processing algorithms and heuristics which greatly affect the overall measurement accuracy.

Passive Infrared and Thermal Image Sensors

Passive infrared sensors (PIS) have been available to the traffic industry for some time and are currently being marketed by some companies as thermal sensors. A PIS measures energy that is emitted from the vehicles, road surfaces, and other objects within view that emit no energy of their own. As the following figure (5) shows, when a vehicle enters the sensor's field of view, it generates a signal that is proportional to the product of the difference in emissivity (ε) between the road and vehicle, and the difference between the absolute temperature of the road surface (TR) and the temperature of the sky (Tsky) (5).

Thermal sensors have the greatest similarity with video image sensors because in the majority of implementations they produce an image akin to a black&white video which is then processed in a similar way. For traffic applications, the major advantage of thermal sensors is that since they do not use visible light to produce the image, they are not affected as much from environmental conditions that limit visibility or other light related artifacts like shadows and glare. Naturally, extremely low or high temperatures that reduce the contrast of the image are a problem.



Video Image Processing Sensors

Video cameras were introduced to traffic management for roadway surveillance because of their ability to transmit closed circuit television imagery to a human operator for interpretation. Present-day traffic management applications use video image processing to automatically analyze the scene of interest and extract information for traffic surveillance and control. A video image processor (VIP) system (sometimes referred to as a machine vision processor) typically consists of one or more cameras, a microprocessorbased computer for digitizing and processing the imagery, and software for interpreting the images and converting them into traffic flow data.

Principles of Operation

Video image processor systems detect vehicles by analyzing the imagery from a traffic scene to determine changes between successive frames. The image processing algorithms that analyze black and white imagery examine the variation of gray levels in groups of pixels contained in the video frames. The algorithms are designed to remove gray level variations in the image background caused by weather conditions, shadows, and daytime or nighttime artifacts and retain objects identified as automobiles, trucks, motorcycles, bicycles, and recently pedestrians. Traffic flow parameters are calculated by analyzing successive video frames. Color imagery can also be exploited to obtain traffic flow data. The improved resolution of color cameras and their ability to operate at low light levels is making this approach more viable.

Three types of data extraction approaches are available to VIPs: tripline, closed-loop tracking, and object detection and classification based tracking. Tripline systems allow the user to define a limited, but usually sufficient number of detection zones in the field of view of the video camera. When a vehicle crosses one of these zones, it is identified by noting changes in the pixels caused by the vehicle relative to the roadway in the absence of a vehicle. Surface-based and grid-based analyses are utilized to detect vehicles in tripline VIPs. The surface-based approach identifies edge features, while the grid based classifies squares on a fixed grid as containing moving vehicles, stopped vehicles, or no vehicles. Tripline systems estimate vehicle speed by measuring the time it takes an identified vehicle to travel a detection zone of known length. The speed is found as the length divided by the travel time (1,6).

The advent of the VIP tracking approaches has been facilitated by low-cost, high throughput microprocessors. Closed-loop tracking systems are an extension of the tripline approach that permits vehicle detection along larger roadway sections. The closed-loop systems track vehicles continuously through the field of view of the camera. Multiple detections of the vehicle along a track are used to validate the detection. Once validated, the vehicle is counted and its speed is updated by the tracking algorithm (7). These tracking systems may provide additional traffic flow data such as lane-to-lane vehicle movements. Therefore, they have the potential to transmit information to roadside displays and radios to alert drivers to erratic behavior that can lead to an incident.

The latest development in VIP is the object detection and classification tracking. These new family of methods utilize neural networks and AI techniques to analyze the entire image of each video frame and identify or “label” all known objects. Although such systems have been used for vehicle detection for some time now, their cost, due to hardware requirements, didn’t allow them to capture the market. In the last five years, great advances in the AI and machine learning paired with a substantial reduction in the cost of computing power, have been increasing the popularity of such systems. One major advantage of these new sensors is that they can also detect pedestrians and other road users that do not always move in well defined regions in the image.

A more involved description of vehicle tracking methods suitable for VIPs can be found in Kanhere, N.K., et al., 2006 (8). A summary of these tracking approaches appears below.

• Blob or region based tracking

- Generates a background model for the scene
- For each input image frame, algorithms analyze the absolute difference between the input image and the background image to extract foreground blobs that correspond to the vehicles – Vehicle tracking possible at region level and vehicle level
- Difficulties reported handling shadows, occlusions, and large vehicles, all of which cause multiple vehicles to appear as a single vehicle

• Active contour based tracking

- Tracks the outside contour or boundary of an object
- Contour initialized using a background difference image and tracked using intensity and motion boundaries
- Occlusions are detected using depth-ordered regions associated with the objects

• Model based tracking

- Matches detected objects with pre-identified 3-D vehicle models
- Emphasizes recovery of trajectories for a small number of vehicles with high accuracy
- Some model-based approaches assume an aerial view of the scene, virtually eliminating all occlusions, and match wire-frame models of vehicles to edges detected in the image

• Feature based tracking

- Tracks sub-features in the object, represented as points, rather than tracking the entire object
- Useful when vehicles are partially occluded
- Tracks multiple objects by identifying groups of features based on similarity criteria, which are tracked over time

• Color based tracking

- Color signatures (chromatic information) are used to identify and track objects
- Vehicle detections are associated with each other by combining chromatic information with driver behavior characteristics and arrival likelihood

• Object based tracking

- Vehicle and other road user detection treated as a classical pattern classification problem using AI and machine learning algorithms.

Video-Radar Hybrid Systems

Hybrid video-radar detection systems combine video and microwave radar detection technologies and merge information to produce detection data. The fusion of multi-sensor data can provide advantages over single sensor systems. An example of a benefit of hybrid detection exists with a moving object, such as an airplane, that is observed by both radar and infrared imaging. Radar has the ability to accurately determine the airplane's range but is unable to determine its angular direction. In contrast, the infrared sensor is able to accurately determine angular direction but not range. If data fusion from both sensors is properly associated, the multi-sensor system could provide improved accuracy in the determination of location over an independent sensor system. Hybrid systems not only employ the use of two or more sensors, but also require a data fusion system or algorithm that is able to analyze and process the multisensory data.

The merging of video and radar information has been widely used in intelligent vehicle systems, but mostly within lane recognition, collision avoidance, and adaptive cruise control applications. There are currently very few video-radar hybrid systems available on the commercial market. To date, no systematic studies involving hybrid detection systems in intersection applications are available and the majority of research has been focused on development and analysis of algorithms for data fusion.

It is also important to note that in several of the commercially available systems the implementation involves only an extremely rudimentary data fusion. Based on anecdotal information (system manufacturers don't divulge such details), we can identify two ways this simplistic data fusion has been accomplished. One such implementation has each sensor type operating individually in parallel and involves heuristics during post-processing handle target identification disagreements. A second implementation, involves the separation of the covered field of view in regions based on distance from the sensor. In these cases the video based sensor has been usually covering the area near the stop line with the radar sensor handling the farther upstream parts of the approach. As can be seen later in this document, there are currently very few available hybrid systems in the market because of many discontinued products.

The following table is taken in its entirety from the FHWA Traffic Detector Handbook Vol 1 and summarizes the strengths and weaknesses of the various sensor technologies. Some of the stated information are not globally accepted as facts.

Table 1.
Strengths and weaknesses of commercially available sensor technologies (Klein, 2001; Rhodes, 2005; Klein, et al., 2006).

Technology	Strengths	Weaknesses
Inductive Loop	• Flexible design to satisfy large variety of applications. • Mature, well understood technology. • Large experience base. • Provides basic traffic parameters (e.g., volume, presence, occupancy, speed, headway, and gap). • Insensitive to inclement weather such as rain, fog, and snow. • Provides best accuracy for count data as compared with other commonly used techniques. • Common standard for obtaining accurate occupancy measurements. • High frequency excitation models provide classification data.	• Installation requires pavement cut. • Decreases pavement life. • Installation and maintenance require lane closure. • Wire loops subject to stresses of traffic and temperature. • Multiple detectors usually required to monitor a location. • Detection accuracy may decrease when design requires detection of a large variety of vehicle classes.
Magnetometer (Two-axis fluxgate magnetometer)	• Less susceptible than loops to stresses of traffic. • Insensitive to inclement weather such as snow, rain, and fog. • Some models transmit data over wireless RF link.	• Installation requires pavement cut. • Decreases pavement life. • Installation and maintenance require lane closure. • Models with small detection zones require multiple units for full lane detection.
Magnetic (Induction or search coil magnetometer)	• Can be used where loops are not feasible (e.g., bridge decks). • Some models are installed under roadway without need for pavement cuts. However, boring under roadway is required. • Insensitive to inclement weather such as snow, rain, and fog. • Less susceptible than loops to stresses of traffic.	• Installation requires pavement cut or boring under roadway. • Cannot detect stopped vehicles unless special sensor layouts and signal processing software are used.
Microwave Radar	• Typically insensitive to inclement weather at the relatively short ranges encountered in traffic management applications. • Direct measurement of speed. • Multiple lane operation available.	• CW Doppler sensors cannot detect stopped vehicles.
Active Infrared (Laser radar)	• Transmits multiple beams for accurate measurement of vehicle position, speed, and class. • Multiple lane operation available.	• Operation may be affected by fog when visibility is less than ≈20 ft (6 m) or blowing snow is present. • Installation and maintenance, including periodic lens cleaning, require lane closure.

Table 1 (continued).
Strengths and weaknesses of commercially available sensor technologies.

Technology	Strengths	Weaknesses
Passive Infrared	• Multizone passive sensors measure speed.	• Passive sensor may have reduced sensitivity to vehicles in heavy rain and snow and dense fog. • Some models not recommended for presence detection.
Ultrasonic	• Multiple lane operation available. • Capable of overheight vehicle detection. • Large Japanese experience base.	• Environmental conditions such as temperature change and extreme air turbulence can affect performance. Temperature compensation is built into some models. • Large pulse repetition periods may degrade occupancy measurement on freeways with vehicles traveling at moderate to high speeds.
Acoustic	• Passive detection. • Insensitive to precipitation. • Multiple lane operation available in some models.	• Cold temperatures may affect vehicle count accuracy. • Specific models are not recommended with slow moving vehicles in stop-and-go traffic.
Video Image Processor	• Monitors multiple lanes and multiple detection zones/lane. • Easy to add and modify detection zones. • Rich array of data available. • Provides wide-area detection when information gathered at one camera location can be linked to another.	• Installation and maintenance, including periodic lens cleaning, require lane closure when camera is mounted over roadway (lane closure may not be required when camera is mounted at side of roadway) • Performance affected by inclement weather such as fog, rain, and snow; vehicle shadows; vehicle projection into adjacent lanes; occlusion; day-to-night transition; vehicle/road contrast; and water, salt grime, icicles, and cobwebs on camera lens. • Requires 30- to 50-ft (9- to 15-m) camera mounting height (in a side-mounting configuration) for optimum presence detection and speed measurement. • Some models susceptible to camera motion caused by strong winds or vibration of camera mounting structure. • Generally cost-effective when many detection zones within the field-of-view of the camera or specialized data are required. • Reliable nighttime signal actuation requires street lighting.

Summary of Earlier NIT Evaluation Studies

The following sections present a very short summary discussion of previous research related to NIT vehicle detection, including video-based, infrared, and video-radar hybrid systems. It is important to note that by default all such studies have been extremely limited in their utility to practitioners. This is because the VID manufacturers' rapid claims in following years regarding improved detection due to for example, shadow processing or compensation for camera movement, among others, result in these evaluations not being able to claim that they represent the performance of VID installations currently in use, but rather the systems available at the time.

In general, previous research involving video-based intersection detection is moderately plentiful and describes testing protocols and evaluation metrics that can be adapted to include other system types (919). The majority of this research was based on product evaluation and compares the accuracy of a system or systems to the accuracy of loop detectors. Many agencies have been employing video detection at intersections for well over two decades, and some states, such as Texas, have developed manuals for implementation (20). Cal Poly's 1990 evaluation of 10 video-based detection systems yielded vehicle count and speed errors of less than 20% over a mix of low, moderate, and high traffic densities. However, transitional light conditions, occlusion, and slow-moving, high-density traffic conditions reduced the accuracy of these systems (2). Video detection research over the past two decades has indicated that lighting conditions are the main cause of detection errors and that night periods are usually characterized as having more problems due to headlight glare (9, 17, 21). Daytime sun position can have an impact on detector operation as well. The sun can create stationary or moving shadows that can confuse the detector, and glare can reduce camera visibility (9).

In discussing specific commercially available systems, all of which have since been discontinued, an evaluation of the Vantage Video Traffic Detection System (VTDS) at three intersections was presented by MacCarley (7) in 1998. Performance was evaluated under twelve conditions, including combinations of weather, time of day, traffic volume and electromagnetic interference. Results were based on 15-minute datasets and showed good performance under ideal lighting and light traffic conditions. Performance degradation due to shadows and low lighting conditions, among others, was also found. Overall, video detection systems were considered not reliable for general signal actuation.

Later in 2001, Minnesota DOT and SRF Consulting Group (4) also evaluated the performance of VD systems at intersections. In this case Peek Video Trak 900, Autoscope 2004, EVA 2000 and TraffiCam systems were installed at different mounting locations and heights. Similar to the MacCarley study, factors such as shadows (both stationary and moving) and wind were also found to affect VD performance. Also in 2001, Grenard, Bullock and Tarko (12) evaluated Econolite Autoscope and Peek VideoTrak-905 for their performance at a signalized intersection. Results from overcast, night rain, and partly sunny conditions from three days were presented. It was concluded that night-time detection was a concern and VID systems should not be used for dilemma zone protection. More recently, a study by Rhodes et al (9) that followed the 2001 study by Grenard, Bullock and Tarko (12), indicated significantly more false and missed detections using VID systems than inductive loop detectors. The study installed three systems next to each other: Autoscope (version 8.10), Peek UniTrak (version 2), and Iteris Vantage (Camera CAM-RZ3). Results from two full days of data were analyzed, finding that all the three VID systems had moderate to high degree of missed and false calls and none was superior to the others. An additional publication by Rhodes et al (10) evaluated the stochastic variation of activation/deactivation times between day and night condition using data from one day, finding earlier detections at night due to headlight reflection in the pavement.

It is very difficult to compare the performance of two or more VID systems at installations located at different intersections or at different points in time. Setups using side-by side comparisons can clearly provide an advantage over other installations as the VID systems are processing the same images using their own camera. Moreover, data used in previous studies seem rather limited, being very difficult to control or to account for specific factors that affect VID performance. In studies of McCarley and Grenard a real-time side-by-side comparison of the VID systems was not performed. In Rhodes and MnDOT 2002 studies a real-time side-by-side comparison of the VID systems was performed, but limited datasets were used in these two studies (2 days in Rhodes and 1 day in McCarley).

The most recent such study (3) was performed by the National Institute for Advanced Transportation Technology (NIATT) at the University of Idaho with funding from Idaho Transportation Department. In that study, field-testing was conducted to evaluate nine alternative vehicle detection systems (four video, two radar, one thermal, and two hybrid) at the stop bar zone of a signalized intersection under six conditions: (a) daytime, (b) nighttime, (c) favorable conditions, (d) windy conditions, (e) rain, and (f) snow. The sensors were set up with two detection zones: one for the through and right-turn movements (Zone 1) and one for the left-turn lane (Zone 2). Trained personnel installed all systems, and decisions on the mounting locations were made by each system manufacturer.

Abbreviation	Manufacturer, Product	Detector Type
Video System 1 (V1)	Aldis, Gridsmart	Video
Video System 2 (V2)	Iteris, RZ-4 Advanced WDR	Video
Video System 3 (V3)	Traficon, FLIR VIP 3D.2 video detection board with an RDP optical camera	Video
Video System 4 (V4)	Peek, Color Video Traffic Detection Camera	Video
Radar System 1 (R1)	MS Sedco, Intersector	Radar
Radar System 2 (R2)	Wavetronix	Radar
Thermal System 1 (T1)	Traficon, FLIR VIP 3D.2 video detection board with a FLIR FC-T Thermal Sensor	Thermal
Hybrid System 1 (H1)	Iteris, Vantage Vector Hybrid	Hybrid
Hybrid system 2 (H2)	Econolite, Autoscope Duo	Hybrid

Based on the results of this study, it can be concluded that there is no single system that universally performs better than all other systems. Depending on the time of day or weather condition, many of the system types tested could claim that their technology outperforms all others. However, based on the percentage of false and missed detections for all of the products representing the different system types, there are opportunities for future improvement and enhancement. The acceptable tolerance level ultimately must be decided upon by the agency operating a particular signal, and it is recommended, based on the results from this study, that specific performance standards be defined when solicitation of signal detection equipment occurs in the future. The following table is an example of the results produced in the Idaho study. All detectors were facing south and Zone 1 consisted of the two northbound through lanes.

Zone 1	**False Detections**		**Missed Detections**	
System	**Day**	**Night**	**Day**	**Night**
Aldis, Gridsmart	3.7%	9.6%*	0.9%	0.7%
Iteris, RZ-4 Advanced WDR	4.3%	12.3%*	0.8%	1.1%*
Trafficon, FLIR VIP 3D.2 Video detection board with an RDP optical camera	2.0%	13.7%*	0.8%	0.9%*
Peek, Color Video Camera	5.4%	9.6%*	1.8%	2.0%

MS Sedco, Intersector	1.4%	1.8%	0.6%	3.4%*
Wavetronix	1.9%	1.3%	0.8%	1.6%*
Trafficon, FLIR VIP 3D.2 Video detection board with a FLIR FC-T Thermal Sensor	5.4%	12.9%*	0.4%	2.0%
Iteris, Vantage Vector Hybrid	4.7%	11.3%*	1.0%	1.2%*
Econolite, Autoscope Duo (Hybrid)	4.8%	1.0%*	1.4%	1.0%

* Indicates nighttime result is statistically significantly different from daytime.

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Commercially Available NIT Vehicle Detection Solutions

Product information for NIT vehicle detection and surveillance technologies used for intersection control was obtained from the web sites of vendors and manufacturers of the equipment. In this report, only Video Image Processing products are included since that is the main focus of the project so far. Material from the 2007 report “A Summary of Vehicle Detection and Surveillance Technologies used in Intelligent Transportation Systems” produced by The Vehicle Detector Clearinghouse (5) was used and updated based on the latest available information. The products are grouped by Vendor in alphabetical order.

General Information and Terms Used

The TAP has raised a number of questions regarding the type of cabling required by each system. For efficiency we thought it will be easier to clarify upfront some of the terms already used in the following sections that answer these questions.

Two-part Analog Video Systems

Two-part analog video systems like the Teledyne Flir VIP 3D.x, the Autoscope RackVision Terra, Iteris Vantage Edge2, ITS+, and Oriux (Peek) VideoTrak, use a regular or thermal camera to produce a video feed and a separate video capture and analysis board in the cabinet. For all of these systems the cabling requirement depends on the actual camera model used. In the majority of cases, involving all older systems, the cabinet board, needs a coaxial cable with a BNC connector to carry the video signal. For those systems, a separate cable is needed to provide power to the camera.

Two-part Digital Video Systems

The Two-part Digital Video systems function in a similar fashion as the analog video equivalents with the difference being that they utilize an digital network camera. Inherently, network cameras are the same as analog cameras with the difference of having an additional frame capture and compression module. No image analysis is performed in the camera part. Systems like that are the Gridsmart and Miovision where the main image analysis component is on the cabinet connected to the cameras either through an isolated private network or over the cabinets Ethernet network. In these cases the camera is most likely an Powerover-Ethernet (POE) device combining into a single Cat-5 or Cat-6 cable power and data (video stream).

Single-part systems

Single part systems combine the camera and image analysis hardware into one device. Autoscope Solo was the first and most utilized device of this type. From the products covered in this report, all remaining Teledyne FLIR products, the Autoscope Vision, and the Iteris Vantage Vector all fit in this category. In reality calling them single-part is kind-of a misnomer since all of them require a data-communication card to be present into the cabinet. These cards, proprietary for each system, receive the serial data information produced by the video detection sensor and relay detection events to the rest of the cabinet. The older models in this category require 9 conductor twisted pair cables to carry the serial communication, provide power, and in some cases carry the video signal for monitoring. More recent systems like all the latest TrafiCam models and all hybrid sensors from Iteris are network devices in which case they require a POE connection through a Cat-5/6 cable.

Teledyne Flir (Trafficon)

Trafficon, a Belgium based company, has been a veteran in the field of video based vehicle detection sensors. In late 2012, Trafficon was acquired by FLIR Systems, a Teledyne group company best-known for its expertise in infrared photonics technology. Currently Flir produces two lines of products, one based on thermal sensors and a separate using visible spectrum sensors (video). There is also a hybrid system that uses both types of sensors.

VIP 3D.x Video Image Processor https://www.flir.com/products/vip-3d/?model=10-4303

GENERAL DESCRIPTION OF EQUIPMENT: The FLIR VIP-3D.1 and FLIR VIP-3D.2 video detection boards are the two products originally marketed by Trafficon. The VIP3D.x Video Image Processor provides traffic data and information concerning the presence of vehicles approaching or waiting at the intersection. The input is analog video 75Ohm 1Vpp, PAL or NTSC.

The VIP3D.x comes in two versions:

- VIP3D.1 monitors 1 camera (1 video input)
- VIP3D.2 monitors 2 cameras (2 video inputs)

In a typical installation, two VIP3D.2 units are combined with one VIEWCOM/E for remote monitoring and change of configurations. The VIP 3D.x is a direct plug-in module for Type 170, NEMA TS-1 and TS-2 controller cabinets. Although not clear in the systems description, these cards could be installed in an ATC cabinet and use the SDLC connection through the VIEWCOM/E.

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – video image processing, pixel tracking, and tripline technology.

SENSOR INSTALLATION: Camera installs on existing signal poles, mast arms, and luminaire standards. Machine vision processor installs in controller cabinet.

INSTALLATION REQUIREMENTS: Bucket truck to mount camera. Camera mounting over center of monitored lanes provides optimum performance. Minimum camera mounting height is 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: Eight with stop bar and advanced vehicle presence detection.

PRODUCT CAPABILITIES/FUNCTIONS:

- VIP3D.1 provides up to 24 presence detection zones. VIP3D.2 provides up to 20 presence detection zones per camera.
- Each presence zone call can be delayed, extended or combined with an input to inhibit the call.
- Queue length measurements and directional counts on the intersection.
- Combination of outputs and inputs using Boolean functions AND, OR and NOR.
- VIP3D.1 provides eight data detection zones. The VIP3D.2 provides four data detection zones per camera.
- Detectors: count, speed, classification, occupancy, density, headway and gap time.
- Generation of alarm events such as: speed alarms (four service levels), speed drop, wrong way driver, queue length threshold and quality alarm.
- Double and single data loop simulation.
- Per zone, detection can be made direction sensitive.
- Single zones can be edited without disturbing the detection.
- Each VIP3D can control up to 24 outputs (four per board and 20 via the I/O extension boards) and 20 inputs (four for each of the five I/O extension boards).
- VIP3D stores up to four configurations per camera.
- Internal non-volatile memory database.
- VIP3D link software handles:
  - Configuration upload and download
  - Data download (database or individual data monitoring)
  - Firmware upload via RS232 port – Event download.

RECOMMENDED APPLICATIONS: Intersection vehicle detection for traffic signal control. Types of information available are vehicle presence; traffic data such as counts, speeds, classification, occupancy, density, headway, gap time; alarm events; wrong way driver detection; queue length; turning movement count.

CLASSIFICATION ALGORITHMS: Available

TELEMETRY: System connection via VIEWCOM/E (Ethernet). VIP3.x Link Software via serial communication RS232. Real time video output on module.

COMPUTER REQUIREMENTS: Not mandatory

DATA OUTPUT: The VIP3D.2 provides 24 digital outputs in total using expansion output modules (available in 3 types: 2 I/O, 4 I/O or 12 I/O). Presence, volume, speed data are provided.

DATA OUTPUT FORMATS: Analog video output with overlay of system information data and detection lines, auto diagnostic LED indicators, VIP3D.2 main board contains four optically isolated open-collector outputs, expansion modules 2 I/O, 4 I/O and 12 I/O: 2, 4 or 12 digital in/outputs (with dip switches for selection of inputs and outputs)

TRAFICAM® Integrated Camera and Presence Sensor for intersection applications – 2nd Generation

GENERAL DESCRIPTION OF EQUIPMENT: TrafiCam® integrates both a CMOS camera and detector in one compact box. This sensor monitors the presence of vehicles approaching or waiting at an intersection.

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – video image processing, pixel tracking, and tripline technology.

SENSOR INSTALLATION: Camera and machine vision processor install on existing signal poles, mast arms, and luminaire standards. Wide field of view and narrow field of view lenses are available, depending on close (0-85 ft) or long range (50-250 ft) viewing, respectively.

INSTALLATION REQUIREMENTS: Bucket truck to mount sensor. Camera mounting over center of monitored lanes provides optimum performance. Minimum camera mounting height is 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: Eight

PRODUCT CAPABILITIES/FUNCTIONS:

- 640 x 480 pixels (VGA), 20 FPS with JPEG compression
- Up to 8 detection zones
- Direction sensitive detection zones
- Real-time traffic view
- Optional: wireless communication/solar power
- Automatic trigger into safe recall mode
- MTBF > 11 years.

RECOMMENDED APPLICATIONS: Intersection vehicle detection for traffic signal control. Types of information available are vehicle presence; traffic data such as counts, speeds, classification, occupancy, density, headway, gap time; alarm events; wrong way driver detection; queue length; turning movement count.

CLASSIFICATION ALGORITHMS: Available

TELEMETRY: Sensor configuration performed via USB connection. With a portable PC or PDA, sensor setup is available in your native language through a user-friendly software interface. RS 485 interface is also available.

COMPUTER REQUIREMENTS: TrafiCam PC Tool

Output Contacts:

- 4 via interface 1TI
- 8 via interface 4TI ETH
- 8 via 4TI ETH EDGE & 4/Os xp

FLIR TrafiCam X-stream2

https://www.flir.com/products/flir-traficam-x-stream2/

GENERAL DESCRIPTION OF EQUIPMENT: The FLIR TrafiCam x-stream2 combines a CMOS 1/4" color digital camera and video detector into a single vehicle presence sensor. Detecting moving and stationary vehicles at signalized intersections. TrafiCam x-stream2 transmits vehicle presence information to a traffic controller via detection outputs or TCP/IP communication for adaptive and responsive signal timing.

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – video image processing, pixel tracking, and tripline technology.

SENSOR INSTALLATION: Camera and machine vision processor install on existing signal poles, mast arms, and luminaire standards. Wide field of view and narrow field of view lenses are available, depending on close (0-85 ft) or long range (50-250 ft) viewing, respectively.

INSTALLATION REQUIREMENTS: Bucket truck to mount sensor. Camera mounting over center of monitored lanes provides optimum performance. Minimum camera mounting height is 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: Eight

PRODUCT CAPABILITIES/FUNCTIONS:

- 640 x 480 pixels (VGA), 25 FPS with H.264, MJPEG
- Real-time traffic view
  - o PoE mode A for configuration, video streaming and data
  - o 80 Mbps Broadband over Powerline communication via TI BPL2 or TI BPL2 Edge interface
- Up to 8 detection zones
- Direction sensitive detection zones
- Optional: wireless communication/solar power
- Automatic trigger into safe recall mode

CLASSIFICATION ALGORITHMS: Available

TELEMETRY: Sensor configuration performed via Web page.

COMPUTER REQUIREMENTS: Web browser

Output Contacts:

- 1 N/O and 1 N/C dry contact direct
- 16 N/C dry contacts via TI BPL2 interface
- 4 N/C dry contacts via TI BPL2 EDGE interface (more with additional 4 I/O USB expansion boards)
- SDLC to traffic light controller via TI BPL2 EDGE interface and PIM module

FLIR TrafiOne,

https://www.flir.com/products/trafione/

GENERAL DESCRIPTION OF EQUIPMENT: FLIR TrafiOne is an all-in-one sensor for traffic monitoring and dynamic traffic signal control. The FLIR TrafiOne uses thermal imaging and Wi-Fi technology to adapt traffic signals based on the presence detection of vehicles, bicycles and pedestrians, even in total darkness or adverse weather. The sensor also generates high-resolution data for measuring travel times for different modes of transport and to improve traffic flows. TrafiOne also includes an HD video camera for additional visual support.

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – video image processing, pixel tracking, and tripline technology

SENSOR INSTALLATION: Camera and machine vision processor install on existing signal poles, mast arms, and luminaire standards.

Two options for field of View (recommended for 2 lanes only)

- 95°H for 0 - 50 ft Detection Distance
- 56°H for 33 - 82 ft Detection Distance

INSTALLATION REQUIREMENTS: Bucket truck to mount sensor. Camera mounting over center of monitored lanes provides optimum performance. Minimum camera mounting height is 11 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

PRODUCT CAPABILITIES/FUNCTIONS:

- Focal Plane Array (FPA), Uncooled VOx microbolometer Long wave Infrared (8 – 14 µm)
- 160 x 120), 9 FPS with H.264, MJPEG
- Curbside and on-crossing pedestrian and bicycle presence detection

- Real-time traffic view
    - 1080 × 1920 pixel HD color CMOS, 30 FPS, H.264, MJPEG
    - PoE mode A and B for configuration, video streaming and data
    - Mbps Broadband over Powerline communication via TI BPL2 (Edge)
    - interface Wi-Fi, IEEE 802.11 type b.g.n. EIRP < 100mW
- Detection zones:
    - 8 vehicle presence zones
    - 8 pedestrian presence zones
    - FLIR VSO data - optional Acyclica license
    - Modules (Reporting Module, Planning Module, Signal Timing Tools) - optional Acyclica licenses
    - Wi-Fi Travel Time analytics - optional Acyclica license

TELEMETRY: Local/remote web page setup via PoE, Wi-Fi, or BPL3

COMPUTER REQUIREMENTS: Web browser

Output Contacts:

- 1 N/O and 1 N/C dry contacts direct
- 16 N/C dry contacts via TI BPL2 or TI BPL2 EDGE interface

TrafiSense2 Dual https://www.flir.com/products/thermicam-dual/

GENERAL DESCRIPTION OF EQUIPMENT: FLIR TrafiSense2 Dual combines best-in-class thermal and visual imaging technology with advanced video analytics to provide vehicle and bicycle presence detection at signalized intersections, day and night. Thermal imaging lets traffic operators see in total darkness and inclement weather. The FLIR TrafiSense2 Dual's visible-light camera provides high-quality images for control room operators.

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – video image processing, pixel tracking, and tripline technology.

SENSOR INSTALLATION: Camera and machine vision processor install on existing signal poles, mast arms, and luminaire standards.

Five options for field of View

- 90°H / 69°V
- 69°H / 56°V
- 45°H / 37°V

- 32°H / 26°V
- 25°H / 20°V

INSTALLATION REQUIREMENTS: Bucket truck to mount sensor. Camera mounting over center of monitored lanes provides optimum performance. Minimum camera mounting height is 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: Eight

PRODUCT CAPABILITIES/FUNCTIONS:

- Focal Plane Array (FPA), Uncooled VOx microbolometer Long wave Infrared (7.5 – 13.5 µm)
- 640 × 512 pixels (VGA), 30 FPS with H.264, MJPEG
- Real-time traffic view
    - 1280 × 720 pixel HD color, 25 FPS, H.264, MJPEG PoE mode
    - For configuration, video streaming and data
    - PoE mode A for configuration, video streaming and data
    - 80 Mbps Broadband over Powerline communication via TI BPL2 or TI BPL2 Edge interface
- Detection zones:
    - Vehicle presence detection & counting (24)
    - Bicycle presence detection & counting (8)
    - Traffic data collection & traffic flow monitoring (6)
    - Wrong-way driver detection (6, requires extra license)

TELEMETRY: Sensor configuration performed via Web page.

COMPUTER REQUIREMENTS: Web browser

Output Contacts:

- 64 output states via TI BPL2 EDGE interface
- SDLC to traffic light controller via TI BPL2 EDGE interface and PIM module

FLIR TRAFICAM AI

https://www.flir.com/products/traficam-ai/

GENERAL DESCRIPTION OF EQUIPMENT: Designed to reliably detect and classify road users, the TrafiCam AI is an intelligent HD visible sensor for traffic monitoring in complex urban environments. Featuring a CMOS Type 1/2.8 color, low-light HD visible camera and AI algorithms built on 25+ years of traffic detection, TrafiCam AI offers detailed vision and data collection for safer, more efficient cities.

Capable of tracking multiple objects, the advanced edge-based AI effectively controls intersections and gathers detailed traffic data for better city planning decisions

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – Object detection: (motor)bike, small vehicles (car, van), big vehicles.

SENSOR INSTALLATION: Camera and machine vision processor install on existing signal poles, mast arms, and luminaire standards. Wide field of view and narrow field of view lenses are available, depending on close (0-85 ft) or long range (50-250 ft) viewing, respectively.

INSTALLATION REQUIREMENTS: Bucket truck to mount sensor. Camera mounting over center of monitored lanes provides optimum performance. Minimum camera mounting height is 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: Eight

PRODUCT CAPABILITIES/FUNCTIONS:

- Full HD (1920 x 1080), 25 FPS with H.264, MJPEG
- Real-time traffic view
    - PoE mode A for configuration, video streaming and data
    - 80 Mbps Broadband over Powerline communication via TI BPL3 (Edge) interface
    - Wi-Fi, IEEE 802.11 type b.g.n. EIRP < 100mW *1
- 24 virtual loops for presence detection
- 8 traffic data zones for classification and counting
- Queue Length Monitoring
- Premium Traffic Data Collection - optional license
    - FLIR VSO data - optional Acyclica license
    - Modules (Reporting Module, Planning Module, Signal Timing Tools) - optional Acyclica licenses
    - Wi-Fi Travel Time analytics - optional Acyclica license

TELEMETRY: Local/remote web page setup via PoE, Wi-Fi or BPL

COMPUTER REQUIREMENTS: Web browser

Output Contacts:

- 4 N/C onboard + maximum 5x N/C via 4I/O USB expansion boards (so maximum 24 outputs in total)
- SDLC: BIU - 64 or SUI - 128

FLIR TrafiSense AI, AI-Powered Thermal Traffic Sensor

https://www.flir.com/products/traficam-ai/

GENERAL DESCRIPTION OF EQUIPMENT: Designed to reliably detect and classify road users, TrafiSense AI is an intelligent thermal imaging sensor for traffic monitoring in complex urban environments. Featuring AI algorithms built on 25+ years of traffic detection and best-in-class thermal imaging, TrafiSense AI delivers continuous vision and data collection. Capable of tracking multiple objects in any lighting condition, the advanced edge-based AI technology controls intersections and gathers detailed traffic data.

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – Object detection: (motor)bike, small vehicles (car, van), big vehicles, and pedestrians.

SENSOR INSTALLATION: Camera and machine vision processor install on existing signal poles, mast arms, and luminaire standards.

Three options for field of View

- 90°H x 69°V for 5 - 180 ft Detection Distance
- 44°H x 35°V for 30 - 260 ft Detection Distance
- 32°H x 26°V for 80 - 300 ft Detection Distance

INSTALLATION REQUIREMENTS: Bucket truck to mount sensor. Camera mounting over center of monitored lanes provides optimum performance. Minimum camera mounting height is 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: Eight

PRODUCT CAPABILITIES/FUNCTIONS:

- Focal Plane Array (FPA), Uncooled VOx microbolometer Long wave Infrared (7 – 14 µm)
- VGA (640 x 480), 30 FPS with H.264, MJPEG
- Real-time traffic view
  - PoE mode A for configuration, video streaming and data
  - 80 Mbps Broadband over Powerline communication via TI BPL3 (Edge) interface
  - Wi-Fi, IEEE 802.11 type b.g.n. EIRP < 100mW
- Detection zones:
  - 24 virtual loops for presence detection
  - 8 traffic data zones for classification and counting
  - 8 Bicycle & Pedestrian detection zones
  - 4 Queue Length Monitoring zones
  - 6 Wrong Way Driver detection zones

- Premium Traffic Data Collection - optional license
- Services:
  - FLIR VSO data - optional Acyclica license
  - Modules (Reporting Module, Planning Module, Signal Timing Tools) - optional Acyclica licenses
  - Wi-Fi Travel Time analytics - optional Acyclica license

TELEMETRY: Local/remote web page setup via PoE, Wi-Fi, or BPL3

COMPUTER REQUIREMENTS: Web browser

Output Contacts:

- 4 N/C onboard + maximum 5x N/C via 4I/O USB expansion boards (so maximum 24 outputs in total)
- SDLC: BIU - 64 or SUI - 128

SUPPORTING DATA BASE AND TRAFFIC MANAGEMENT SYSTEMS:

FLIR FLUX.

FLUX is an intelligent software platform for use with a FLIR video detection system. FLUX collects traffic data, events, alarms and video images generated by the video detectors, sensors and cameras. FLUX also offers video management capacity and can control network video recorders, video walls, mobile and fixed cameras.

CAMELEON ITS

Cameleon ITS is a central software platform for transportation monitoring and management that allows for the control of ITS-specific devices, including cameras, DMS signs, detector stations, gates, signal heads and incident detection. Cameleon ITS includes a complete video management solution native to the application.

Gridsmart – Cubic

GRIDSMART specializes in video detection at the intersection utilizing image processing, computer vision modeling and machine learning along with a single camera solution providing data for controlling the flow of people and traffic through intersections. This solution tracks cars, trucks and bicycles while recording turning movements, vehicle counts, incidents and classifications. GRIDSMART Technologies, Inc. has operated out of Knoxville, Tennessee, since 2006. Initially called Aldis, it changed the name to Gridsmart in 2015. Gridsmart was acquired by Cubic Co. in 2019 creating a new business division called Cubic Transportation Systems. The product still carries the name Gridsmart (https://gridsmart.com/).

GENERAL DESCRIPTION OF EQUIPMENT:

The Gridsmart vehicle sensor is a combination of two parts, the Smartmount Bell Camera that captures the video feed and the GS2 Processor which processes the video and produces the vehicle detection information. The Gridsmart software, commonly referred to as the Client, allows the management of intersections in real-time. The Client is typically installed on a laptop and used to configure the Gridsmart Processor on-site during installation. If the cabinet is on a network, the Client can remotely access the system to view and configure sites, replay recorded video, calls and phases, generate reports and email alerts.

SMARTMOUNT Bell Camera

GRIDSMART App

GS2 Processor

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – Object detection: (motor)bike, small vehicles (car, van), big vehicles, and pedestrians.

Video Capture

The SMARTMOUNT Bell Camera delivers tracking through the entire intersection, including the center where vehicles and vulnerable road users cross. The horizon-to-horizon approach offers turn counts, situational awareness, views and functionality from the center of the intersection, and unobstructed incident management views. The camera's virtual pan-tilt-zoom enables users to set up multiple views and adjust those anytime as needed without impacting performance. The Bell Camera shape protects the lens by mitigating sun glare and adverse weather conditions.

5MP CMOS IP-camera with Power over Ethernet in a IP68 Internally pressurized and leak tested enclosure. Image resolution : 2560 x 1920 pixels

A traditional camera is to be used for advanced detection or other hard to see areas like underpasses and garage exits.

The SMARTMOUNT Bell Camera includes the Bell Camera, Junction Box, GRIDSMART custom modular pole assembly, SMARTMOUNT Bracket and Electronic Protection Module (EPM). The pole assembly has been independently tested for wind speeds up to 150 mph.

SENSOR INSTALLATION: Camera installs on existing signal poles, mast arms, and luminaire standards.

INSTALLATION REQUIREMENTS: Bucket truck to mount camera. Minimum camera mounting height is at least 30 ft. and preferably within 75ft of the intersection center and within 150ft from the furthest stopbar.

If the camera is going to be more than 300ft from the cabinet, additional signal repeaters must be used to avoid communication issues.

GRIDSMART System Processor

The GRIDSMART System Processor runs the GRIDSMART Engine, a suite of vision-tracking algorithms that build a 3-dimensional model of cars, trucks, pedestrians, and other objects approaching the intersection. The object trajectories are tracked through user-defined zones at the intersection and follows them until vehicles exit, delivering unmatched accuracy.

The GS2 Processor can be installed horizontally, vertically, or rack mounted. GS2 is housed in a rugged, powder coated aluminum housing with a latch release allowing access to internal components without tools. Supports two fisheye cameras, or one fisheye and multiple traditional cameras.

Detector I/O: TS1, TS2, 170/2070, or ITS interface. 24 optically isolated outputs, SDLC interface conforming to TS2 specs. Programmable up to 64 detectors.

Connectivity: Wide Area Network (WAN)

COMPUTER REQUIREMENTS: Web browser

Product Evolutions

There are no official info on the hardware and software prior to 2015. On September 2015, shortly after the name change to Gridsmart, GRIDSMART 6.0 became available along with the new version of the Gridsmart system processor the GS2. The GS2, is field repairable without the need for tools, was reduced in size by two-thirds from the original GRIDSMART Processor and has multiple USB 3.0 expansion ports for flexibility, and an intuitive LED front panel display showing calls and light states. Another new addition to GS2 was a built-in Wi-Fi connection or a standard Ethernet connection.

GRIDSMART 6.0 introduced the new Performance Module replacing the Counts and Realtime Data Modules. The Performance Module enables historical reporting on performance-related data that was previously only available for the last hour through the Realtime Data API. New report types became available with the Performance Module, including multi-day aggregation, by sum or average, on volume and turning movement reports, as well as red and green occupancy.

March 2018 GRIDSMART Version 6.8 was released. This version improved startup speed, reduced camera discovery time, and added the Occupancy Based Actuation (OBA) feature. OBA lets customers create vehicles zones that trigger different outputs based on the estimated number of vehicles in the zone.

GRIDSMART version 19.3 released April 2019, delivered an entirely new way to manage bicyclists at signalized intersections. The system tracks cyclists as they travel through the intersection, providing the correct amount of green time for individuals based on their chosen path and speed.

Released in January of 2019, Version 19.10 deploys pedestrian and cyclist safety features in the base GRIDSMART System. Previously, both pedestrian zones and bikes-in-the-box were only available at an added cost.

GRIDSMART System Software Version 19.12, released July 2020 introduced Streams independently from the Performance Plus Module. This change meant that users can do remote monitoring network, video recording, and use it with third-party video management systems that support RTSP 2.0. 19.12 also came with the ability to edit phase-to-channel mappings in the Device Manager dynamically. This ability let users control how they customize their maps to channels.

Version 20.10, released October 2020 introduces departure pulses for vehicle zones. Zones can now be set to send a single pulse for each vehicle that exits, simplifying use and integration into ATSPM platforms such as UDOT's Signal Performance Measures. It also introduced a User-defined timed recall. Users can set recall on individual zones or the entire site for a specified duration. This can be useful for unforeseen extreme weather events, accidents, or construction that are not handled by the normal programming. Finally, new Vehicle Zone Detection Type setting that supports Stop-line, Advanced, or Other. Now you can set phases on zones other than Stop-line. This can simplify bookkeeping for analytics (e.g., via the API). Also, Advanced zones with phases will now conform to the min/max recall setting.

Version 21.3, released March 2021 introduces GRIDSMART Protect. GRIDSMART Protect is a new value offering in the GRIDSMART solution family to provide Vulnerable RoadUser (VRU) safety - such as bikesin-the-box, pedestrian actuation and pedestrian all-clear where existing detection such as loops may already be inplace. Both GRIDSMART Protect and GRIDSMART System support the add-on VRU Data Module (VDM) to provide VRU analytics such as bike and pedestrian counting. 21.3 Introduces also the Pedestrian Wait Zone for touchless actuation. Pedestrian Wait Zones are included in both the existing GRIDSMART System software and the new GRIDSMART Protect software. Finally, this version adds pedestrian counting to the Performance Module and the VRU Data Module, including a Pedestrian Count report and access via the API.

Image Sensing Systems – Econolite

Image Sensing Systems (ISS), is a provider of above-ground detection and information management solutions for the Intelligent Transportation Systems (ITS) sector. ISS Autoscope video detection, RTMS radar detection, and IntellitraffiQ software provides accurate, intersection, highway, and wrong way detection and transportation data solutions. ISS emerged in 1984 when Dr. Panos Michalopoulos, at the University of Minnesota, foresaw the potential that video image processing technology could have to advance traffic management. The NIT sensors developed by ISS are manufactured and distributed through Econolite along with other vehicle detection solutions. In this document we will only discuss current and past products based or including video image processing offered under the Autoscope product line. For convenience we include only products marketed after 2007.

Autoscope Solo Terra Video Detection System (Discontinued)

GENERAL DESCRIPTION OF EQUIPMENT: The Autoscope Solo Terra sensor contains a color video camera as part of this integrated detection and surveillance machine vision system. It installs with three wires and reduces maintenance with ClearVision faceplate coating. The Solo Terra sensor provides timely vehicle detection, traffic data measurement, speed, and incident detection data.

A cabinet card version of the same sensor was also available accepting video from any analog CCTV camera. Operation and capabilities were identical.

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – video image processing, pixel tracking, and tripline technology.

SENSOR INSTALLATION: Autoscope Solo Terra unit installs on existing signal poles, mast arms, and luminaire standards.

INSTALLATION REQUIREMENTS: Camera and sensor are integrated into one unit. Camera mounting over center of monitored lanes provides optimum performance. Minimum camera mounting height is 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: Six to seven

PRODUCT CAPABILITIES/FUNCTIONS:

- Connectivity for IP-addressable broadband communications − EasyLink connectivity for simple installation into the traffic cabinet and integration into an agency's IP-based communications network. A standard CAT-5 cable connects Terra Technology products into a network providing access to video, traffic data, and the Autoscope Solo Terra vehicle detection system.
- Web server interface for easy setup
- Streaming digital MPEG-4 video output

- Vehicle detection, traffic data measurement, speed, and incident detection
- Integrated color camera, zoom lens, and dual-core processor for advanced image processing
- Direct real-time iris and shutter speed control
- Fail-safe detector outputs with the Autoscope Terra Access Point (TAP)
- High energy transient protection
- Technologically advanced faceplate heater and ClearVision faceplate coating

CLASSIFICATION ALGORITHMS: User selectable by length into 5 – 6 bins.

DATA OUTPUT:

Detection zones provide traffic count, presence, speed, and incident detection alarms. Incident types include freeway congestion, stopped vehicles, wrong direction vehicles, slow-moving vehicles, bicycles, pedestrians, smoke/fire, debris, or other customized alarms. Real-time polling or stored data include volume, occupancy, five vehicle classes by length, density, and other traffic data for selected periods or by phase.

Detector outputs can be assigned to interface with NEMA TS1/TS2, Type 170/179 and 2070 ATC controller via the optional Autoscope Terra Access Point (TAP).

Autoscope ENCORE (discontinued)

Encore was an upgrade in the sensor hardware and looks but in terms of functionality and video image analysis technology it had very little differences from the Autoscope Solo Terra. The connection to the rest of the cabinet was achieved through the same Autoscope Terra Access Point showed above.

Autoscope Duo (discontinued)

GENERAL DESCRIPTION OF EQUIPMENT: Autoscope® Duo™ was a hybrid radar and video vehicle detection system. In essence, the Duo combined together the earlier video image processing technology of the Terra and Encore with an SmartMicro radar sensor. The two sensors operated independently, sending detection information to the Duo Detection Module (DDM). The DDM is a detector card for a standard Detector Rack or Input File. It performs the decision logic process to combine radar and video information for optimal detector performance. The DDM converts standard NTSC analog video to streaming digital MPEG-4 video to view locally at the traffic cabinet or remotely from the office. The DDM input/output capabilities include detector port master capabilities. The DDM interfaces detector outputs directly to NEMA TS1/TS2, Type 170/179, or 2070 ATC controllers.

Sensor Information:

Radar

- Max range (passenger car from typical mast arm mount location) 290 ft
- Total field of view: ±35° AZ; ±8° EL

- Max transmit power (EIRP) 20 dBm
- Frequency Band: 24.0—24.25 GHz
- Bandwidth < 100 MHz

Video Sensor

- *Lens: 10x zoom, 5° to 46° horizontal, 4° to 35° vertical*
- 1/4*in. color CCD, NTSC format*
- *Resolution > 470 TVL horizontal*
- *Sensitivity at lens, full video, no AGC, 3.0 Lux (typical)*

Communications

- Ethernet 10/100 Base-T RJ45 connection for setup and operational use
- Port 1 SDLC DB-15 connector for TS2 Serial Detector I/O communications with the controller
- RS-485 bus on card edge for inter-processor Detector Port communications (master-slave)
- USB connector for serial communications to the radar sensor via interface panel

Autoscope RackVision Terra and Autoscope RackVision™ Pro 1 & 2

GENERAL DESCRIPTION OF EQUIPMENT: The Autoscope RackVision Terra Autoscope RackVision™ Pro 1 & 2 Machine Vision Processors (MVP) are video detection solutions that feature simple setup, robust color or black and white image processing. Both products connect to existing color or black and white Autoscope or (other compatible camera) analog video camera.

These two currently available products are the last ones using the original video image processing, pixel tracking, and tripline technology. Both versions use analog video provided by dedicated CCTV cameras. Upgrades in the software have added improved bicycle detection. In a recent upgrade these sensors support the Autoscope Cyclescope feature which provides Bicycle Differentiation, meaning that as a tracked object approaches the detection zone, Cyclescope determines whether or not the object is a bicycle—in any lane. Cyclescope was introduced in version 10.5.0 of the Autoscope Software Suite.

Another recent addition to this products is the decoupling from the need of an external computer to setup and manage the sensor operation. SmartMouse allows the traffic engineer or signal technician to connect a mouse and monitor to the video output of the RackVision, without having to use a laptop. By using SmartMouse, you can configure stop-bar and advance extension video detection zones in moments, without extensive training. Also available is a C1Y Cable for easy cabinet integration without the need for re-wiring or modifications to the traffic cabinet detector rack.

The RackVision Terra detector card interfaces detector outputs directly to NEMA TS1/TS2, Type 170/179, or 2070 ATC controllers. The optional Terra Access Point (TAP) can also assign detector outputs. For central systems, the optional Software Developer's Kit (SDK) can quickly integrate traffic data into a proprietary database. In TS1 or 33x cabinets, the RackVision Terra can interface to select TS2 traffic controllers with a Port 1 SDLC communications cable.

Autoscope Vision®

GENERAL DESCRIPTION OF EQUIPMENT: Autoscope Vision® is an integrated camera-processor sensor provides high performance stop bar vehicle detection, bicycle detection and differentiation, advance vehicle detection, traffic data collection, and High-Definition video surveillance. Autoscope Vision is capable of concurrently satisfying multiple transportation management objectives:

- Stop bar vehicle detection
- Bicycle detection and differentiation
- Advance vehicle detection up to 600 feet from Vision sensor
- Traffic data collection
- HD video surveillance

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – Object tracking (unverified). From the Vendor the following has been stated:

> Autoscope Vision uses a completely new detection algorithm, combined with a high-definition (HD) (720p) video sensor to provide the highest levels of video detection accuracy and versatility.
>
> Because of this the standard way of setting up the Field of View for Vision, as well as placement and size of zones isn't the same as past Autoscope products like Encore, Solo Terra or RackVision Terra.
>
> The suggestions is that the machine vision algorithms used process the entire image and not only specific small parts of the frame (triplines).

SENSOR INSTALLATION: Autoscope Vision installs on existing signal poles, mast arms, and luminaire standards.

INSTALLATION REQUIREMENTS: Camera and sensor are integrated into one unit. Camera mounting over center of monitored lanes provides optimum performance. Minimum camera mounting height is 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: Six to seven

PRODUCT CAPABILITIES/FUNCTIONS:

Video

- HD streaming video output
- H.264 720p (1280 x 720) video output
- Image snapshot resolution 1280 x 720

Lens

- 10X motorized zoom
- Standard configuration:
- Horizontal: 7.6 to 67.0 degrees
- Vertical: 4.3 to 37.7 degrees
- Focal Length 3.8mm to 38mm

Camera

- 1/2.8” CMOS sensor
- 2MP
- Signal-to-noise > 50 dB
- Wide dynamic range
- Noise reduction
- High sensitivity mode

Communications

- System connections via Autoscope Vision Comm Manager Ethernet RJ-45 WAN Port
- Ethernet RJ-45 for installation/maintenance
- WiFi communications via Autoscope Vision Comm Manager for installation/maintenance and video streaming
- The Vision Comm Manager supports SDLC and wired I/O interface for convenient integration to TS1, 170/2070/33x and TS2 cabinets

Iteris

Iteris along with its subsidiaries provides smart mobility infrastructure management solutions. Co.'s reportable segments consist of: Roadway Sensors and Transportation Systems. The Transportation Systems segment includes engineering and consulting services, transportation performance measurement and traffic analytics solutions, end-to-end solutions delivered as cloud-enabled managed services. The Roadway Sensors segment provides detection sensors and systems for traffic management that comprise Co.'s family of Vantage sensors and BlueTOAD line of products, as well as communication systems and roadway traffic data collection applications that complement its sensor products.

The Iteris detection sensors have followed an similar evolutionary path as the ones by Flir-Trafficon, Image Sensing Systems, and Peek in that they started early with the capture of analog video and the use of pixel tracking and tripline image analysis methods. Like ISS, Iteris also produced a Hybrid video and Radar sensor product but unlike ISS Iteris has continued the development of such hybrid sensors and still includes them in the available product line. Iteris, like Gridsmart, Miovision, and ISS has recently switched to more advanced machine vision algorithms based on object recognition and tracking.

VersiCam™

https://www.iteris.com/products/detection-sensors/versicam

GENERAL DESCRIPTION OF EQUIPMENT: VersiCam™ is an integrated machine vision processor and camera solution, designed for small or semi-actuated intersections. VersiCam is a versatile, high resolution video traffic camera specially optimized for machine vision processor technology. The camera offers remote zoom and focus functions to simplify setup and includes a high sensitivity color imager (CCD) to ensure accurate vehicle detection in all lighting conditions.

The VersiCam solution includes the Interface Communication Controller (ICC) that resides in the roadside cabinet. All user interface functions are performed through the ICC such as virtual zone placement, detector output assignment, and video monitoring.

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – video image processing, pixel tracking, and trip-line technology. Cameras are analog color or monochrome CCD units.

SENSOR INSTALLATION: Camera installs on existing signal poles, mast arms, and luminaire standards.

INSTALLATION REQUIREMENTS: Camera mounting over center of monitored lanes is ideal, with minimum height of 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: 2 lanes

PRODUCT CAPABILITIES/FUNCTIONS:

Camera

- Color CCTV, 530 TV Lines, Automatic white balance
- Focal length and focus adjustable for horizontal FOV ranging from 4.6° wide to 46.0° wide (65° wide for VersiCam Flex).

Interface Communication Controller

- NEMA TS-1 and TS-2 controller compatible.
- Detector zones are normally placed in one lane with multiple zones per lane.
- Detector zones can be AND’d or OR’d together to provide enhanced operation.

- Each detector zone holds a call for presence while vehicle remains in the zone.
- Programming is facilitated with a pointing device using menus shown as an overlay on the displayed video.

TELEMETRY: Via RS 232 serial port or RJ45 Ethernet using eAccess communication module, which is an 802.3 compliant TCP/IP interface.

COMPUTER REQUIREMENTS: None for setup or operation

DATA OUTPUT: Presence

DATA OUTPUT FORMATS:

- Connector (6-way) for camera.
- 1 BNC video output
- USD female for pointing device per Edge2 or eAccess module
- DB9 male for RS-232 interface
- 2 open collector outputs

SUPPORTING DATA BASE MANAGEMENT SYSTEM: VRAS – Vantage Remote Access Software for remote access

Vantage Edge2 Video Detection System

https://www.iteris.com/products/detection-sensors/vantageedge2

GENERAL DESCRIPTION OF EQUIPMENT: Iteris' Vantage Edge2™ is a machine vision processor consisting of a family of modules that provide 170/2070, TS-1, or TS-2 detection outputs to an intersection traffic controller for actuated operation. The modular approach allows the configuration to grow and adapt as the size and complexity of the intersection change. It is programmed using built-in menus that appear as a graphics overlay on the video image. The Vantage Edge2™ provides failsafe operation mechanisms and motion stabilization in high wind conditions.

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – video image processing, pixel tracking, and trip-line technology. Cameras are analog color or monochrome CCD units.

SENSOR INSTALLATION: Camera installs on existing signal poles, mast arms, and luminaire standards.

INSTALLATION REQUIREMENTS: Camera mounting over center of monitored lanes is ideal, with minimum height of 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: 6 lanes

PRODUCT CAPABILITIES/FUNCTIONS:

Camera

- Any analog color CCTV camera with 540 TV lines minimum is technically compatible. Following info is about the preferred Iteris RZ-4 Advanced WDR camera.
- Color CCTV, 530 TV Lines, Automatic white balance, .003 lux capable
- Focal length and focus adjustable for horizontal FOV ranging from 4.5° wide to 48.0° wide
- Adjustable/auto focus

Cabinet Card

- NEMA TS-1 and TS-2 controller compatible.
- TS-2 Bus Interface Unit (BIU) supports use in TS-2 Type 1 systems.
- 24 detector zones per camera configuration.
- Edge2 processor modules support 1, 2, or 4 video inputs.
- Extension modules support 2, 4, 24, or 32 output channel configurations.
- Detector zones are normally placed in one lane with multiple zones per lane.
- Detector zones can be AND’d or OR’d together to provide enhanced operation.
- Each detector zone holds a call for presence while vehicle remains in the zone.
- Three detector configurations can be stored for each camera and swapped according to Time of Day (TOD).
- Programming is facilitated with a pointing device using menus shown as an overlay on the displayed video.
- Communication modules provide remote programming and streaming video.

TELEMETRY: Via RJ45 Ethernet using Edge® 2 SDLC Interface Module.

COMPUTER REQUIREMENTS: None for setup or operation

DATA OUTPUT: Presence, Delay, Extend, Count, CSO (Count, Speed, and Occupancy), Pulse, Demand and Passage.

SmartCycle patented technology is embedded in all new Vantage® video detection systems and is a simple upgrade to existing systems in the field. Additional zones can then be drawn to separate bicycle detections from vehicle detections. Detects and differentiates in unique situations: bike boxes, lane splitting, other innovative configurations.

PedTrax was added as an extension providing pedestrian presence, counts and speed data. PedTrax provides automatic counting, direction and speed tracking of pedestrians within the crosswalk. Along with collecting this information with normal vehicle and bicycle detection, PedTrax can provide discrete outputs when detecting pedestrians moving in the crosswalk. The PedTrax feature is embedded within Iteris detection algorithms, there is no need for any additional equipment for operation.

DATA OUTPUT FORMATS:

Edge2 card

- Up to 2 BNC video inputs per Edge2 module, NTSC or PAL
- 1 BNC video output per Edge2 module
- USB A for pointing device per Edge2
- USB B for Communications

Edge® 2 SDLC Interface Module

- Standard detector interface
- 8 x RJ45 receptacles (4 input to connect with up to 4 Edge2 cards, 4 output)
- SDLC DB15 connector

SmartSpan®

https://www.iteris.com/products/detection-sensors/smartspan

GENERAL DESCRIPTION OF EQUIPMENT: SmartSpan, for intended purposes can be considered as a special version of the Vantage Edge2 system because it is using a regular analog video camera input to capture the road scene. SmartSpan specifically includes Dynamic Zone Stabilization (DZS) algorithms. With DZS, camera movement is tracked and compensated to provide accurate stop-bar and advanced detection.

All remaining information are identical to the Vantage Edge2 system including the actual camera sensor.

Vantage Vector Hybrid

https://www.iteris.com/products/detection-sensors/vantage-vector-hybrid

GENERAL DESCRIPTION OF EQUIPMENT: The Vantage Vector® system is an all-in-one detection sensor that combines video and radar for stop bar and advance zone detection to enable advanced safety and adaptive control applications. Compatible with the Vantage Edge2®, Vantage Next® and Vantage Apex™ systems, the Vantage Vector detection sensor includes all the benefits of Iteris video detection, including remote video viewing, pedestrian detection, and bicycle differentiation.

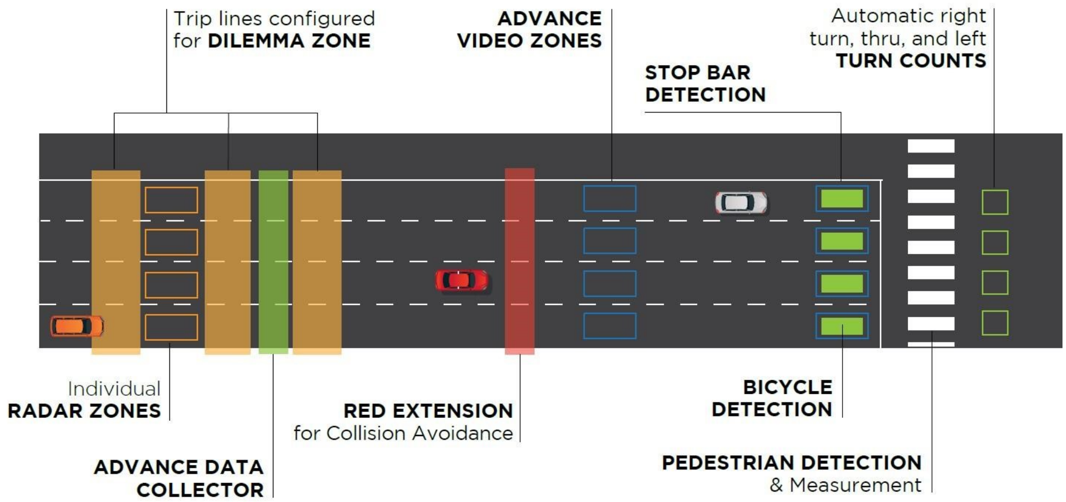
SENSOR TECHNOLOGY AND CONFIGURATION:

- Machine vision – video image processing, pixel tracking, and trip-line technology.
- Radar - advanced 4D, high-definition (HD).

SENSOR INSTALLATION: Sensor installs on existing signal poles, mast arms, and luminaire standards.

INSTALLATION REQUIREMENTS: Sensor mounting over center of monitored lanes is required with minimum height of 30 ft.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: four



PRODUCT CAPABILITIES/FUNCTIONS:

Camera

- Focal Length 5.4° tele to 50.7° wide
- 1.0 Lux Minimum Illumination with 3D-DNR Noise Reduction
- 12x Optical Zoom
- No information regarding image resolution is provided. Given that the new product Vantage Apex is described as the only full HD video sensors, it implies that the camera in the Vector is not full HD.

Radar

- 24GHz (K-band)
- Speed 0 to 150mph ±1mp, up to 60 tracked objects
- Vehicle detection up to 600 feet

TELEMETRY: Vantage Vector is just the sensor. It requires an Iteris detection platform in the cabinet to complete the system and connect with the rest of the traffic control equipment.

Vantage Next® Platform

https://www.iteris.com/products/detection-sensors/vantagenext

GENERAL DESCRIPTION OF EQUIPMENT: Vantage Next® is Iteris' second generation vehicle detection platform that capitalizes on the latest technology. Vantage Next uses a powerful processor that enables future functional growth while maintaining proven Iteris video detection performance and reliability. One significant difference to the Edge2 product family is that the camera sensor is now a POE IP camera connected to the system through a CAT5 network cable. The platform also supports different types of sensors like the video and radar hybrid (Vantage Vector) and radar only (Vantage Radius).

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – video image processing, pixel tracking, and trip-line technology.

Can also connect to Vantage Vector a video/radar hybrid sensor and the Vantage Radius a radar detector.

SENSOR INSTALLATION: Camera installs on existing signal poles, mast arms, and luminaire standards.

INSTALLATION REQUIREMENTS: Camera mounting over center of monitored lanes is ideal, with minimum height of 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: Up to 4 sensors

PRODUCT CAPABILITIES/FUNCTIONS:

Camera

- Focal Length 5.4° tele to 50.7° wide
- 1.0 Lux Minimum Illumination with 3D-DNR Noise Reduction
- 12x Optical Zoom
- RJ-45 CAT5 connection
- No information regarding image resolution is provided

Video Processor

- 4 open-collector outputs and 4 inputs per processor card.
- 128 total outputs /64 total inputs using extension modules
- Video Output: MPEG-4 and H.264, XGA 1024 X 768
- Fixed frame rate of 15fps

TELEMETRY: Ethernet and Wi-Fi

DATA OUTPUT: Presence, Delay, Extend, Count, CSO (Count, Speed, and Occupancy), Pulse, Demand and Passage. SmartCycle and PedTrax modules (described earlier).

DATA OUTPUT FORMATS:

- USB A x2 for pointing device and memory
- HDMI for monitor connection.
- Standard detector interface
- SDLC DB15 connector

Vantage Apex (preliminary data)

https://www.iteris.com/products/detection-sensors/vantage-apex

GENERAL DESCRIPTION OF EQUIPMENT: This info is based on news releases and product advertisement. No datasheet is still available for this product.

Vantage Apex is Industry's First 1080p HD Video and 4D/HD Radar Sensor with Integrated AI Algorithms. The AI-powered smart sensor delivers unmatched detection, tracking and classification accuracy of vehicles, pedestrians and cyclists, as well as HD video display for traffic management center monitoring. Vantage Apex identifies objects using Iteris' powerful AI video analytics, extensive image library, highperformance GPU/CPU-based computing, machine learning and neural network algorithms. This enables the high-precision and detailed classification of many different vehicle types and vulnerable road users, such as pedestrians and cyclists. Using forward-fire radar technology to virtually eliminate occlusion, the Vantage Apex hybrid sensor uses industry-leading 4D/HD radar technology with a field of view exceeding 600 feet. The Vantage Apex system enables decision-zone safety functions, collision avoidance and advanced lane-by-lane detection that delivers precise traffic detection and data.

SENSOR TECHNOLOGY AND CONFIGURATION:

- Machine vision – video image processing, object classification and tracking.
- Radar - advanced 4D, high-definition (HD).

SENSOR INSTALLATION: Sensor installs on existing signal poles, mast arms, and luminaire standards.

INSTALLATION REQUIREMENTS: Sensor mounting over center of monitored lanes is required with minimum height of 30 ft.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: four

TELEMETRY: Vantage Apex is just the sensor. It requires an Iteris platform in the cabinet to complete the system and connect with the rest of the traffic control equipment. It is unclear if and how the cabinet hardware are different with ones in the Vantage Next platform. From the online info and pictures it looks like that if they are not the same hardware they at least have the same communication and data exchange features.

+ITS PLUS

ITS Plus is a relative newcomer in the vehicle detection arena so very little is known regarding their product line. The company sales pitch is that they offer the most cost effective product in the market. All the information in this document is taken from the company website.

“Lightning Series” VIVDS Cards

https://itsplus3.com/1623-2/

GENERAL DESCRIPTION OF EQUIPMENT: ITS Plus claims to provide a camera combines both analog and HD digital video outputs into a single device. It is designed to work with current analog VIVDS detection cards as well as ITS Plus’s next generation digital VIVDS cards. It is unclear how this camera is different to other analog video cameras especially since the web site indicates NTSC, an analog video format, and the video input. No information was found regarding any digital VIVDS products.

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – video image processing, pixel tracking, and trip-line technology. This information is assumed based on the offered descriptions as well as the offered examples of detector layouts.

SENSOR INSTALLATION: Camera installs on existing signal poles, mast arms, and luminaire standards.

INSTALLATION REQUIREMENTS: Camera mounting over center of monitored lanes is ideal, with minimum height of 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: Unknown, evidence of at least 5 lanes although the VIVDS card shows only 4 detector outputs.

PRODUCT CAPABILITIES/FUNCTIONS:

Camera

- 1080p Analog or Digital
- 1/3 inch 2.1MP CMOS
- 20x Digital Zoom
- BNC Less Connector with coax cable
- Single lens camera with “never clean” lens cover

Video Processor

- 1 or 2 channel video processors with NTSC input via BNC
- 4 relay outputs
- 30 detection zones with flexible logic for mapping to relay outputs
- 128 total outputs /64 total inputs using extension SLDC module

- TS1, TS2, ATC, 170/2070 compatible

TELEMETRY: programming via USB mouse and analog video monitor or a Laptop PC

DATA OUTPUT: Presence and Count.

Miovision

Founded in 2005 as a traffic solution company, Miovision was originally created by three University of Waterloo friends with a shared vision: to help cities make smarter urban planning decisions by improving their understanding of traffic flow. Miovision has since grown into a global leader of “Smart City” technology. Initially Miovision started as a developer of a traffic management platform designed to collect in-house and outsourced traffic data for advanced traffic signal operations. The company's platform offers an easy way to request, deliver and analyze traffic data, all in one place. Only recently Miovision entered the arena of real-time detection.

TrafficLink Platform

https://miovision.com/trafficlink/video-detection

GENERAL DESCRIPTION OF EQUIPMENT: The Miovision product resembles the one by Gridsmart in the fact that is also based on a single fish-eye lens camera placed as close as possible to the center of the intersection. One 4k camera captures the entire intersection. As of December 2021, some of the parts of the TrafficLink platform have been redesigned. Specially, before December 2021 the intersection hardware comprise of the Smartview camera, delivering IP based video to the SmartSense Graphic processor unit which provided data to SmartLink module that connects to the signal controller. In December 2021 Miovision launched Miovision Core® – a powerful new hardware platform for intersections capable of supporting the next generation of software-based solutions. It offers twice the processing power as Miovision SmartLink™ and provides new capabilities to run more sophisticated software solutions at the intersection. Adding Miovision Core DCM – a small plug-in module – increases compute capability by over 50%, allowing it to support complex computer vision applications such as video detection and multimodal traffic counts.

As per the companies press release, Miovision Core will ultimately supersede Miovision SmartLink™ and Miovision SmartSense™ although the company states that they will continue to support SmartLink and SmartSense and offer refinement and improvements. The information in the rest of this section apply to the new Miovision Core product.

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – Object detection and Tracking: (motor)bike, small vehicles (car, van), big vehicles, and pedestrians.

SENSOR INSTALLATION: Camera installs on existing signal poles, mast arms, and luminaire standards.

INSTALLATION REQUIREMENTS: Bucket truck to mount camera. Minimum camera mounting height is at least 30 ft. and preferably within 75ft of the intersection center.

Miovision Core® Hardware

- NVIDIA ProcessorCPU: Quad-core ARM® A57 @ 1.43 GHz GPU: 128-core Maxwell
- Mass storageBuilt-in 240GB solid state
- Wireless connectivity
  - CellularLTE Cat 4 bands B2, B4, B5, B12, B13, B14, B66, B71
  - Location servicesGPS, GLONASS
  - Wi-Fi 802.11 a/b/g/n Restricted to customer-authorized communications
- Inputs and Outputs
  - 1 x 10/100/1000 Ethernet WAN port
  - 2 x 10/100/1000 Ethernet LAN ports
  - 3 x 10/100/1000 Ethernet LAN ports with PoE
  - 1x SDLC port (proprietary connector, DB15 adapter included)
  - 2 x EIA RS-232 over RJ45 interface (cable included)
  - 1 x USB-A port
  - 4 x +5V open drain I/Os
  - 8 x NEMA compliant I/Os

Miovision Core® DCM Hardware plugin module

- DCM NVIDIA Processor CPU:
  - 6-core NVIDIA Carmel ARM® 64-bit
  - GPU: 384-core NVIDIA Volta™ GPU with 48 Tensor Cores
- Inputs and Outputs (additional to the existing)
  - Detector I/O
    - 8 x NEMA compliant I/Os (fail passive)
    - 16 x NEMA compliant I/Os (fail active)

Oriux – Peek

Peek Traffic Corporation provides transportation management systems in North America. It offers data/AVCC products; traffic control products, including cabinets; IQ Central, a central traffic network management software; ATC Link, a controller management software; Viper, a service-based software platform, TOPS, a traffic, operations, and planning software; and Spinnaker ATMS, a Web-based advanced traffic management system software. The company also provides traffic signal products, such as vehicle signals, pedestrian signals, countdown pedestrian signals, audible pedestrian signals, lenses and visors, back plates, and loop detection products; video detection products, including video detection cards, video traffic detection cameras, camera interface panels, shelf mounted detector racks, rack power cards, and channel extender cards; and uninterruptible power supplies (UPS) products, such as UPS units and UPS cabinets.

The company was founded in 1888 and is based in Houston, Texas. As of July 25, 2008, Peek Traffic Corporation operates as a subsidiary of Signal Group, Inc. and as of February of 2020, Peek Traffic and its parent Signal Group have changed their names to Oriux in a rebranding exercise.

VideoTrak® IQ

https://www.oriux.com/videotrak-iq.html

GENERAL DESCRIPTION OF EQUIPMENT: VideoTrak is designed for use in fully actuated vehicle detection systems for intersection control and for traffic surveillance systems. Detection features are compatible with NEMA TS-1/TS-2, Type 170/179, Type 2070 and ATC controllers. Video Processing Module supports RS-170, NTSC, CCIR or PAL format CCD cameras.

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – video image processing, pixel tracking, and tripline technology.

SENSOR INSTALLATION: Camera installs on existing signal poles, mast arms, and luminaire standards. Machine processor installs in controller cabinet.

INSTALLATION REQUIREMENTS: Bucket truck to mount sensor. Camera mounting over center of monitored lanes provides optimum performance. Minimum camera mounting height is 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: See below

PRODUCT CAPABILITIES/FUNCTIONS:

- Available in two models, which support up to 4 or 8 cameras with as many as 32 detection zones per camera − providing up to 128 or 256 detection zones, depending on model.
- Vehicle counting and classification.
- Collection of traffic statistics such as number of vehicles (volume/counts), average speed (mph/kph), lane occupancy (% time lane is occupied), density (volume/speed), headway (avg. in seconds), delay (avg. delay in sec), queue length (ft/m), vehicle length (avg. in ft/m).

COMPUTER REQUIREMENTS: Standard laptop or notebook computer for detection zone setup.

DATA OUTPUT FORMATS:

- SDLC communication port allows direct connection for all TS2 environments which also makes available up to 64 output assignments and 16 phase color inputs.
- Two USB 2.0 connections allow one to be used for a mouse while the other is being used to save system configurations via a Flash Drive. It can also be used to upload new Firmware and Upgrades as they become available.

- Aux I/O connector provides an additional 8 outputs, 4 inputs, and allows for direct wiring to cabinet terminals or connection to extender cards for routing detectors to other rack slots.
- Ethernet Port – Units are “IPAddressable” allowing video streaming for hi quality remote monitoring and configuration adjustments.
- A three-color status LED for each video channel.
- Edge output status LED’s 1 – 4.
- Standard RCA.

VideoTrak XCam™

https://www.oriux.com/vehicle-video-detection.html

GENERAL DESCRIPTION OF EQUIPMENT: VideoTrak XCam™ is Oriux and Citilog's newest video detection technology combined into one easy-to-use and powerful video detection product. Pairing the latest technology of Oriux, VideoTrak family of video detection products and the innovative XCam smart camera from Citilog, the VideoTrak XCam™ is the future of ITS video detection. It supports up to 8 XCam cameras per Cabinet Interface Unit (CIU) allowing unparalleled modularity and compact space-saving installations in NEMA or CALTRANS style cabinets. VideoTrak XCam™ centralizes the set-up and configuration of all connected cameras without the need for additional wiring or a PC computer- Just a mouse and a monitor!

SENSOR TECHNOLOGY AND CONFIGURATION: Machine vision – video image processing, pixel tracking, and tripline technology.

SENSOR INSTALLATION: Camera installs on existing signal poles, mast arms, and luminaire standards. Machine processor installs in controller cabinet.

INSTALLATION REQUIREMENTS: Bucket truck to mount sensor. Camera mounting over center of monitored lanes provides optimum performance. Minimum camera mounting height is 30 ft. Greater heights may be required to minimize vehicle occlusion when using side-mounted cameras.

MAXIMUM NUMBER OF LANES MONITORED SIMULTANEOUSLY: See below

PRODUCT CAPABILITIES/FUNCTIONS:

- Available in two models, which support up to 4 or 8 cameras with as many as 32 detection zones per camera − providing up to 128 or 256 detection zones, depending on model.
- Vehicle counting and classification.
- Collection of traffic statistics such as number of vehicles (volume/counts), average speed (mph/kph), lane occupancy (% time lane is occupied), density (volume/speed), headway (avg. in seconds), delay (avg. delay in sec), queue length (ft/m), vehicle length (avg. in ft/m).
- Video streaming capability

COMPUTER REQUIREMENTS: none. Web Interface

DATA OUTPUT FORMATS:

- SDLC communication port allows direct connection for all TS2 environments which also makes available up to 64 output assignments and 16 phase color inputs.
- Two USB 2.0 connections allow one to be used for a mouse while the other is being used to save system configurations via a Flash Drive. It can also be used to upload new Firmware and Upgrades as they become available.
- Aux I/O connector provides an additional 8 outputs, 4 inputs, and allows for direct wiring to cabinet terminals or connection to extender cards for routing detectors to other rack slots.
- Ethernet Port – Units are “IPAddressable” allowing video streaming for hi quality remote monitoring and configuration adjustments.
- A three-color status LED for each video channel.
- Edge output status LED’s 1 – 4.
- HDMI video out

Appendix D: Task 4 & 5 Deliverable

Performance Evaluation of Different Detection Technologies for Signalized Intersections in Minnesota

TASK 4 DELIVERABLE:

Site selection and preparation of data collection equipment

TASK 5 DELIVERABLE:

Deployment and operation of data collection systems: Phase 1

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April 2022

Introduction

The goal of Task 4 was to select intersections with NIT for vehicle detection and prepare the equipment/methods for collecting video and data from the field. The aim of Task 5 was to initiate data collection, specifically video of the operation of the selected sites starting on the winter season of 2021-2022. This report is the combined deliverable for both tasks.

During the course of the effort, in collaboration with the Mr Derek Lehrke it became clear that the most efficient and, at least in the case of MnDOT, allowed way to collect the same video the NIT detectors are using is to target MnDOT owned signals that are connected to the fiber backbone. Video from such intersections can be streamed to the MnDOT cloud media provider (Wowza) and from there stream it to the public or at least to whomever has the right stream address, in the case of the project a specifically designed video recording server. In addition to the video, given that these intersections are in the MnDOT fiber network, high-resolution signal data are also been recorded by MnDOT and will be made available to the research team. Because of delays in successfully establishing the streams and working with MnIT in troubleshooting the connections with the cloud service, in order not to lose much of the winter season weather conditions, we opted to start recording on all available sites.

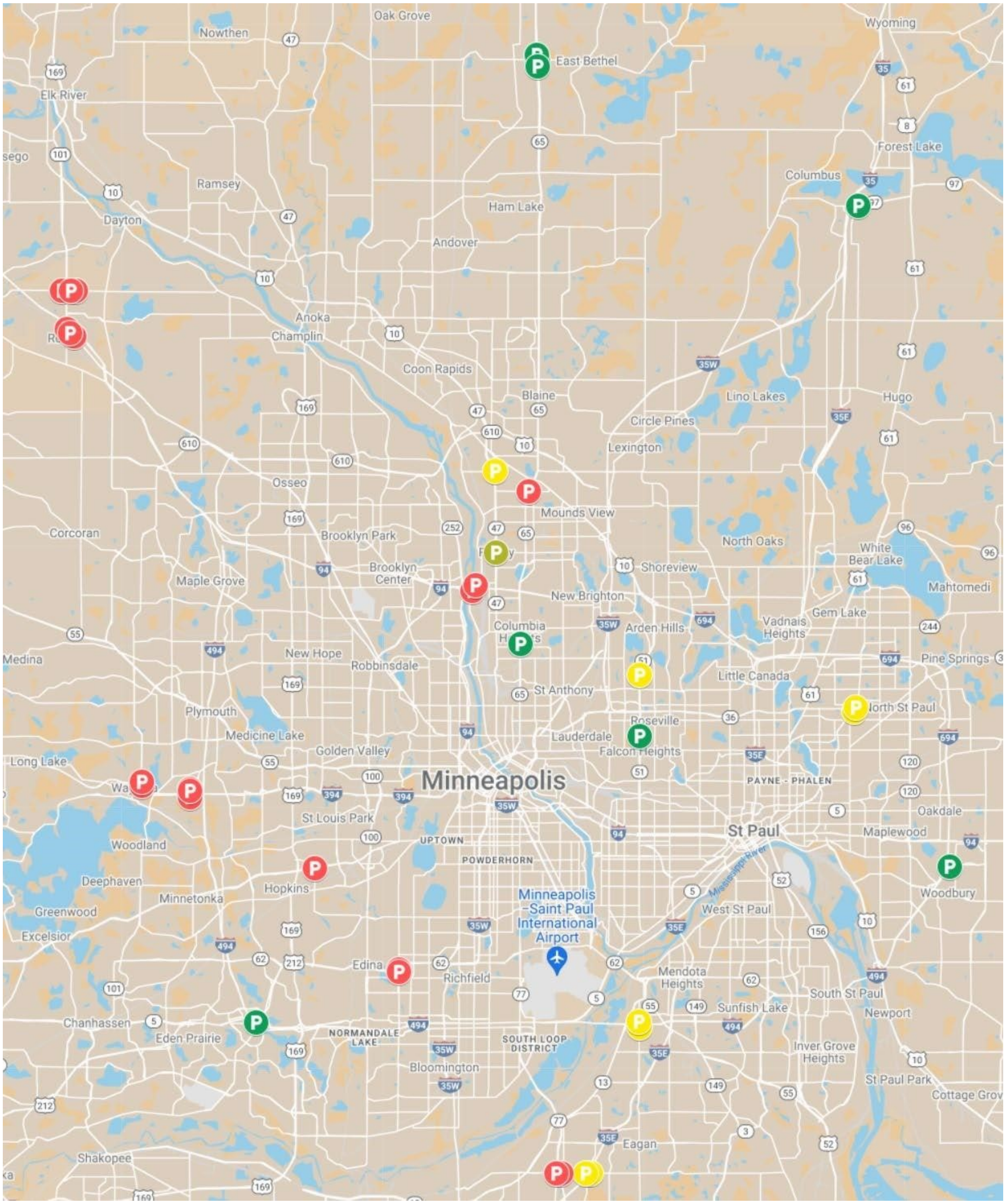
This report presents the currently selected sites along with their geometric characteristics, as seen from the NIT video. In total, 33 intersections are currently been recorded. Some of these intersections are covered by more than one camera due to geometry complexity or size. Barring changes in the data analysis planned in the project, the project budget cannot handle the effort of fully analyzing all approaches on all 33 intersections. Given that video recording is the cheap part of the process, we opted to record all of them and finalize the ones that will be fully analyzed later in the project with the help of the TL and TAP.

Proposed Sites

Table 1 presents a summary of the currently proposed sites. The NITs covered include Autoscope Vision, Iteris Vantage Next, Gridsmart, and one site with Miovision. These sites have been recorded since December 2021 and up to now we have captured at minimum three major snow events and one ice storm. The remainder of the report has screenshots from the recorded video on each site to aid in the discussion regarding which sites have priority to be analyzed in greater depth. It is interesting to note that at least in the case of the Autoscope Vision systems, the device, when it detects that image quality is not good for accurate enough (unknown threshold) detection, it deactivates the affected detectors, which turn red in the video feed. An example of this can be seen in the intersection of MN-7 and Blake Rd on page 12. Iteris Vantage Next seems to also have a similar feature (example cyan colored detectors on page 6) although we still need to verify its operation since by design this system has multiple detectors on each lane and not all of them go off-line. For these systems, all recorded video from all intersections will be used to produce relevant performance statistics since extraction is relatively simple.

Major Road	Minor Road	Detection system	Approaches	Max/Min Lanes
I-35E (East Ramp)	Cliff Road	Iteris Vantage Next	3	3/1
I-35E (West Ramp)	Cliff Road	Iteris Vantage Next	3	3/1
MN-36 (North Ramp)	White Bear Ave	Iteris Vantage Next	3	3/2
MN-36 (South Ramp)	White Bear Ave	Iteris Vantage Next	3	3/2
MN-47 (ped)	85th Ave	Iteris Vantage Next	1	3
MN-47	Mississippi St	Miovision	4	4/4
MN-51	Roselawn Ave	Gridsmart	4	4/2
I-494	Flying Cloud Dr	Gridsmart	3	4/4
I-494 (North Ramp)	Pilot Knob Rd	Iteris Vantage Next	3	3/2
I-494 (Camera 1) **I-494 (Camera 2)**	Tamarack Rd	Gridsmart	4	4/3
MN-51	County Road C2	Iteris Vantage Next	4	4/2
MN-62 (North Ramp)	France Ave	Autoscope Vision	3	3/2
MN-62 (South Ramp)	France Ave	Autoscope Vision	3	3/2
MN-65	41st Ave	Gridsmart	4	4/1
MN-65	81st Ave	Autoscope Vision	4	5/2

MN-7	Blake Rd	Autoscope Vision	4	4/4
MN-65 (East side)	Viking Blvd	Gridsmart	3	3/1
MN-65 (North Uturn)	Viking Blvd	Gridsmart	2	2/2
MN-65 (South Uturn)	Viking Blvd	Gridsmart	2	2/2
MN-65 West Side)	Viking Blvd	Gridsmart	3	3/1
I-694 (North Ramp)	East River Rd	Autoscope Vision	4	2/1
I-694 (South Ramp)	East River Rd	Autoscope Vision	4	2/1
MN-77 (East Ramp)	Cliff Road	Autoscope Vision	3	3/2
MN-77 (West Ramp)	Cliff Road	Autoscope Vision	3	3/2
MN-97 (Camera 1) **MN-97 (Camera 2)**	Hornsby St	Gridsmart	4	4/3
County Road 81	John Deere Ln	Autoscope Vision	4	4/1
County Road 81	Industrial Blvd	Autoscope Vision	4	4/3
County Road 81	Memorial Dr	Autoscope Vision	4	4/2
US-12 (North Ramp)	Carlson Pkwy	Autoscope Vision	4	4/3
US-12 (South Ramp)	Carlson Pkwy	Autoscope Vision	3	3/2
Carlson Pkwy	Twelve Oaks Ctr Dr	Autoscope Vision	4	4/3
US-12 (North Ramp)	CSAH-101	Autoscope Vision	3	3/2
US-12 (South Ramp)	CSAH-101	Autoscope Vision	3	3/2
County Road 144	James Rd	Autoscope Vision	4	4/3
County Road 144	Northdale Blvd	Autoscope Vision	4	4/2
County Road 144	Rogers High Sc Rd	Autoscope Vision	4	3/2



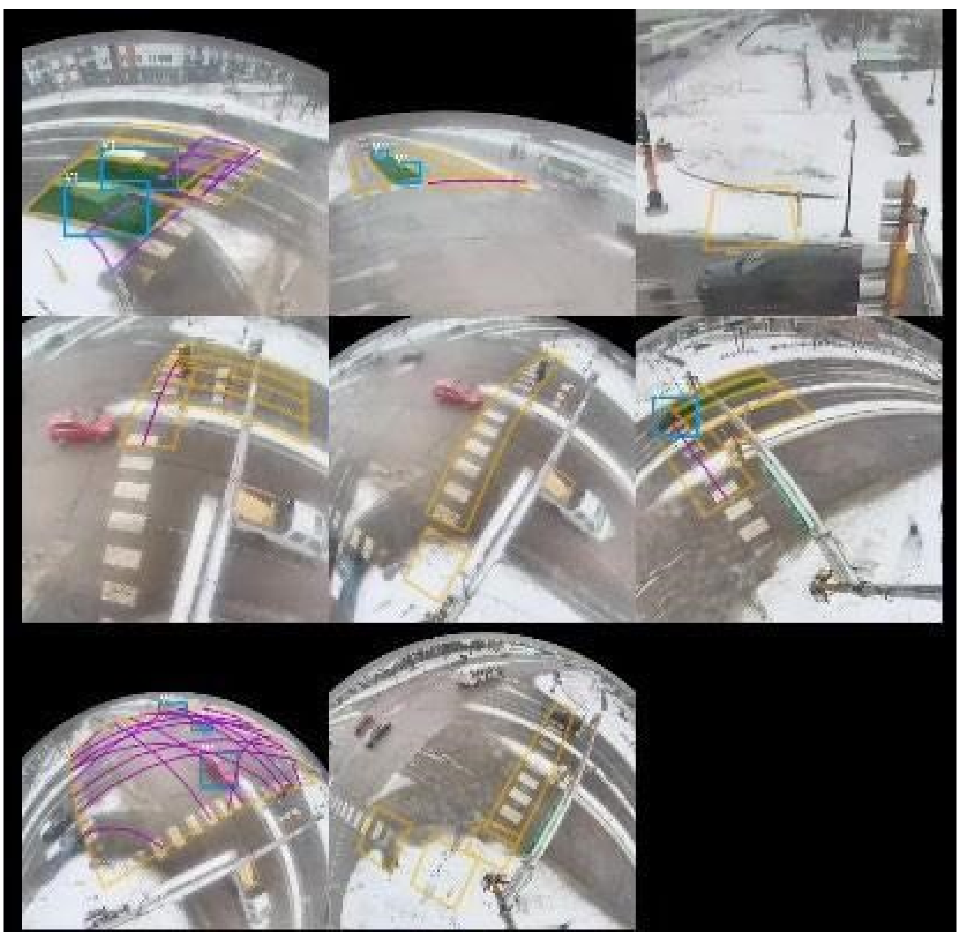
Red = Autoscope, Yellow = Iteris, Green = Gridsmart, Light Green = Miovision

I-35E and Cliff Road (East and West Ramps)

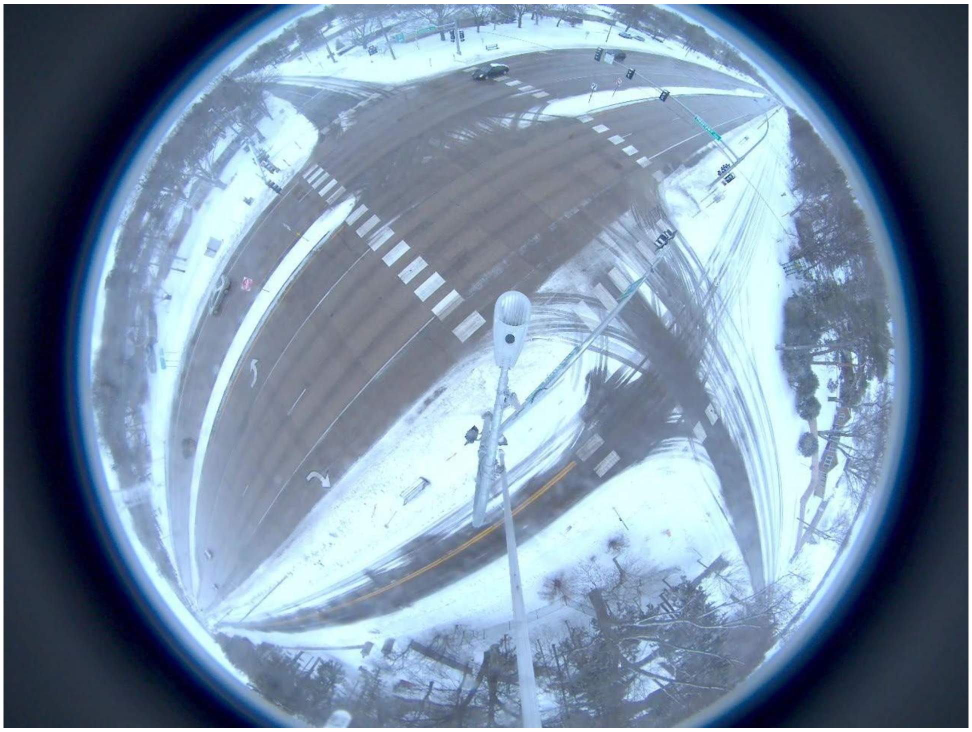
MN-36 and White Bear Ave (North and South Ramps)

MN-47 and 85th Ave (One approach with Ped crossing)

MN-47 and Mississippi St



MN-51 and Roselawn Ave

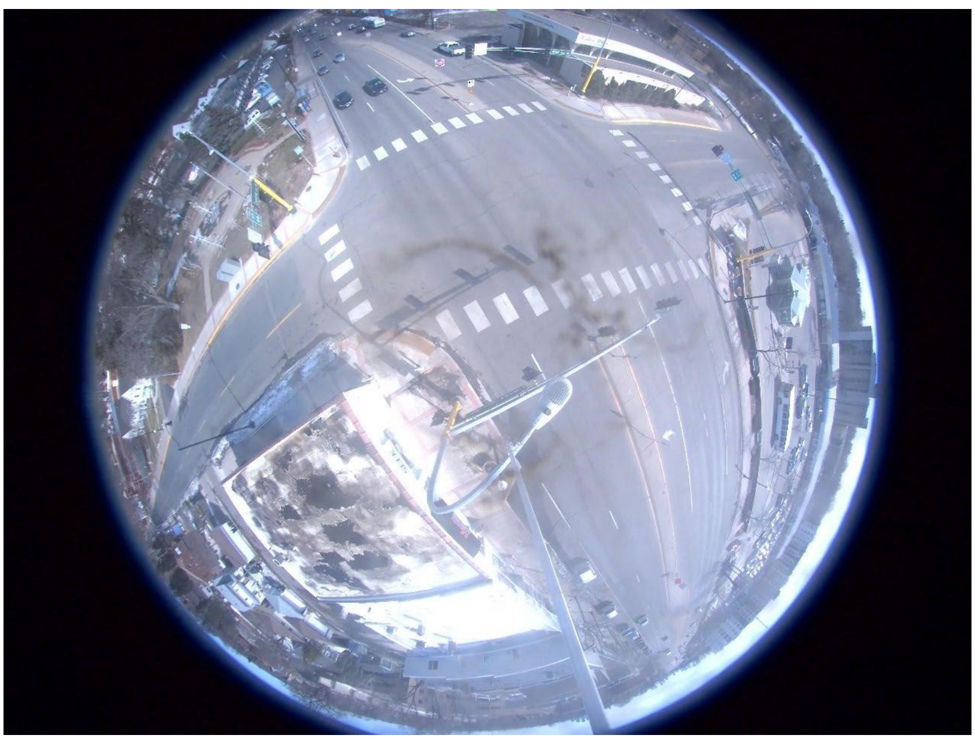


I-494 and Flying Cloud Dr

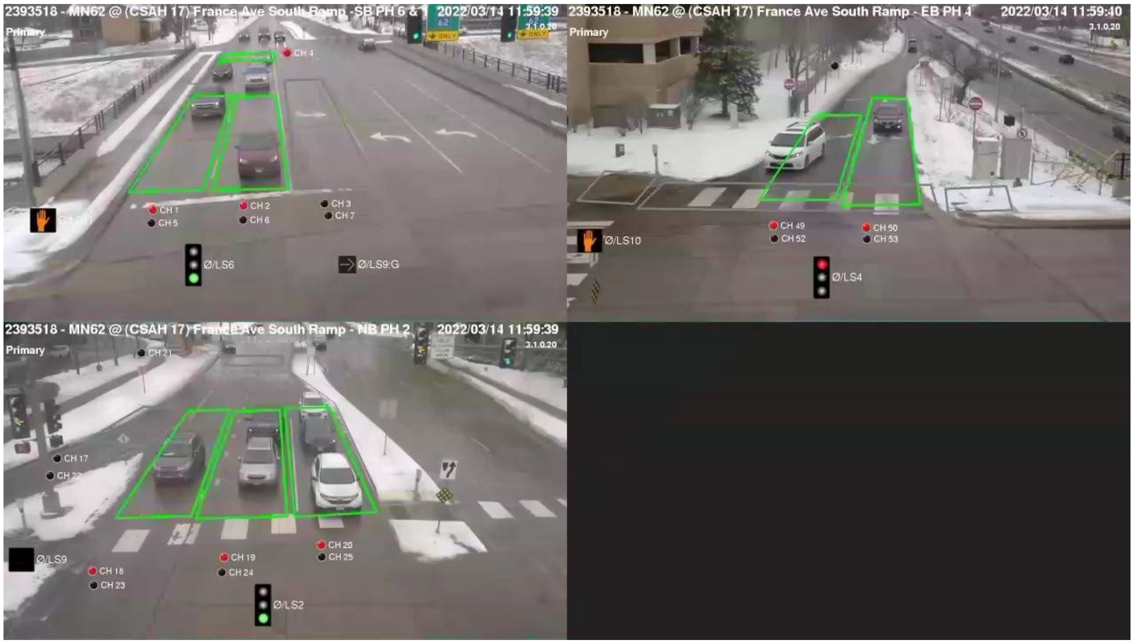
I-494 and Pilot Knob Rd (North Ramp)

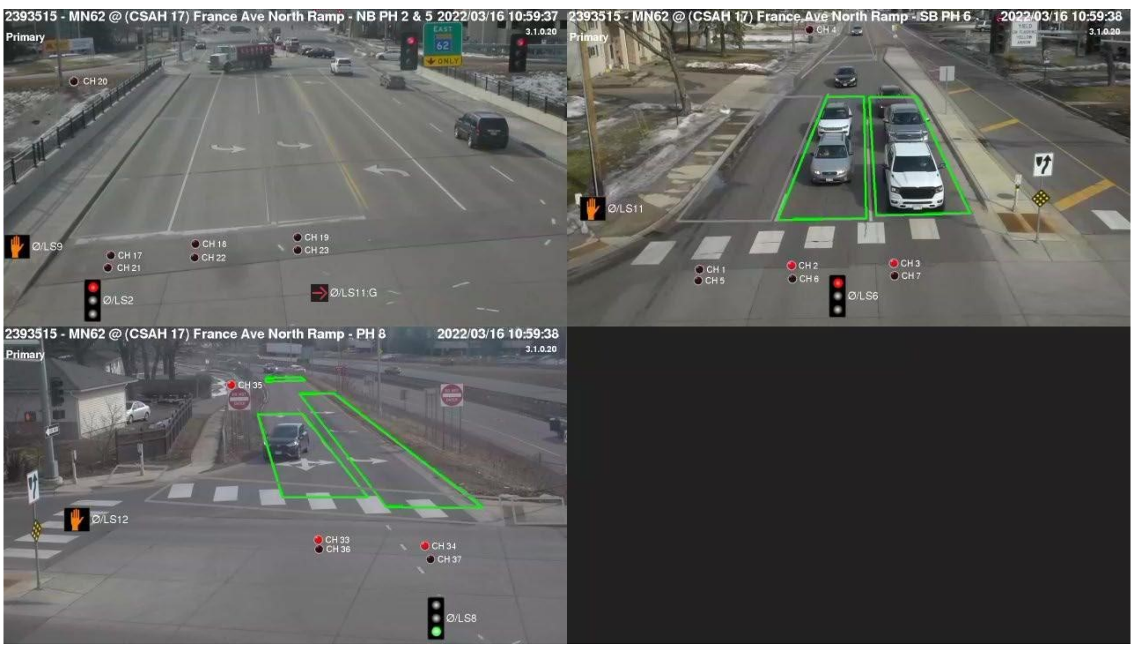
MN-51 and County Road C2

MN-65 and 41st Ave

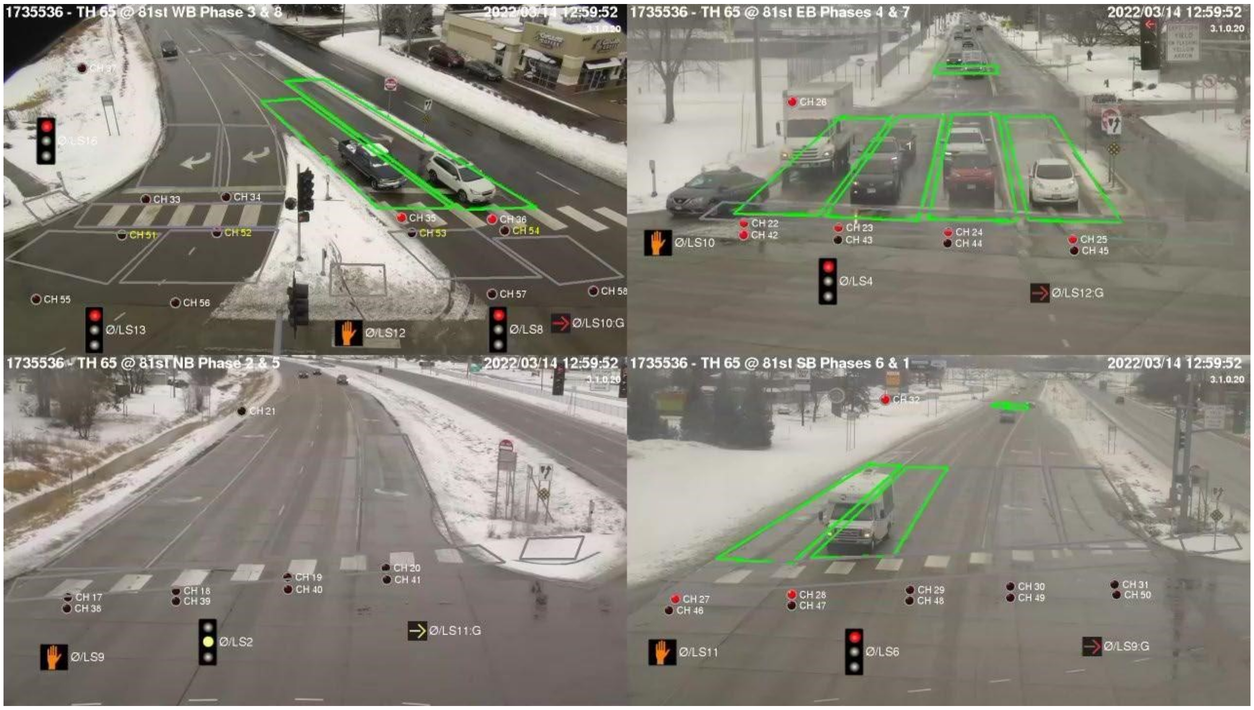


MN-62 and France Ave (North and South Ramps)

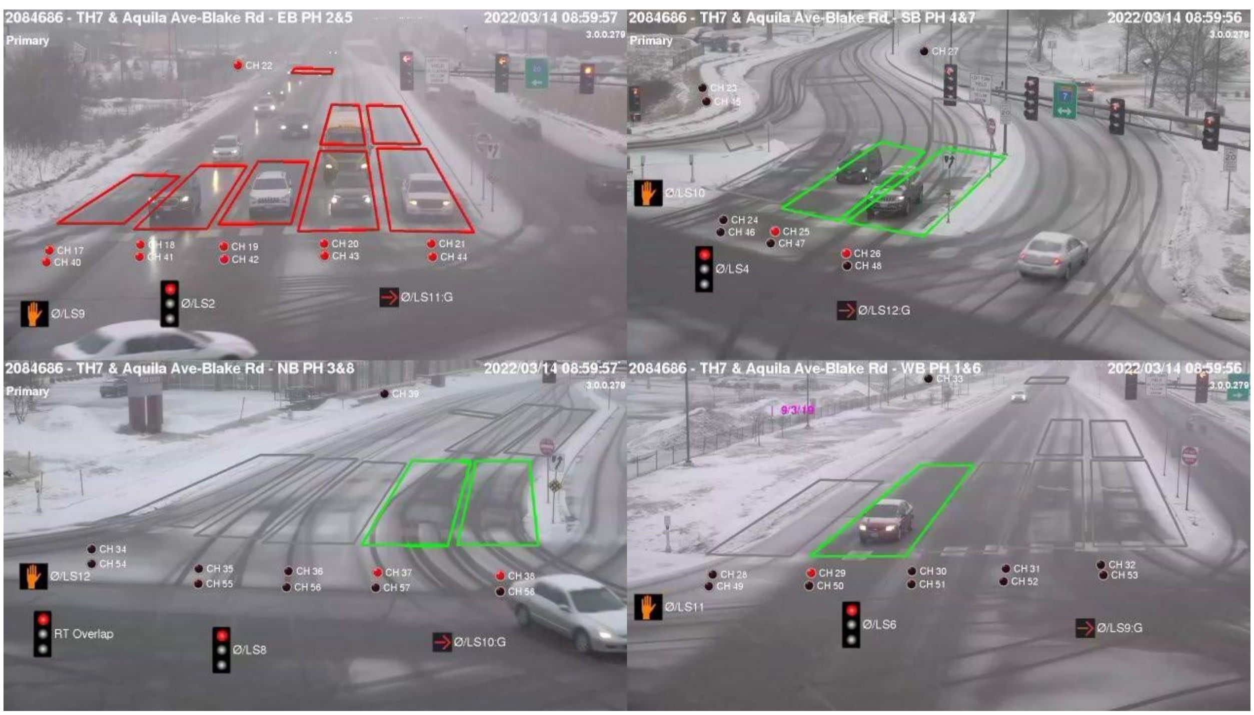




MN-65 and 81st Ave



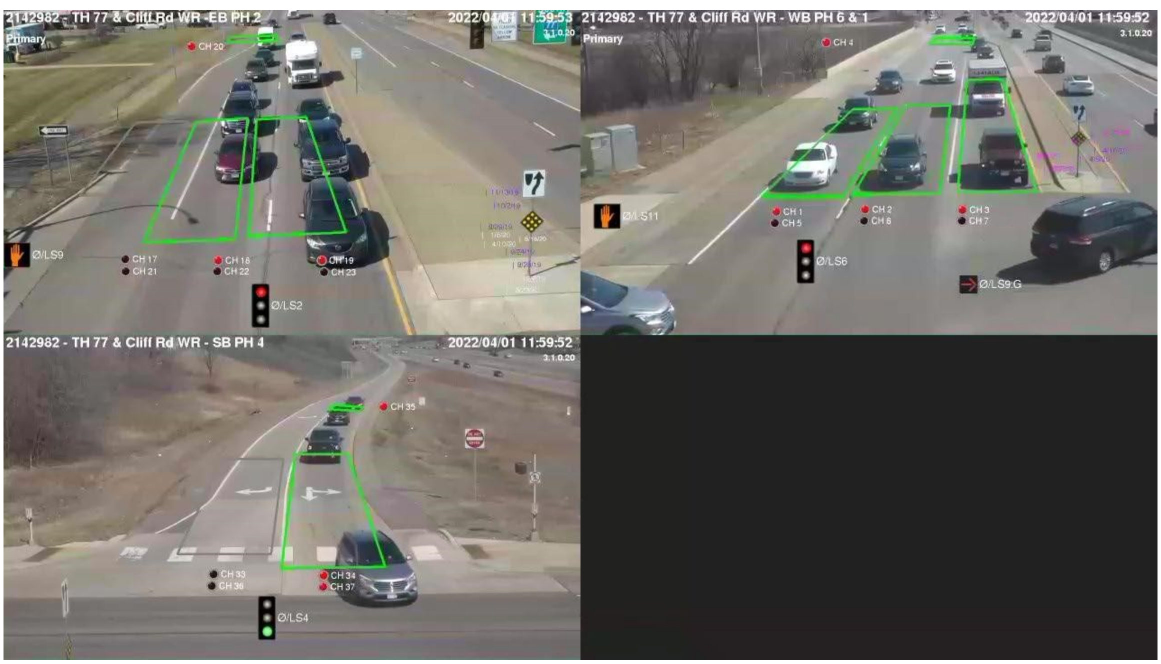
MN-7 and Blake Rd



I-694 and East River Rd (North and South Ramps)

MN-77 and Cliff Road (East and West Ramps)


2142984 - TH77 & Cliff East Ramp -WB PH 6
2022/04/01 12:59:47
Primary
2142984 - TH77 & Cliff East Ramp - NB PH 8
2022/04/01 12:59:47
Primary
2142984 - TH77 & Cliff East Ramp - EB PH 2,5
2022/04/01 12:59:46
Primary

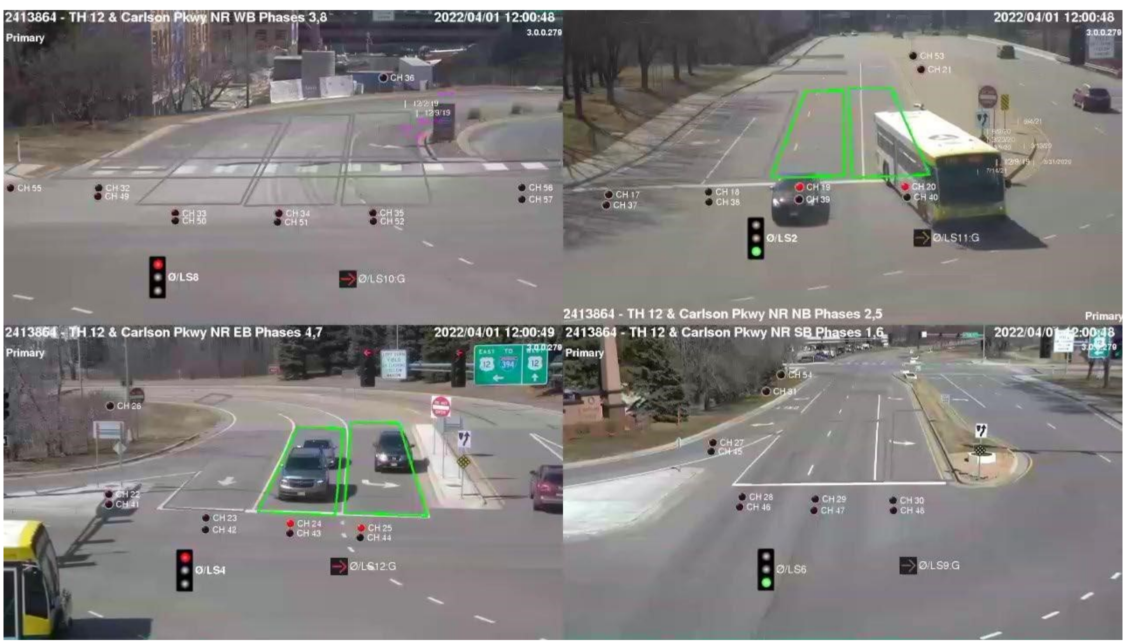

2142982 - TH 77 & Cliff Rd WR -EB PH 2
2022/04/01 11:59:53
Primary
2142982 - TH 77 & Cliff Rd WR - WB PH 6 & 1
2022/04/01 11:59:52
Primary
2142982 - TH 77 & Cliff Rd WR - SB PH 4
2022/04/01 11:59:52

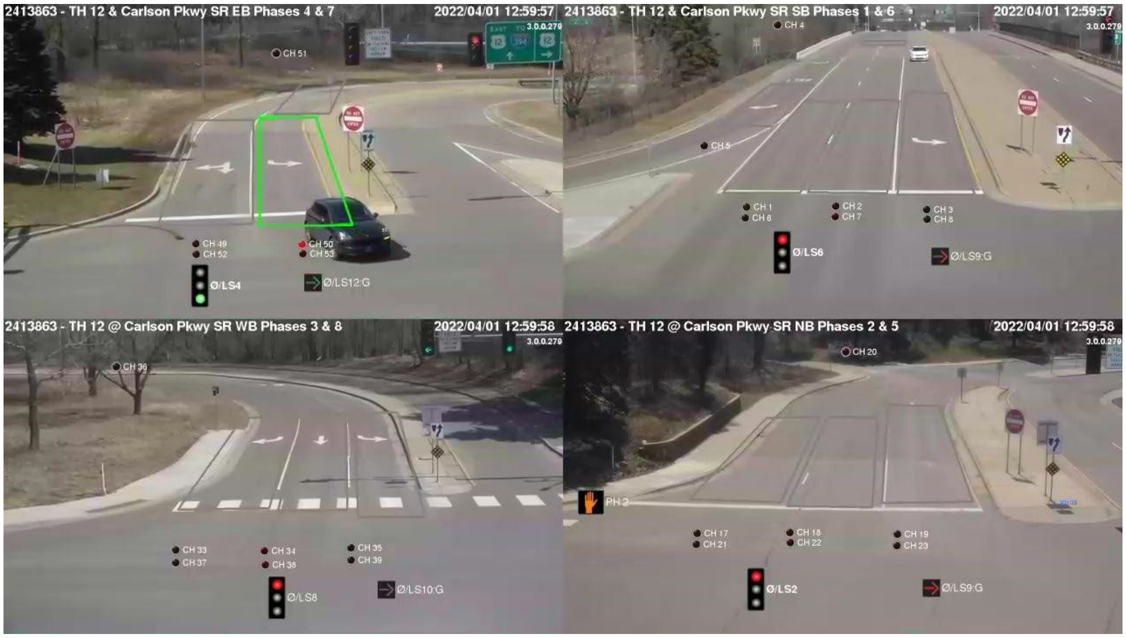
County Road 81 and John Deere Ln

County Road 81 and Industrial Blvd

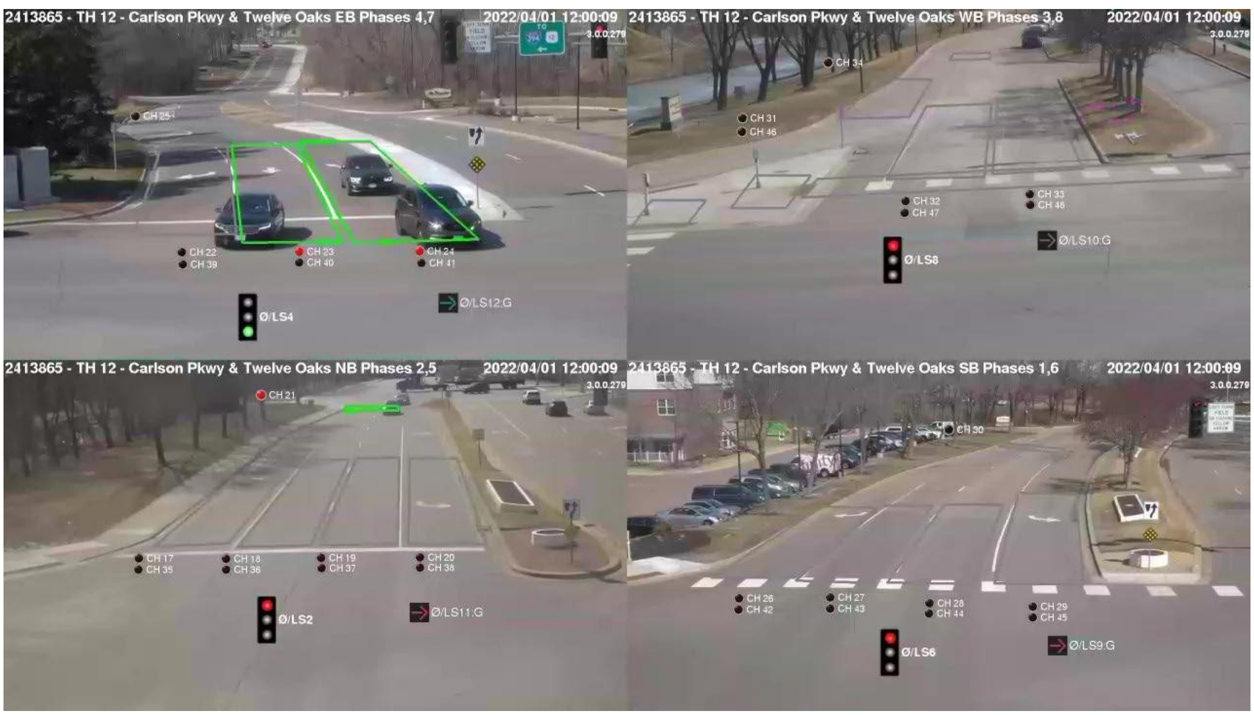
County Road 81 and Memorial Dr

US-12 and Carlson Pkwy (North and South Ramps)



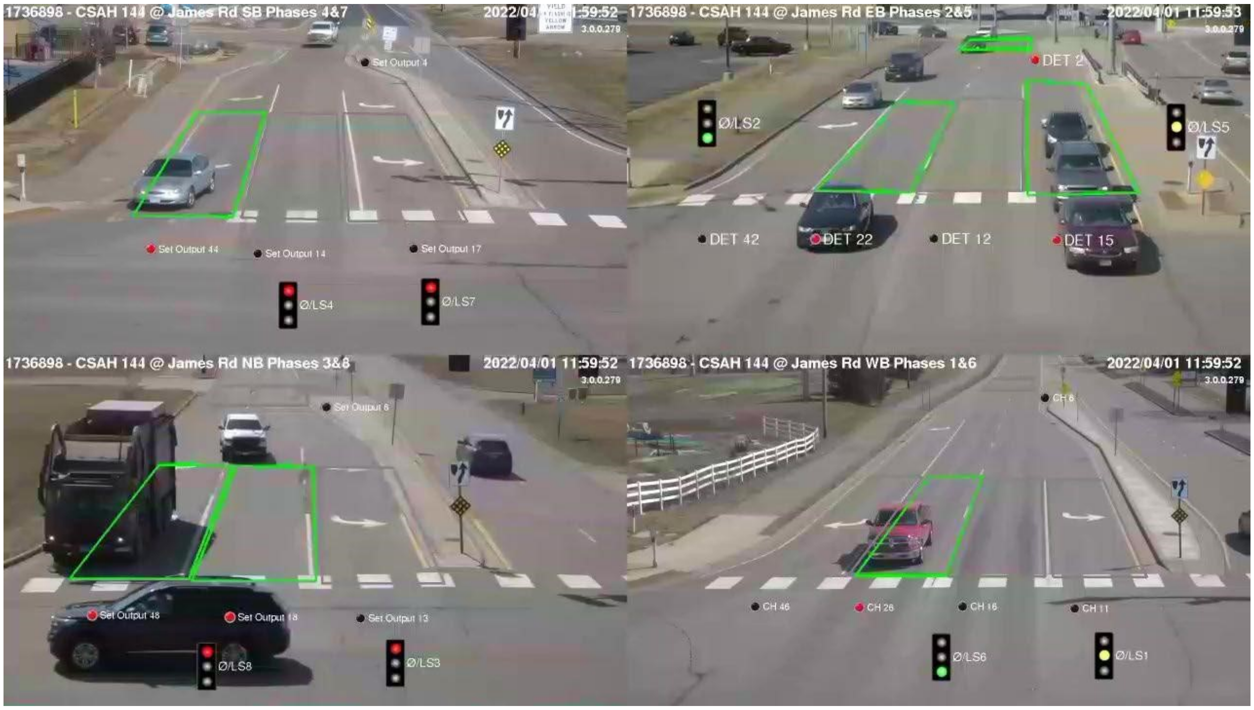


Carlson Pkwy and Twelve Oaks Ctr Dr

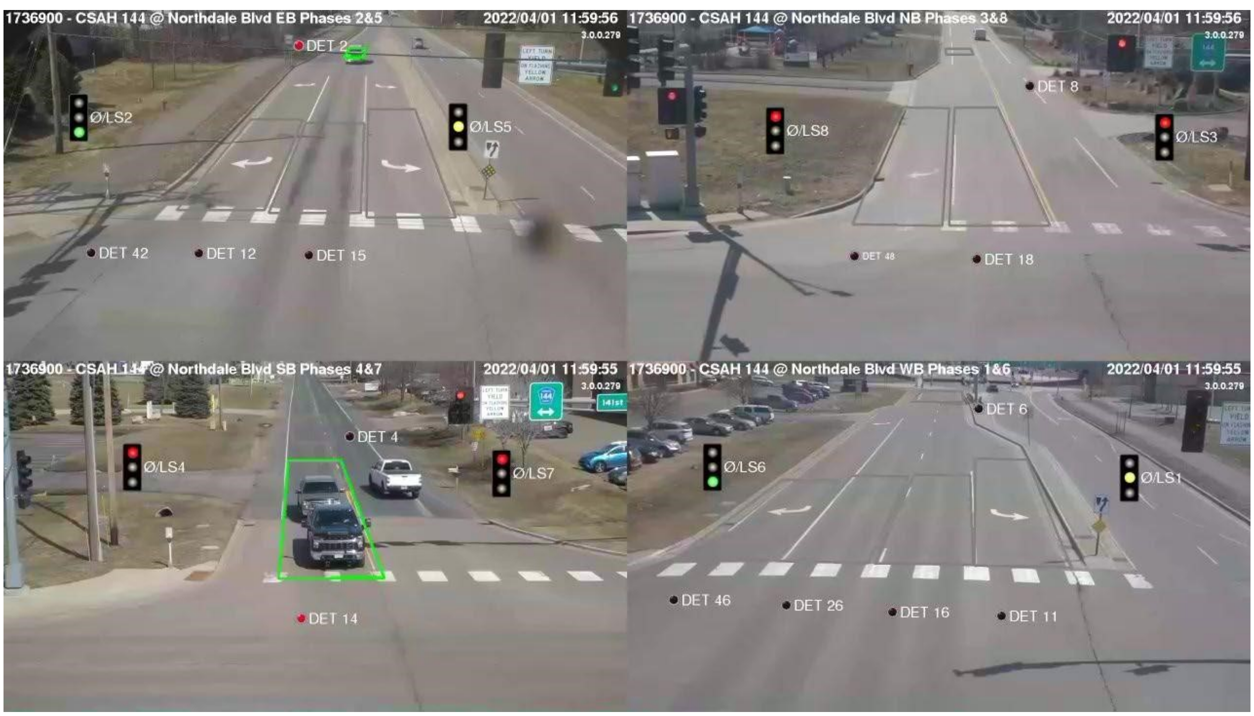


US-12 and CSAH-101 (North and South Ramps)

County Road 144 and James Rd



County Road 144 and Northdale Blvd



County Road 144 and Rogers High School Rd


1736899 - CSAH 144 @ Rogers High School NB Phase 8
2022/04/01 11:59:54
Primary
Ø/LS8
Ø/LS12
DET 28
DET 18
1736899 - CSAH 144 @ Rogers High School EB Phases 2&5
2022/04/01 11:59:54
Primary
DET 2
Ø/LS2
Ø/LS5
DET 12
DET 15
Ø/LS9
1736899 - CSAH 144 @ Rogers High School WB Phases 1&6
DET 6
2022/04/01 11:59:54
Primary
Ø/LS6
Ø/LS1
Ø/LS11
DET 46
DET 16
DET 11
1736899 - CSAH 144 @ Rogers High School SB Phase 4
2022/04/01 11:59:54
Primary
Ø/LS4
DET 44
DET 24
DET 14
Ø/LS10

Appendix E: Task 6 Deliverable

Performance Evaluation of Different Detection Technologies for Signalized Intersections in Minnesota

Task 6 Deliverable:

Deployment and operation of data collection systems: Phase II

Prepared by:

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Problem Description

The Minnesota Department of Transportation (MnDOT) has worked to deploy Non-Intrusive Detection Technologies (NIT) for vehicle detection at intersections to detect cars, bikes, and pedestrians. They have been used to alert other drivers and allow the traffic signal to modify timing to serve the immediate traffic needs better. The main goal of this project is to evaluate the operational performance and costs of the various technologies deployed by MnDOT at intersections around the Twin Cities Metropolitan Area. The research team will accomplish this goal by evaluating the performance of these NIT under various conditions.

The aim of Task 6 is to continue on Task 5 and finalize data collection, specifically for videos of the operation of the selected sites starting in the winter season of 2021-2022. This document presents the selected and collected datasets collected by the research team and their plans for using them to address the overall project goal. Including video data, the datasets collected by the research team have been broken down into three sections by data type; Traffic, Weather, and Geography. In collecting these datasets, the research team hopes to evaluate the performance of the detection technologies used by the cameras under various environmental conditions. Once we have completed the evaluation, we will submit a proposal to help MnDOT and Local Road Research Board (LRRB) members select the most appropriate technology from deployed NIT for a given location and estimate the effort and cost of maintaining each system year-round in Minnesota.

This document is structured as follows. Section 2 provides an overview of the types and sources of the data and the research team's methods to collect and analyze the data. Section 3 overviews the research team's initial data analysis methods and results. Section 4 explains the future steps for further data analysis and how the research team plans to meet the overall project goal.

Data Types and Sources

This section describes the datasets we have collected and the methods used to prepare them. Below we describe their source, attributes, spatial coverage, temporal coverage, resolutions, any justifications for why these data sources were selected, and preprocessing steps. We categorize the data sources into traffic (Section 2.1), weather (Section 2.2), and geographic (Section 2.3) data.

Traffic Data

Traffic Camera Data

Summary: The Traffic Camera Data is video data collected from the traffic cameras around the Twin Cities Metropolitan Area. MnDOT provides the data and contains the video recordings from traffic cameras in *.mp4 format. The research team will use the video data to look for detection failures of the cameras and help confirm failures in other NITs.

Data Source: MnDOT provides 39 cameras in the Twin Cities Metropolitan Area, with traffic camera names assigned to each camera.

Attributes: Camera Name, Latitude, Longitude, Link (Google Maps) (Table 1). The camera name is a designation given by MnDOT and contains information about the intersecting streets, the camera technology used, and the ramp direction (if next to a highway). The Latitude, Longitude, and the Link of Google Maps reference the location of each camera (this process is outlined in the Spatial Coverage section below) and were identified by the research team using Google Maps.

Spatial Coverage: MnDOT provides 39 cameras named after camera locations and types covering the Twin Cities Metropolitan Area, including four counties or 13 cities. The research team collected the point geographic coordinates of each camera location by searching the road intersection on Google Maps. Take “35e_cliff_eramp_iteris” as an example. We searched “I-35E” and “Cliff” on Google Maps and found the road intersection of “I-35E” and “Cliff Rd” and acquired the geo-coordinates on the east ramp. “Iteris” refers to the camera type. After removing the cameras that could not be accurately located using this process, we saved the 31 individual cameras (No.1- No.31 in Table 1) with geographic coordinates for further sampling and analysis (Figure 1).

Collected Temporal Coverage: All camera locations were extracted on December 31, 2022.

Camera recordings were collected from 11/22/2021 to 05/08/2023

Collected Spatial Coverage: Twin Cities Metropolitan Area, covering four counties **Why we collected these data:** Collecting this data will help the research team analyze traffic patterns throughout the Twin Cities Metropolitan Area.

Point Locations:

No.	Camera Name	Type	Latitude	Longitude	Link (Google Maps)
1	35e_cliff_eramp_iteris	iteris	44.790136	-93.198956	https://goo.gl/maps/24skT2KbrnrMoU1JA
2	35e_cliff_wramp_iteris	iteris	44.790131	-93.205099	https://goo.gl/maps/HZ2SHM65K83eTTog77
3	36_whitebear_nramp_iteris	iteris	45.012665	-93.020928	https://goo.gl/maps/KieTBYXEXENGR6dY9
4	36_whitebear_sramp_iteris	iteris	45.010636	-93.022571	https://goo.gl/maps/zgHTW9FXs4WwYts988
5	47_85th_Iteris_Stream1	iteris	45.125053	-93.264553	https://goo.gl/maps/A48DyvcpYnLMF29p8
6	47_Mississippi_Movision_Stream 3	movision	45.086136	-93.263535	https://goo.gl/maps/kV5jmgUQ26DopU9q7
7	494_flyingcloud_sramp_gridsmart	gridsmart	44.861405	-93.425593	https://goo.gl/maps/hjjbYwgqjXQGMmkD6
8	494_pilotknob_nramp_iteris	iteris	44.861479	-93.167119	https://goo.gl/maps/KTBLqUaRBo45sv9V7
9	51_crc2_iteris	iteris	45.027917	-93.167081	https://goo.gl/maps/1VwBnov8FEq7tvkS77
10	62_france_nramp_vision	vision	44.887507	-93.328961	https://goo.gl/maps/AA2CmQ5MdAqmbCRh9
11	62_france_sramp_vision	vision	44.886547	-93.328982	https://goo.gl/maps/P31VNKuaC9LCvqnn7
12	65_41st_gridsmart	gridsmart	45.042744	-93.247337	https://goo.gl/maps/SEp3jd6vY7UHZvCKA
13	65_81st_Vision_Stream1	vision	45.11504	-93.241732	https://goo.gl/maps/vTJozXz3D2wy8GLY9
14	694_eriver_nramp_vision	vision	45.069585	-93.278772	https://goo.gl/maps/LAGPMU2MyM6Soepk7
15	694_eriver_sramp_vision	vision	45.068929	-93.279158	https://goo.gl/maps/ZKiHcteNBToFauu47
16	77_cliff_eramp_vision	vision	44.790226	-93.21963	https://goo.gl/maps/cnTfPvzrihw4eEgm9

17	77_cliff_wramp_vision	vision	44.790237	-93.223347	https://goo.gl/maps/Nbewbfn3NogrT8R18
18	CR81_deere_visions_stream	vision	45.190296	-93.550583	https://goo.gl/maps/PfWNoeWpfnirCQmh9
19	CR81_industrial_visions_stream	vision	45.192302	-93.55264	https://goo.gl/maps/2eonYzcRxoWLQRNw7
20	CR81_memorial_visions_stream	vision	45.188553	-93.547743	https://goo.gl/maps/Et7H17RuUAnQBNZN7
21	s_12_carlson_nramp_vision	vision	44.972593	-93.469741	https://goo.gl/maps/hQ4cu5LSTH5XYPc36
22	s_12_carlson_sramp_vision	vision	44.969558	-93.469776	https://goo.gl/maps/uLjGo5sdCg9u8k7v9
23	s_12_csah101_nramp_vision	vision	44.976979	-93.50213	https://goo.gl/maps/FMrxWoYBbAR7uFB98
24	s_12_csah101_sramp_vision	vision	44.975039	-93.502106	https://goo.gl/maps/f1bJe7qj2vRihaX1A
25	s_65_viking_eside_gridsmart	gridsmart	45.319684	-93.235698	https://goo.gl/maps/VqgHYCqXZBmjtcac8
26	s_65_viking_nuturn_gridsmart	gridsmart	45.322122	-93.236216	https://goo.gl/maps/Si6BYYFV3nM7Cb9dA
27	s_65_viking_suturn_gridsmart	gridsmart	45.317065	-93.235865	https://goo.gl/maps/DW8TqZkE1ttYz2X56
28	s_65_viking_wside_gridsmart	gridsmart	45.319638	-93.236458	https://goo.gl/maps/UWS7Cc5PyAj7gRh58
29	s_cr144_james_vision	vision	45.210298	-93.550016	https://goo.gl/maps/i8dBxffTY6PUi6SJA
30	s_cr144_northdale_vision	vision	45.210364	-93.55579	https://goo.gl/maps/sQxo359WMDgVNAXj8
31	s_cr144_rogershighscool_vision	vision	45.210303	-93.546439	https://goo.gl/maps/L2e4wecC3rcx93kf9
32	169_main_gridsmart	gridsmart			
33	47_Roselawn_Gridsmart_Stream 1	gridsmart			
34	494_tamarack_eramp_gridsmart1	gridsmart			
35	494_tamarack_eramp_gridsmart2	gridsmart			
36	65_Blake_Vision_Stream1	vision			
37	97_hornsby_gridsmart1	gridsmart			
38	97_hornsby_gridsmart2	gridsmart			
39	s_12_carlson_twelveoaks_vision	vision			

Table 1: Traffic camera names, locations (latitude, longitude), address, and Google Maps link

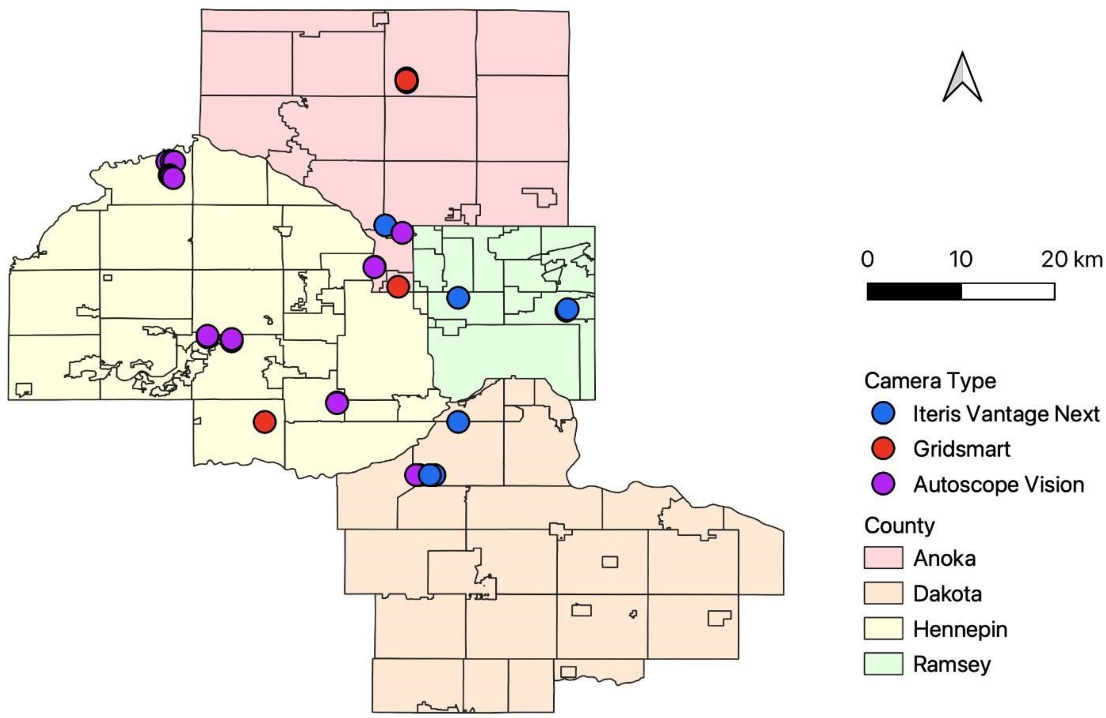


Figure 1: Locations of cameras colored by type overlaid on the county map of the Twin Cities Metropolitan Area

Traffic Volume Data

Summary: The Traffic Volume Data are the time-series traffic flow statistics collected from traffic detectors. The data was provided by the MnDOT website [1] in *.csv format. The research team will use the traffic volume data to observe abnormal traffic patterns and as a reference to find failure cases in the Actuated Signal Data and to understand general traffic trends over time within the Twin Cities Metropolitan Area.

Data Source: MnDOT Automatic Traffic Recorder (ATR) / Weigh-in-Motion (WIM) Yearly Vehicle Classification Data [1]

Attributes: Traffic Recorder ID (station_id), Driving Direction & the Order of Lane (dir_of_travel, lane_of_travel), Time (year, month, day, hour), Total Volume (total_intverval_vol), Volume Counted by 15 Vehicle Classes (class1, class2, class3, class4, class5, class6, class7, class8, class9, class10, class11, class12, class13, class14, class15). The station_id is the traffic recorder ID shown on the MnDOT traffic mapping application [10]. The dir_of_travel is the direction of vehicles counted in the current record. The lane_of_travel is a numerical representation of the lane the vehicle was detected in. The year, month, day, and hour represent the time the data was recorded. The total_intverval_vol is the number of vehicles on a road lane (defined in the "lane_of_travel" column (Table 2)) heading in a direction (defined in the “dir_of_travel” column (Table 2)) in a one-hour time slot (defined in the “hour” column (Table 2)).

According to the MnDOT, the 15 types of vehicle classification were based on MnDOT Vehicle Classification Scheme [9]. These vehicle classifications are primarily based on the vehicle's length detected moving through the intersection. The dataset also records the number of vehicles on a road lane (defined in the “lane_of_travel” column (Table 2)) heading in a direction (defined in the “dir_of_travel” column (Table 2)) in a one-hour time slot (defined in the “hour” column (Table 2)) by vehicle classes. Table 2 is an example of the dataset.

station_id	dir_of_travel	lane_of_travel	year	month	day	hour	total_intverval_vol	class1	class2
26	1	1	2023	1	1	0	61	0	32
26	1	1	2023	1	1	1	67	0	19
26	1	1	2023	1	1	2	43	0	12
26	1	1	2023	1	1	3	47	0	6
26	1	1	2023	1	1	4	51	0	5

class3	class4	class5	class6	class7	class8	class9	class10	class11	class12	class13	class14	class15
9	0	1	2	0	1	16	0	0	0	0	0	0
25	3	4	1	0	2	8	0	0	1	1	2	1
10	0	2	0	2	0	2	0	0	1	8	0	6
8	0	3	0	0	1	8	1	0	1	11	2	6
7	1	1	0	0	0	4	0	0	1	19	4	9

Table 2. Data example of the traffic volume dataset

Spatial Resolution: Point locations of 59 individual traffic recorders

Spatial Coverage: The State of Minnesota

Temporal Resolution: 1 hour

Temporal Coverage: The available dates downloaded from MnDOT by 4/24/2023 is Jan. 1, 2017 - Jan. 31, 2023. The data provider continues uploading more recent data as time goes on. **Collected Spatial Resolution:** Point locations of 19 individual traffic recorders out of the 59 locations in total (Selected Traffic recorder IDs: 26, 27, 30, 31, 32, 33, 34, 35, 38, 39, 40, 41, 43, 44, 45, 46, 47, 48, 49)

Collected Spatial Coverage: Twin Cities Metropolitan Area

Collected Temporal Coverage: Jan. 1, 2022 - Dec. 31, 2022

Why we collected these data: As the traffic volume data directly records the number of cars in Minnesota, this dataset could provide general information about the traffic volume trend over time. This data will help guide data collection and will be used to determine traffic patterns. We intend to use this data as a point of comparison for the Actuated Signal Data to evaluate detector performance. This data can only partially be relied on due to sections of missing data. Section 3.1.2 will show three examples of missing data from the year 2022. Figure 2 is a map of all traffic volume detectors in the State of Minnesota. Figure 3 shows the selected traffic volume detector distribution.

Data Preparation: The original dataset is in *.csv format. Our observations show that the dataset is well organized and does not include many empty rows. The research team uses Pandas [7] to organize the data. The outcome is in the DataFrame format.

Visualization of Traffic Recorder Locations:

Figure 2: Map of Traffic Data detection locations in Minnesota

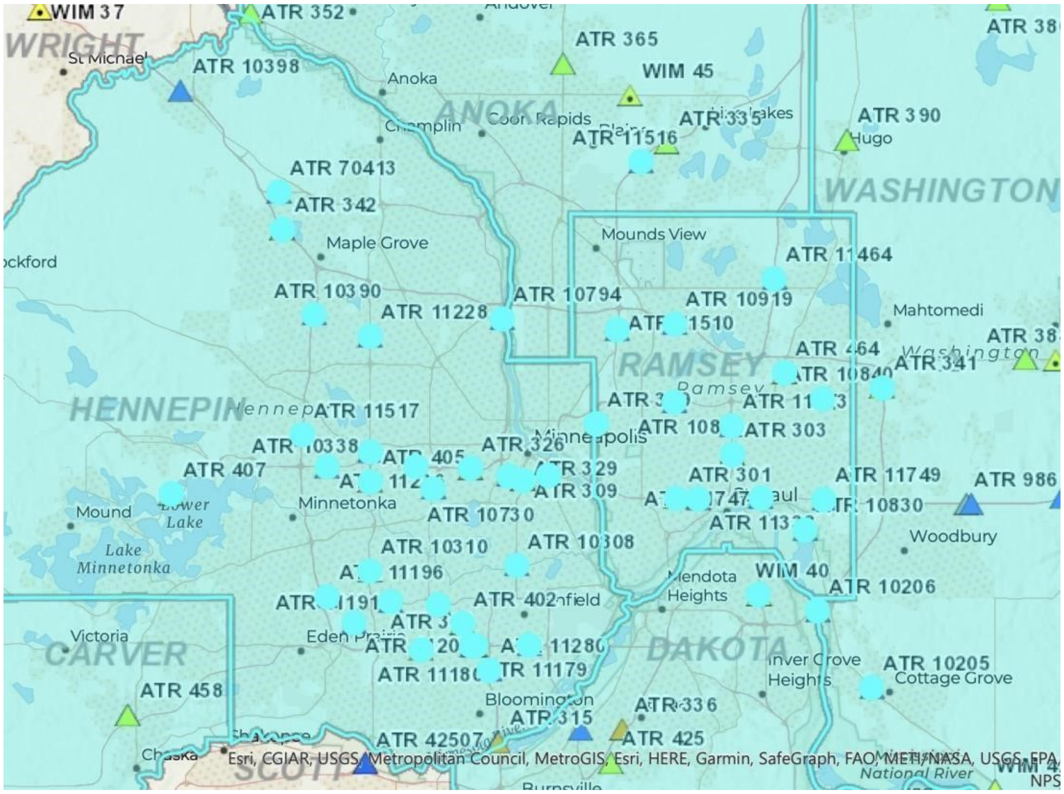


Figure 3: Zoom-in of Figure 2. Only include traffic detection stations within the research study area

Actuated Signal Data

Summary: The Actuated Signal Data has been collected from intersections with cameras. MnDOT provides it in *.csv format in the form of a downloadable link that is emailed to the research team. It contains temporal event data on signal changes, maintenance, and traffic passing through the intersection. This data will be used to evaluate the performance of NIT in detecting traffic moving through an intersection.

Data Sources: MnDOT; delivered on request

Attributes: Time (Year, Month, Day, Hour, Minute, Second, Millisecond), Camera ID, Event

Code, and Event Parameter [2]. Table 3 displays an example sequence of the Actuated Signal

Data. We observe that the first two entries occur at the same timestamp and have the same Event Parameter, 3. Having the same timestamp indicates that the events coincide, and having the same Event Parameter indicates that the events occur in the same direction in the intersection. Event Codes 10 and 9 correspond to Phase Begin Red Clearence (beginning of a red light) and Phase End Yellow Clearence (end of a yellow light) [2]. Several seconds later, we see Event Code 11 on Event Parameter 3. Event Code 11 is associated with Phase End Red Clearance (end of red light). This sequence of events describes the transition from a yellow light to the end of a red light at a specific intersection for traffic moving in a specific direction. Events with different Event Parameters do not affect one another and can have overlapping sequences.

Spatial Resolution: Point locations of 31 individual cameras with locations out of the original 39
Temporal Resolution: The record is updated every time a traffic-related event occurs at an intersection (0 milliseconds-10 seconds). The time interval is irregular and varies depending on traffic.

Temporal Coverage: The data has been continuously collected by MnDOT starting 11/2021
Collected Spatial Resolution: The research team samples 10 cameras out of the original 31 to cover more cases of the location distribution, camera types, environmental features, and intersection types. Figure 4 displays the locations of the 10 cameras. The selected 10 cameras are:

1. 694_eriver_nramp_vision
2. 694_eriver_sramp_vision
3. 65_81st_Vision_Stream1
4. 47_85th_Iteris_Stream1
5. 65_41st_gridsmart
6. 51_crc2_iteris
7. s_65_viking_nuturn_gridsmart
8. s_65_viking_suturn_gridsmart
9. 77_cliff_eramp_vision
10. 77_cliff_wramp_vision

Collected Temporal Coverage: December 20, 2022 - January 10, 2023, June 20, 2022 - July 10, 2023, January 17, 2023 - February 7, 2023 (Pending), November 10, 2023 - December 1,

2023 (Pending)

Why we collected these data: We sampled these 10 cameras out of the 31 to cover all types of camera location distribution (from urban to suburban), 3 camera types (Iteris Vantage Next, Autoscope Vision, and Gridsmart), and 6 classes of environmental features, refer to Table 6 (classes derived from OpenStreetMaps and categorized on the profile of the surrounding area for each camera). This signal data gives precise timestamps for many types of traffic events, such as red lights, green lights, car detection, pedestrian detection, maintenance signal, etc., at a very high temporal resolution, allowing us to accurately describe the behavior of the signals at intersections. The research team has chosen to focus on event codes 82/81 because they directly correspond to cars entering and leaving the intersection. These codes will be used to evaluate traffic detector performance.

Data Preparation: MnDOT delivers the data to the research team in CSV format. The data is partially unordered and has to be ordered by timestamps using Pandas [7]. The research team also removes any unnecessary event codes that do not pertain to evaluating camera performance. The outcome of this preprocessing is a Pandas DataFrame.

Time	Camera ID	Event Code	Event Parameter
2022-12-01 04:03:12.400	596	10	3
2022-12-01 04:03:12.400	596	9	3
2022-12-01 04:03:14.900	596	11	3
2022-12-01 04:03:14.900	596	12	3
2022-12-01 04:03:14.900	596	0	6
2022-12-01 04:03:14.900	596	31	2
2022-12-01 04:03:14.900	596	0	2
2022-12-01 04:03:14.900	596	1	2
2022-12-01 04:03:15.000	596	1	6
2022-12-01 04:03:15.000	596	3	2

2022-12-01	596	3	6
04:03:29.900			
2022-12-01 04:03:29.900	596	2	6
2022-12-01 04:03:36.200	596	7	6
2022-12-01 04:03:36.200	596	8	6
2022-12-01 04:03:41.700	596	4	6

Table 3: Sample of Actuated Signal Data

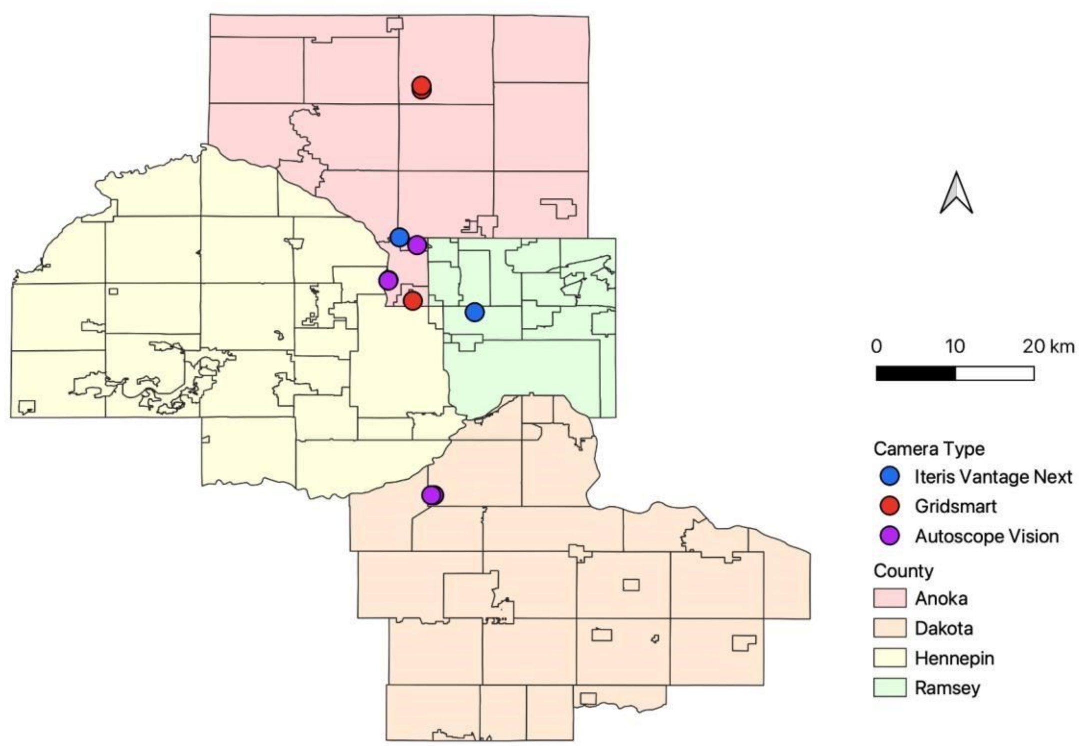


Figure 4: The locations of the subset cameras that will be studied by the research team, colored by type and overlaid on the county map of the Twin Cities Metropolitan Area.

Weather Data

Weather Station Data

Summary: The Weather Station Data is data that was collected directly from weather station detectors around Minnesota and contains metrics describing temperature, humidity, visibility, etc. We use this data to better understand localized weather conditions near the cameras described in section 2.1.1.

Data Source: Weather Real-Time Reports [3] from MnDOT

Attributes: Air Temp, Max Temp, Min Temp, Wet Bulb Temp, Dewpoint, Surface Temp, Subsurface Temp, Humidity, Visibility, Precip Rate, Wind Speed, Wind Direction, Surface Status, Precip Type. Table 4 is an example of all attributes the data provides.

Spatial Resolution: Point locations of 154 distributed individual weather stations in Minnesota
Spatial Coverage: The State of Minnesota

Temporal Resolution: Data is collected every 5-10 minutes (the time interval varies depending on different weather stations)

Temporal Coverage: February, 2022 - present

Collected Spatial Resolution: Point locations of 10 selected weather stations close to the Twin Cities Metropolitan Area from all weather stations in Minnesota Selected Weather stations:

1. I-35W: Minnesota River
2. I-35E: Cayuga
3. I-35E: Little Canada
4. MN 62: Inver Grove Hts
5. MN 65: East Bethel
6. I-494: I-494 @ Minnetonka Blvd
7. I-494: Maple Grove
8. US 12: Delano
9. MN 25: Mayer
10. US 52: Coates

Collected Temporal Coverage: June 20, 2022 - July 10, 2022, and December 20, 2022 - January 10, 2023

Why we collected these data: This data source has a high temporal resolution compared to multiple other available datasets. We sampled these two time slots to cover diverse weather conditions (i.e., snow, rain, and fog), extreme weather events, and holidays/workdays/weekdays in exactly two seasons half a year apart. In this project, the research team uses weather data to extract time-series weather features in the Twin Cities Metropolitan Area to find potential weather factors influencing detector performance. Figure 5 is a map of all weather stations in the State of Minnesota. Figure 6 shows the selected weather station distribution within the Twin Cities Metropolitan Area. Below is a list of weather conditions:

- Temperature and humidity in summer and winter
- Precipitation in rain and snow formats in summer and winter
- Actively snowing vs. ground covered with snow after a snowstorm
- Visibility conditions

Data Preparation: The original dataset is in CSV format. It contains some missing data and multiple attributes are not in a suitable format for statistical analysis. Pandas [7] handles empty values, converts anomalies, and generates timestamps. The outcome from preprocessing is in DataFrame format indexed by timestamp with 18 attribute columns organized by weather stations.

No.	Station	EVENTDATE	WEATHER SENSOR	VISIBILITY	HUMIDITY	PRECIP RATE	WIND DIR	WIND SPEED	MAX TEMP
1	I-35W MN RVR	06/20/2022 12:05 a.m.	WS0086	12.4 mi.	60%	0	SW	6 MPH	97° F

2	I-35W MN RVR	06/20/2022 12:10 a.m.	WS0086	12.4 mi.	60%	0	SW	11 MPH	97° F
3	I-35W MN RVR	06/20/2022 12:15 a.m.	WS0086	12.4 mi.	60%	0	SW	8 MPH	97° F
4	I-35W MN RVR	06/20/2022 12:20 a.m.	WS0086	12.4 mi.	61%	0	SW	9 MPH	97° F
5	I-35W MN RVR	06/20/2022 12:25 a.m.	WS0086	12.4 mi.	61%	0	SW	8 MPH	97° F
6	I-35W MN RVR	06/20/2022 12:30 a.m.	WS0086	12.4 mi.	62%	0	SW	11 MPH	97° F

(table continue…)

No.	MIN TEMP	WET BULB TEMP	DEW POINT	FRICTION	SURFACE TEMP	SURFACE STATUS	SUBSURFACE TEMP	AIR TEMP	PRECIP TYPE
1	71° F	74° F	70° F	-	86° F	dry	72° F	85° F	noPrecipitation
2	71° F	74° F	70° F	-	87° F	dry	72° F	85° F	noPrecipitation
3	71° F	74° F	70° F	-	86° F	dry	72° F	85° F	noPrecipitation
4	71° F	74° F	70° F	-	86° F	dry	72° F	85° F	noPrecipitation
5	71° F	74° F	70° F	-	86° F	dry	72° F	85° F	noPrecipitation
6	71° F	74° F	70° F	-	85° F	Trace Moisture	72° F	85° F	noPrecipitation

Table 4: Examples of weather station data.

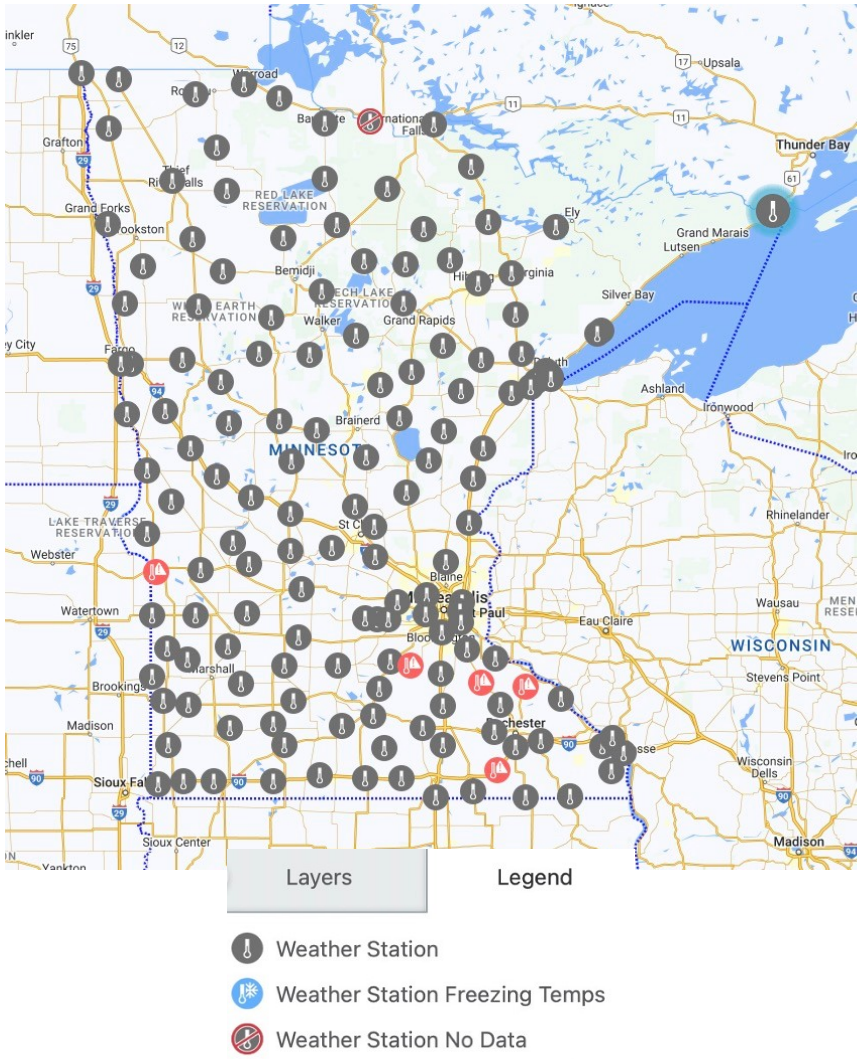


Figure 5: Map of weather station locations throughout the State of Minnesota

Figure 6: Subset of Figure 5. Only includes weather stations within the research study area

Daily Weather Reports

Summary: We collected the Daily Weather reports from MnDOT, which contain general information about the weather (temperature, precipitation, visibility, etc.) in the Twin Cities Metropolitan Area. We collected this data from the World Weather website, which is presented in weather report format (Figure 7). We use this data to more easily select which date ranges we should observe the NIT on to find blockages or poor performance due to the weather.

Data Source: Daily Weather Event Reports [4] **Attributes:** Date, Temperature, Weather Events.

Spatial Coverage: Twin Cities Metropolitan Area

Temporal Resolution: One day

Collected Temporal Coverage: January 1, 2022 - December 31, 2022

Why we collected these data: Initial analysis demonstrates that it is easy to observe the failure of detectors in extreme weather conditions. We also collect weather data for normal weather days which allows us to isolate more failure cases.

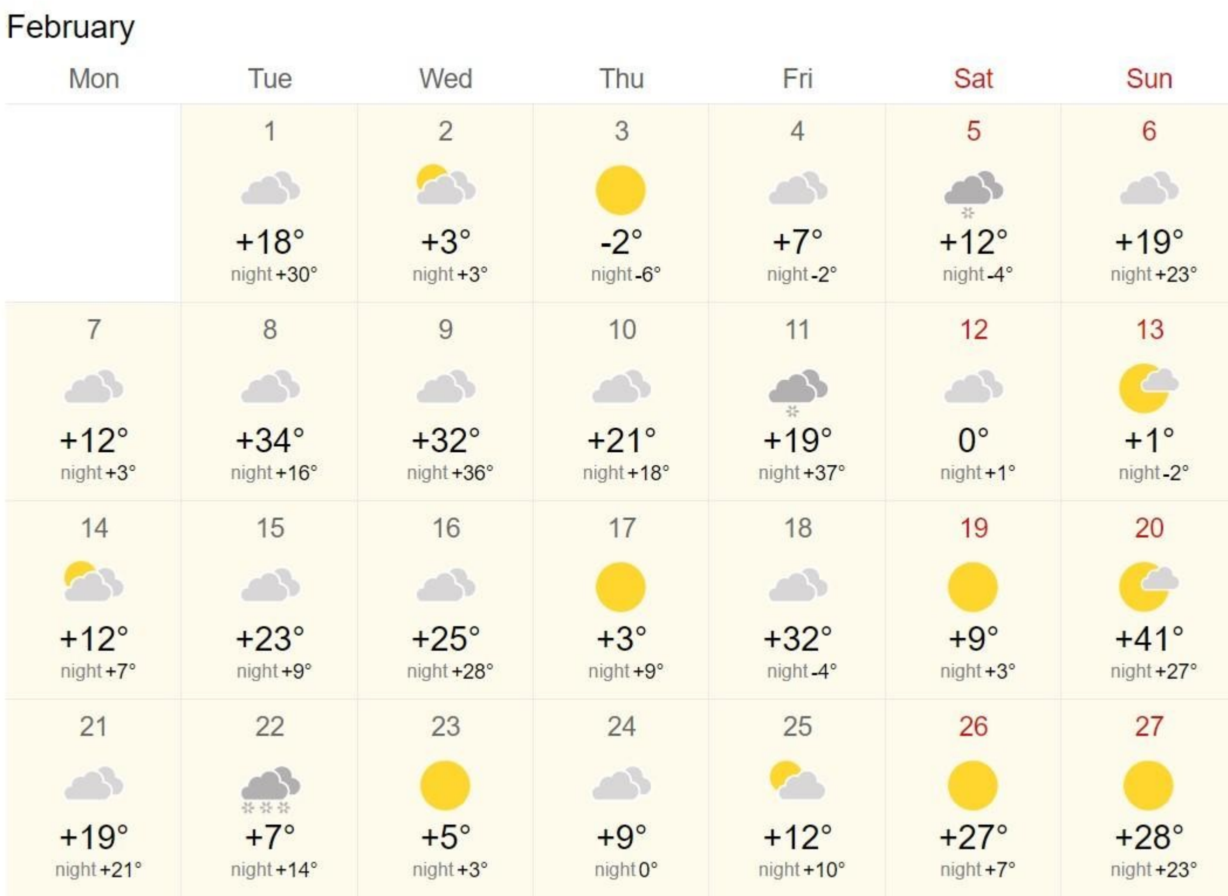


Figure 7: Example of data records in February

Geographic Data

Summary: We collected the Geographic data using OpenStreetMaps, which contains information about spatial features in most places in the world (e.g., roads, buildings, cities, trees, rivers, etc.). We used this data to find information about the surrounding environment of the cameras described in section 2.1.1.

Data Source: OpenStreetMaps Fabrik Download Server [5]

Information of Geographic Data: The data source provides three vector data types: point, line, and polygon, which contains natural, traffic, buildings, water, human places, etc. Table 5 shows the geographic data geometry types, layers, and attribute descriptions in the original dataset. More details are in the help document [6]. The 66 attributes used in this project, which are generated by buffer analysis with buffer radiuses 2000 m and 5000 m, are listed in Table 6.

Geometry	Layer	Description
Point	places	Cities, towns, suburbs, villages,...
	pois	Points of Interest, therein: Public facilities such as government offices, post office, police, ...; Hospitals, pharmacies, ...; Culture, Leisure, ...; Restaurants, pubs, cafes, ...; Hotel, motels, and other places to stay the night; Supermarkets, bakeries, ...; Banks and atms; Tourist information, sights, museums, ...; Miscellaneous points of interest
	pofw	Places of worship such as churches, mosques, ...
	natural	Natural features
	traffic	Traffic related
	transport	Parking lots, petrol (gas) stations, …
Line	roads	Roads, tracks, paths, ...
	railway	Railway, subways, light rail, trams, ...
	waterways	Rivers, canals, streams, ...
Polygon	buildings	Building outlines

	landuse	Forests, residential areas, industrial areas,...
	water	Lakes, ...

Table 5: Geographic data attributes

Spatial Coverage: OpenStreetMaps provides vector maps of the all of the seven continents of the world.

Temporal Coverage: The latest version of OpenStreetMaps collected was updated before January 25, 2023.

Collected Spatial Coverage: The State of Minnesota

Why we collected these data: OpenStreetMaps provides detailed geographic information to extract rich environmental features of traffic cameras in this study. It is also a widely-used opensource geographic data source. In this project, the research team uses geographic data to generate the environmental features of each camera to find potential environmental factors influencing camera performance.

Data Preparation: The original dataset is in shapefile format. The errors of OpenStreetMaps mainly come from the crowd of volunteer data providers. We assume that the data does not include significant errors affecting the calculation. We use Geopandas [8] to reproject the geographic layer, initially in a degree-based geographic coordinate system, to a meter-based projected coordinate system which is helpful for the measurements in the following steps section. The outcome from preprocessing is in GeoDataFrame format with the coordinate reference system of UTM-zone15 + WGS84 datum.

Initial Data Analysis

Our initial analysis aims to provide a deep understanding of different data sources and show some initial results for analyzing datasets. To accomplish this, we identify common patterns within each dataset. These common patterns are used to identify correlations between the different datasets. Based on these correlative patterns, we can align some of these datasets to demonstrate the potential for aggregated analysis toward our overall goal of evaluating the failures of different detection technologies.

Traffic Data

3.1.1: Traffic Camera Data

Analysis process:

We identified the dates with extreme weather events, including heavy snow, heavy rain, very high temperatures (above 30 degrees Celsius), very low temperatures (below -5 degrees Celsius), and heavy fog. We then manually watched the video at selected intersections. We focused on the cameras with detection results overlaid in the video to directly evaluate how the camera detection technology performs under adverse conditions. We also present the initial observations on the signal data. This process could identify representative abnormal patterns in camera and inductive loop detectors' performance. We can use this as the ground truth for verifying the effectiveness of developed anomaly detection methods. We plan to use anomaly detection methods to identify the failures of different detection technologies. Also, these representative abnormal patterns could be used as references to help understand other abnormal patterns better.

Below is a list of selected extreme weather events:

1. 2023 Jan 13th-17th normal conditions in the winter.
2. 2022 Feb 14th heavy intensive rain.
3. 2022 Mar 22nd heavy intensive rain.
4. 2022 Mar 27th low night temp.
5. 2022 Mar 30th rain and snow.
6. 2023 Mar 16th high night temp.
7. 2023 Jan 1st-7th low night temp, in which Jan 3rd-4th heavy snow.
8. 2022 May 14th thunderstorm with rain
9. 2022 May 25th heavy intensive rain
10. 2022 Jun 15th heavy intensive rain
11. 2022 Jun 28th thunderstorm with rain
12. 2022 Jul 7th, 23rd thunderstorm with rain
13. 2022 Nov 17th-20th low day temp
14. 2022 Dec 18th-26th low day temp

Data Interpretation:

One notable characteristic of the camera video is that computer vision technology has been applied in cameras to detect cars entering and leaving zones in the intersections. Some of these camera detectors have visual indicators represented by red and green boxes (for the interaction zones) along with small red circle indicators (for entering and leaving) (Figure 8). Other factors (e.g., weather conditions) could affect these detectors' performance. Below are some examples of how the performance is affected by different weather conditions:

1) Camera is affected by heavy snow.

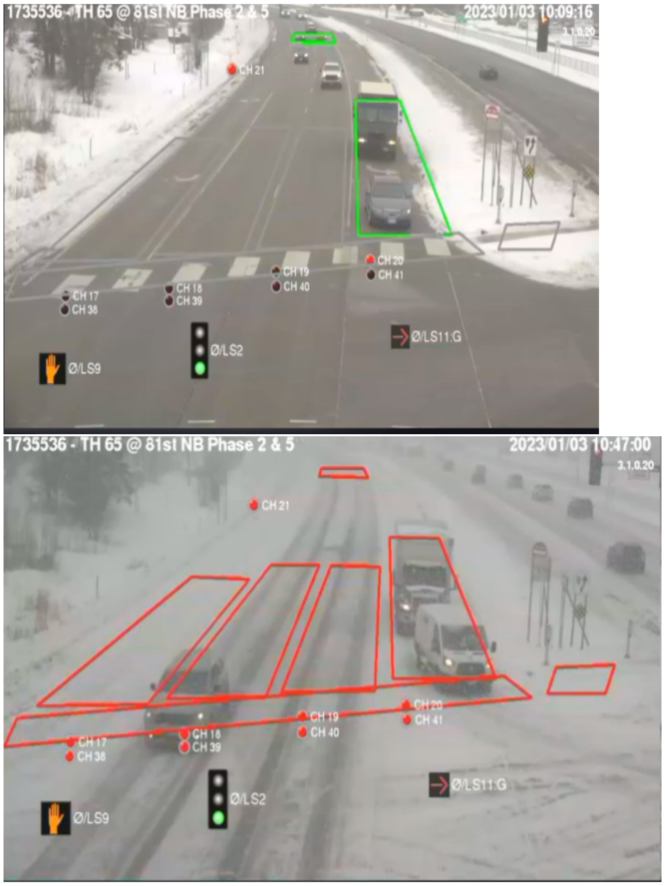


Figure 8: Image of camera affected by heavy snow.

When the cameras encounter some issue (e.g., poor conditions caused by bad weather) and cannot work, all the detected areas (red rectangles and red dots) stay red consistently until the poor conditions resolve. When the cameras function well, the (green) rectangle area will be activated once cars enter the area. Simultaneously, a red dot (e.g., CH20 in the left plot of Figure 8) is activated and remains on as long as a car remains in the area. If a car leaves this area, another red dot (e.g., CH41) will be activated for a short period. Corresponding traffic lights can also be observed.

2) Camera is affected by fog

All the camera detections fail due to the fog interference on the perception ability in Figure 9.

Figure 9: Image of camera affected by fog.

3) Camera is affected by heavy rain

The detection areas marked by the green boxes are not activated due to the raindrop (Figure 10). The raindrop occluding the camera's view of this area so that no cars are detected, even though cars appear in the detection areas.

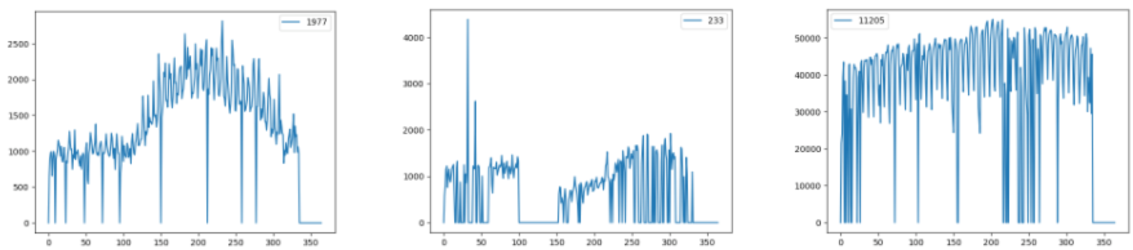
Figure 10: (a) Camera image without rain (b) Camera image affected by rain

Data missing:

1. Not all the cameras explicitly show the computer-vision-based detection results (e.g., the green and red boxes).
2. We have been missing videos for many days. The recorded dates are in Appendix I.

Traffic Volume Data

Functionality: To find traffic trends over time using the traffic volume data, the research team plotted examples of daily traffic volumes at 19 different locations, as shown in Figure 11 (a-c). MnDOT collects this data from subsurface pressure sensors installed under the pavement at specific intersections. We can use this data to understand the properties of traffic volume over time. Also, we can compare this volume data with traffic volume detected by cameras and inductive loops to evaluate the detection performance.



(a) Station 1977 (b) Station 233 (c) Station 11205 Figure 11 (a-c): Daily traffic volume for 2022 from different stations.

Observation:

1. The trend of traffic volume changes with time and shows seasonal characteristics.
2. Spatial correlation: The traffic volume trends show distinct patterns across locations if they are distant; otherwise, their trends have some similarities.
3. Large festivals and holidays are usually associated with a sudden decrease in traffic flow.

Data missing:

1. We observed missing records at the hour, daily, chunk (i.e., consecutive days), and location level (i.e., not all locations have records).

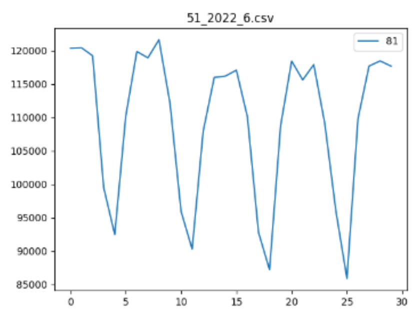
Actuated Signal Data – detector on/off phases

Analysis process:

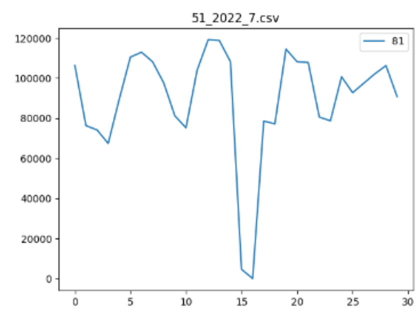
We check the general trends and study the patterns at different temporal granularities to learn the (e.g., second-level patterns, hourly-level patterns, daytime and nighttime patterns, daily patterns, weekly patterns, and seasonal patterns). Also, we align the signal data with the camera video to study abnormal behaviors. We aim to explore how we can discover abnormal behaviors based on the analysis of Actuated Signal Data. We plan to develop methods to monitor how the signal data behaves in normal conditions (i.e., the detected number of cars in this signal data is expected to be close enough to the number detected by object detection tech from the video we are going to develop) and abnormal conditions (i.e., the detected number of cars is inconsistent with the ground truth number observed in the video, which usually occurs in the frigid days) in the future.

Data Interpretation:

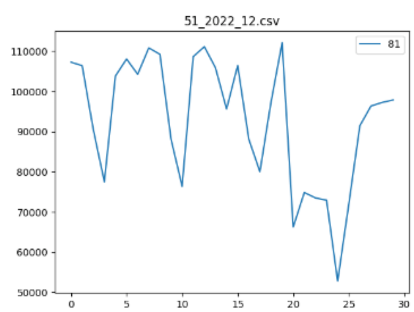
We focus on the records with the detector on/off (Event Codes 82/81) phases representing a car entering and leaving a specific lane (indicated by the event parameter) at an intersection. Figure 12 (a-d) below are the daily frequency of on-phase 82 (off-phase 81 results in the same plot) at location 51. We can observe weekly patterns (higher volume on weekdays and lower volume on weekends), seasonal patterns (higher volume in summer and lower volume in winter), sudden dese patterns in big holidays (e.g., Christmas and new year) and frigid days (i.e., a snowstorm on Jan 3rd-4th). We also confirm the daily patterns (higher volume in the daytime and lower volume in the nighttime). Most of these patterns are consistent with the general trend in the traffic volume data in section 3.1.2.



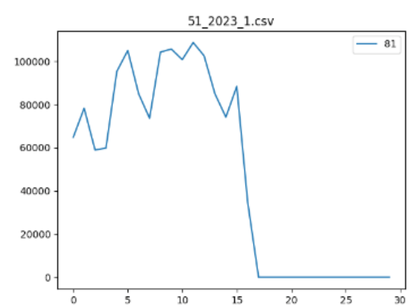
(a) Daily volume in June



(b) Daily volume in July



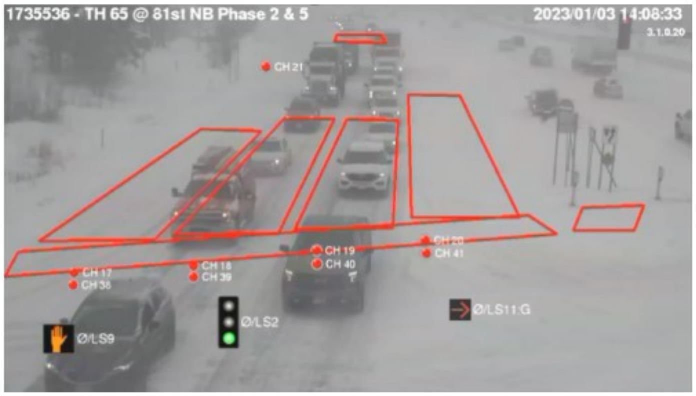
(c) Daily volume in December

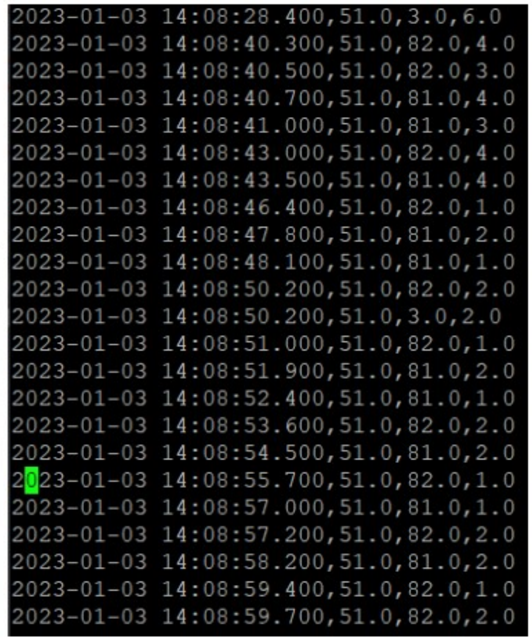


(d) Daily volume in Janurary

Figure 12(a-d): Daily detected traffic (frequency) volumes in different months at interaction 51

When an intersection experiences heavy snow, the detectors are not sensitive enough to detect all the cars passing through. Figure 13 (a) below is an example of an intersection on 81st facing south. Cars are seen moving through one way of the intersection (with green light) from 14:08:28-14:08:40, but there is no record in the actuated signal data (Figure 13 (b)). This indicates the failure of all sensors (e.g., camera sensors and inductive loops).





```
2023-01-03 14:08:28.400,51.0,3.0,6.0
2023-01-03 14:08:40.300,51.0,82.0,4.0
2023-01-03 14:08:40.500,51.0,82.0,3.0
2023-01-03 14:08:40.700,51.0,81.0,4.0
2023-01-03 14:08:41.000,51.0,81.0,3.0
2023-01-03 14:08:43.000,51.0,82.0,4.0
2023-01-03 14:08:43.500,51.0,81.0,4.0
2023-01-03 14:08:46.400,51.0,82.0,1.0
2023-01-03 14:08:47.800,51.0,81.0,2.0
2023-01-03 14:08:48.100,51.0,81.0,1.0
2023-01-03 14:08:50.200,51.0,82.0,2.0
2023-01-03 14:08:50.200,51.0,3.0,2.0
2023-01-03 14:08:51.000,51.0,82.0,1.0
2023-01-03 14:08:51.900,51.0,81.0,2.0
2023-01-03 14:08:52.400,51.0,81.0,1.0
2023-01-03 14:08:53.600,51.0,82.0,2.0
2023-01-03 14:08:54.500,51.0,81.0,2.0
2023-01-03 14:08:55.700,51.0,82.0,1.0
2023-01-03 14:08:57.000,51.0,81.0,1.0
2023-01-03 14:08:57.200,51.0,82.0,2.0
2023-01-03 14:08:58.200,51.0,81.0,2.0
2023-01-03 14:08:59.400,51.0,82.0,1.0
2023-01-03 14:08:59.700,51.0,82.0,2.0
```

Figure 13: (a) A camera image with heavy snow (b) The corresponding actuated signal data.

Other malfunctions indicate partial failure where some but not all cars are detected. Below is an example of this type of behavior (Figures 14 & 15). There are at least 3 cars entering the interaction shown in Figure 14 during 14:10:08-14:10:18, but only two 82 (on) phrases are observed in the actuated signal data in Figure 15. Note that we only show two ways of the interaction in 14(a)-(d), while the signal data records four ways. Even without another two ways, we can still observe there are more cars passing than detected cars in Figure 14(a)-(d). It implies that there are several car entrances missing.

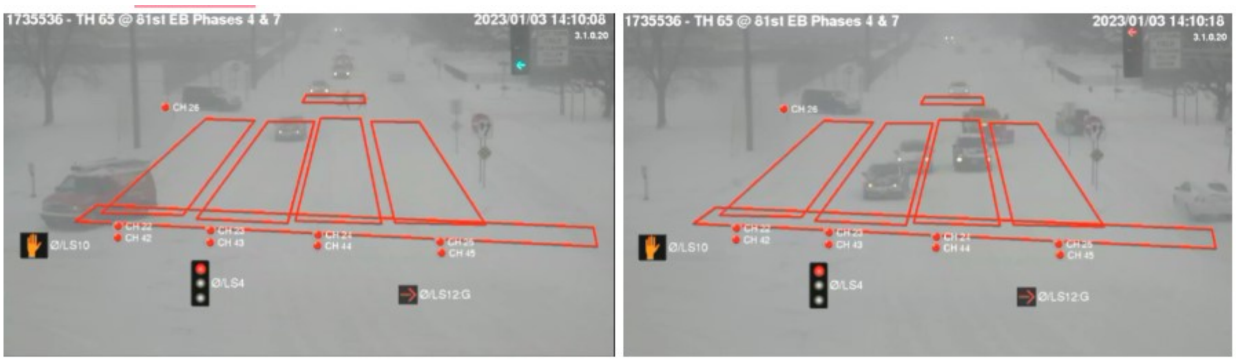


Figure 14: (a) EB way image at 14:10:08 (b) EB way image at 14:10:18

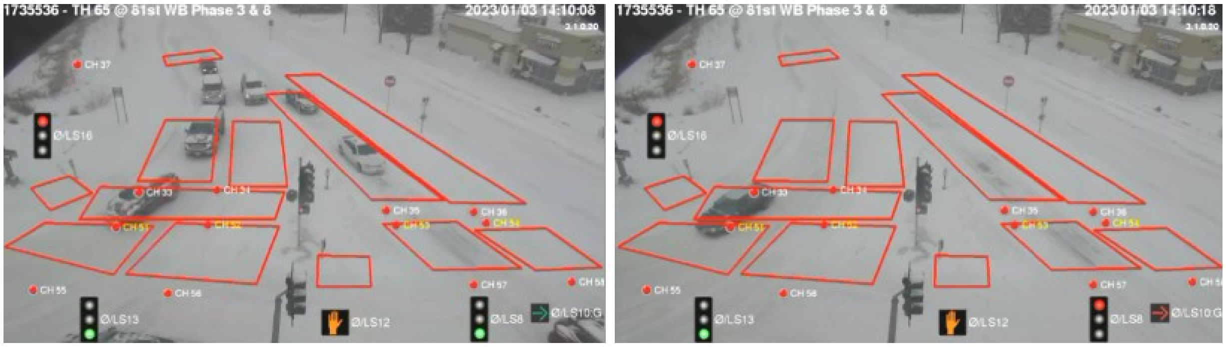


Figure 14: (c) WB way image at 14:10:08 (d) WB way image at 14:10:18

```
2023-01-03 14:10:07.100,51.0,82.0,2.0
2023-01-03 14:10:08.500,51.0,81.0,2.0
2023-01-03 14:10:08.500,51.0,3.0,8.0
2023-01-03 14:10:09.700,51.0,81.0,1.0
2023-01-03 14:10:13.000,51.0,7.0,3.0
2023-01-03 14:10:13.000,51.0,6.0,8.0
2023-01-03 14:10:13.000,51.0,8.0,8.0
2023-01-03 14:10:13.000,51.0,8.0,3.0
2023-01-03 14:10:13.000,51.0,63.0,6.0
2023-01-03 14:10:13.000,51.0,6.0,3.0
2023-01-03 14:10:13.000,51.0,7.0,8.0
2023-01-03 14:10:13.900,51.0,82.0,4.0
2023-01-03 14:10:14.500,51.0,81.0,4.0
2023-01-03 14:10:16.000,51.0,65.0,6.0
2023-01-03 14:10:16.000,51.0,10.0,3.0
2023-01-03 14:10:16.000,51.0,9.0,3.0
2023-01-03 14:10:16.300,51.0,82.0,1.0
2023-01-03 14:10:16.500,51.0,9.0,8.0
2023-01-03 14:10:16.500,51.0,10.0,8.0
2023-01-03 14:10:19.500,51.0,11.0,3.0
2023-01-03 14:10:19.500,51.0,12.0,3.0
2023-01-03 14:10:19.900,51.0,81.0,1.0
2023-01-03 14:10:20.000,51.0,31.0,2.0
```

Figure 15: Actuated Signal data in reference to Figure 14

Observations:

1. Based on Jun.-Jul. and Dec.-Jan. records obtained from MnDOT, we confirmed that there are more detected cars in the summer than in other seasons.
2. Weekly traffic patterns can be observed (Weekdays vs. Weekends).
3. Religious and National holidays are often associated with a sudden decrease in traffic.
4. Heavy snow is associated with a sudden decrease in traffic.
5. The detector performance is affected by heavy snow. Further analysis is necessary on cold days without snow before a determination about temperature affecting performance can be made.

Missing data:

1. The expectation is that MnDOT will deliver the majority of the requested actuated signal data. Therefore, the research team expects missing data will not be a significant problem.
2. There are days or hours of data missing in July around the 15th-16th. The research team will continue investigating to identify other durations with missing data

Weather Data

Weather Station Data

Date Interpretation: We attempt to find trends in all the weather attributes (specified in the "Attributes" section of section 2.2.1 Weather Station Data) over two time ranges, three weeks in summer and three weeks in winter. This data could provide information to study how the behaviors of detection technologies are affected by different weather attributess at the highresolution level. Our initial analysis focuses on the temporal patterns in the original time-series weather dataset. After we confirm the detection technologies are affected by extreme weather events, we are interested in quantifying the weather events and seeing which level of weather conditions are specified by various weather attributes could affect the detection technologies. The research team plots all the weather attributes. Below are examples of a sample three-week weather attributes at ten stations (Figure 16-20).

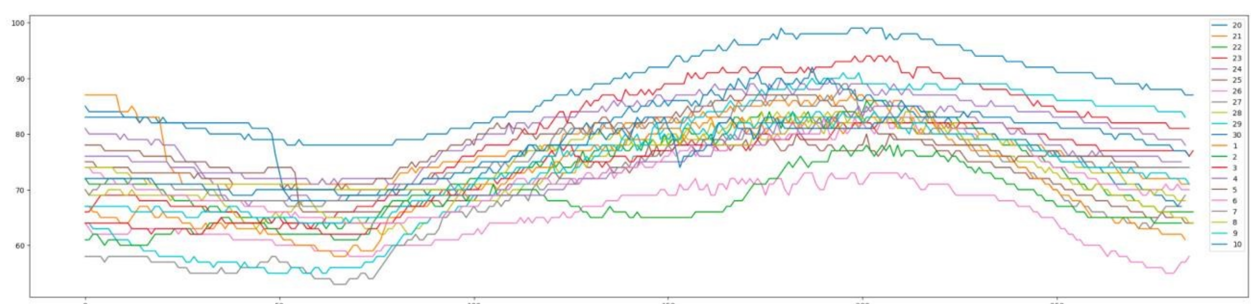


Figure 16: Average Air Temp across 10 weather stations by date.

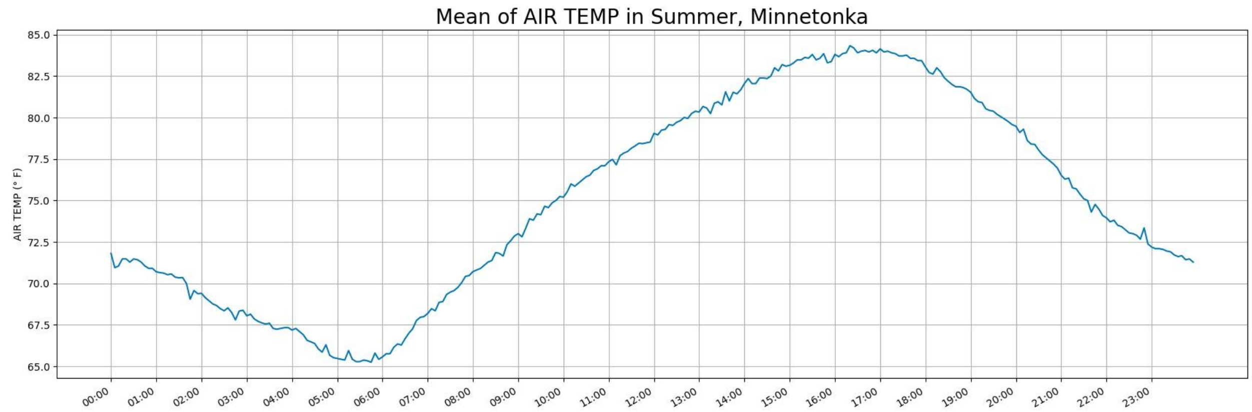


Figure 17: Mean air temperature in Minnetonka weather station in the summer

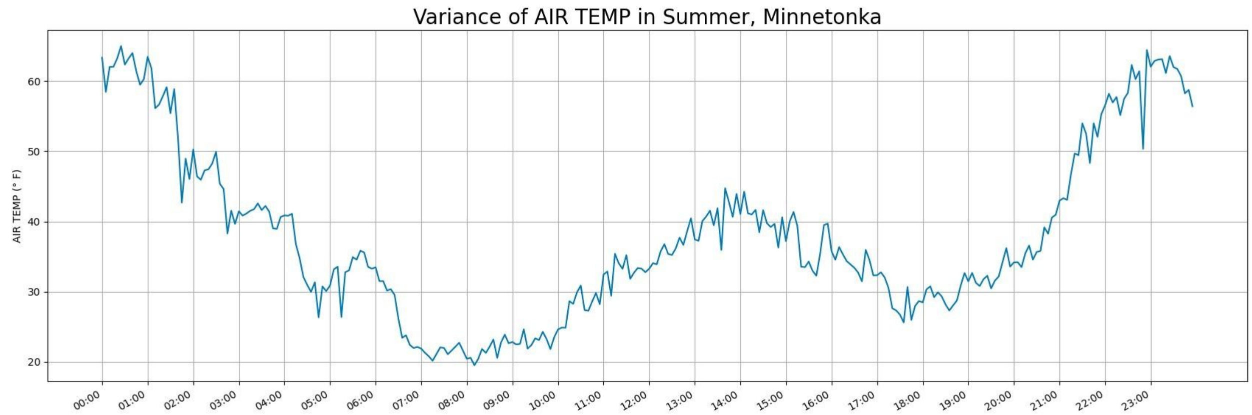


Figure 18: Variance of air temperature in Minnetonka weather station in the summer

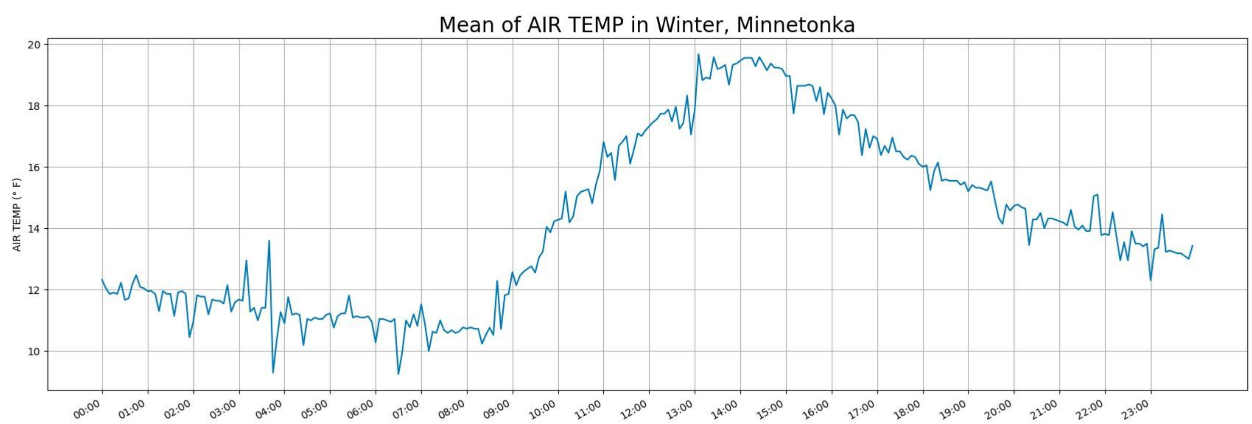


Figure 19: Mean air temperature in Minnetonka weather station in the winter

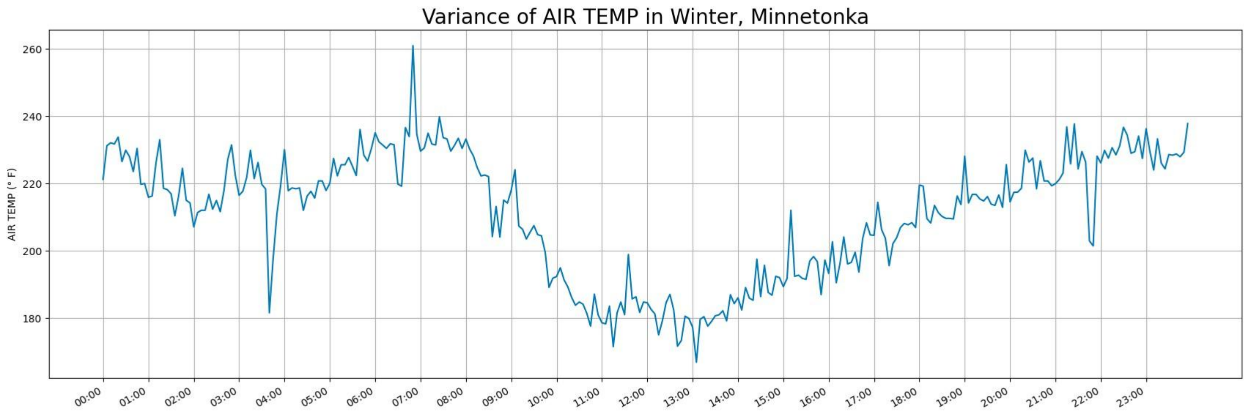


Figure 20: Variance of air temperature in Minnetonka weather station in the winter

Observations:

1. Air Temperature: Daytime is higher than nighttime. Achieve the highest around 2 PM and the lowest around 5 AM.
2. Surface Temperature: Daytime is higher than nighttime. Achieve the highest around 4 PM and the lowest around 7 AM.
3. Subsurface Temperature: Daytime is lower than nighttime. Achieve the highest around midnight and the lowest between 12 PM to 2 PM.
4. Visibility: Visibility in summer is generally higher than in winter. There is a relatively fixed pattern within a day: it achieves the lowest in the morning between 4 AM - 8 AM and reaches the highest in the afternoon. Winter visibility shows more significant change over the day depending on weather events.
5. Humidity: The humidity shows a fixed pattern within a day, which achieves the highest between 0 AM and 7 AM and the lowest between 2 PM and 6 PM.
6. Wind Speed: It shows a general pattern within a day. Daytime is higher than nighttime. Wintertime has more variance than summertime.
7. Wet Bulb Temperature: It shows a fixed pattern within a day, which achieves the lowest around 6 AM (summer) or 9 AM (winter) and the highest around 6 PM (summer) and 3 PM (winter).
8. The temperature variations of different locations show distinct patterns. Some are stable, while others have more sudden changes.

Daily Weather Data

Method: We collected all the dates with extreme weather events indicated in the Weather Events attribute, including heavy rain, heavy snow, very high temperatures, and frigid temperatures. Then, we used these event dates to select date ranges to analyze possible detection errors in the actuated signal data and the camera data. The results of this analysis can be found in sections 3.1.1 and 3.1.3

Geographic Data

Data Interpretation: To represent the environmental features of cameras in vector space, we generated a buffer with a radius of 2,000 meters and 5,000 meters for each camera location. Next, we split all the point, line, and polygon geographic layers by attributes and values of attributes. We traversed the split layers and calculated the number of points, the total length of lines, and the total area of polygons located in each buffer circle.

Below is the list of 66 buffer statistical attribute results from this procedure (Table 6). We can observe two attribute examples across all cameras (Figures 21 & 22). We can also observe the number of crossings within a 2000-meter buffer of all 39 cameras (Figure 21) and the total length of pathways within a 2000-meter buffer of all 39 cameras (Figure 22).

Data source type	Data source layer	Feature generated within buffer	Buffer radius	
			2000 m	5000 m
Polygon	OSM_building_a	Building area (m^2)	✓	✓
	OSM_water_a	Water area (m^2)	✓	✓
	OSM_pofw_a	Religious place area (m^2)	✓	✓
	OSM_pois_a	Points of Interest area (m^2)	✓	✓
	OSM_traffic_a	Parking lot area (m^2)	✓	✓
	OSM_landuse_a	Grass area (m^2)	✓	✓
Point	OSM_pois	Point of Interest number	✓	✓

	OSM_transport	Bus stop number	✓	✓

	OSM_traffic	Road crossing number	✓	✓
		Motorway junction number	✓	✓
		Turning circle number	✓	✓
		Traffic signal number	✓	✓
		Stop number	✓	✓
		Street lamp number		✓
		Parking number		✓
		Bicycle Parking number		✓
Polyline	OSM_railways	Total railway length (m)	✓	✓
	OSM_roads	Total cycleway length (m)	✓	✓
		Total motorway length (m)	✓	✓
		Total motorway link (m)	✓	✓

		Total service road length (m)	✓	✓

		Total residential road length (m)	✓	✓
		Total footway length (m)	✓	✓
		Total primary road length (m)		✓
		Total primary link length (m)		✓
		Total bridleway length (m)		✓
Polyline	OSM_roads	Total secondary road length (m)	✓	✓
		Total secondary link length (m)	✓	✓
		Total tertiary road length (m)	✓	✓
		Total tertiary link length (m)	✓	✓
		Total track road length (m)	✓	✓
		Total path road length (m)	✓	✓
		Total steps road length (m)		✓

		Total trunk road length (m)	✓	✓
		Total trunk link length (m)	✓	✓
		Total pedestrian road length (m)		✓
		Total unclassed road length (m)	✓	✓

Table 6: Table of 66 buffer statistical attributes retrieved from OSM

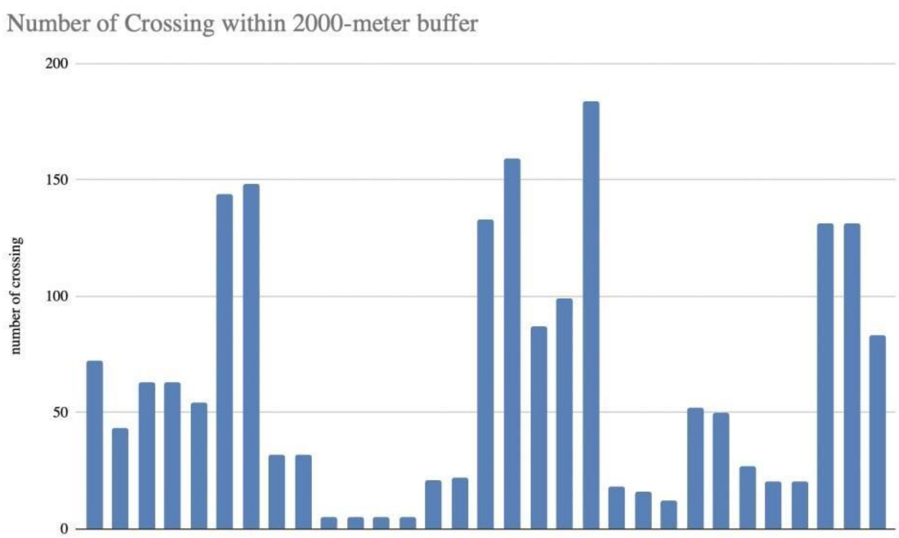


Figure 21. The number of crossings within a 2000-meter buffer.

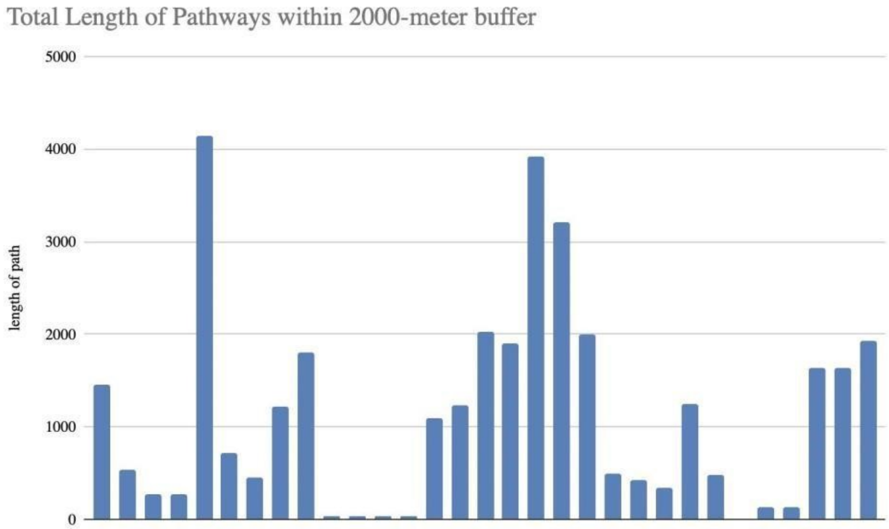


Figure 22. The total length of pathways within a 2000-meter buffer.

4. Next Step (Task 7)

The research team will develop methods to evaluate the performance of different detection techniques by automatically detecting their performance in normal and abnormal weather and traffic conditions. We will select representative time points and manually label the data

(including camera videos and the actuated signal data) for verification. Within the context of this project, abnormal conditions are the conditions that could make the detection techniques fail. The specific abnormal conditions could be distinct for different detection techniques and locations. For the camera, the abnormal conditions (from what we have observed) are extreme weather, including heavy snow, heavy rain, and heavy fog. For other detectors, abnormal conditions are frigid days.

Appendix:

I. Video data recorded:

'2021-11-22', '2021-11-23', '2021-11-24', '2021-11-25', '2021-11-26', '2021-11-27', '2021-11-28',

'2021-11-29', '2021-11-30', '2021-12-01', '2021-12-02', '2021-12-03', '2021-12-04', '2021-12-05',

'2021-12-06', '2021-12-07', '2021-12-08', '2021-12-09', '2021-12-10', '2021-12-11', '2021-12-12',

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'2022-08-29', '2022-09-14', '2022-09-15', '2022-09-16', '2022-09-17', '2022-09-18', '2022-09-19',

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'2022-09-27', '2022-09-28', '2022-09-29', '2022-09-30', '2022-10-01', '2022-10-02', '2022-10-03',

'2022-10-04', '2022-10-05', '2022-10-26', '2022-10-27', '2022-10-28', '2022-10-29', '2022-10-30',

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'2023-03-31', '2023-04-01', '2023-04-02', '2023-04-03', '2023-04-04', '2023-04-05', '2023-04-06', '2023-04-07', '2023-04-08', '2023-04-09', '2023-04-10', '2023-04-11', '2023-04-12', '2023-04-13', '2023-04-14'

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Appendix F: Task 7 Deliverable

Performance Evaluation of Different Detection Technologies for Signalized Intersections in Minnesota

Task 7 Deliverable:

Analysis of collected data and development of draft guidelines

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Data Analysis

Our analysis here aims to provide a deep understanding of different data sources and show the initial results for analyzing the collected datasets. To accomplish this, we identify common and valuable patterns within each dataset. These patterns help understand the datasets and show their potential correlations. Based on these patterns, we can align some of these datasets to demonstrate the potential for aggregated analysis toward our overall goal of evaluating the failures of different detection technologies.

Traffic Data

1.1.1: Traffic Camera Data

Analysis process:

We identify the dates with extreme weather events, including heavy snow, heavy rain, very high temperatures (above 30 degrees Celsius), very low temperatures (below -5 degrees Celsius), and heavy fog. We then manually watch the video at selected intersections to generate a “gold dataset” for the ground truth. We focus on the cameras with detection results overlaid in the video to directly evaluate how the camera detection technology performs under adverse conditions. We also incorporate the initial observations on the signal data. This process could identify representative abnormal patterns in camera and inductive loop detectors' performance. We will use these abnormal patterns as the ground truth for verifying the effectiveness of developed anomaly detection methods. We plan to use anomaly detection methods to identify the failures of different detection technologies. Also, these representative abnormal patterns will be used as references to help understand other abnormal patterns better in the next task (Task 8) to produce a final memorandum. After observing the traffic camera data, we noticed frame-skipping and long pauses occurring on data collected before November 2022. Traffic camera data collected after this point has minimal frame-skipping and pausing issues making this data ideal for our future analysis. Therefore, data collected after this date will be the focus of future analysis.

Below is a list of selected extreme weather events:

1. 2023 Jan 13th-17th normal conditions in the winter.
2. 2022 Feb 14th heavy intensive rain.
3. 2022 Mar 22nd heavy intensive rain.
4. 2022 Mar 27th low night temp.
5. 2022 Mar 30th rain and snow.
6. 2023 Mar 16th high night temp.
7. 2023 Jan 1st-7th low night temp, in which Jan 3rd-4th heavy snow.
8. 2022 May 14th thunderstorm with rain
9. 2022 May 25th heavy intensive rain
10. 2022 Jun 15th heavy intensive rain
11. 2022 Jun 28th thunderstorm with rain
12. 2022 Jul 7th, 23rd thunderstorm with rain
13. 2022 Nov 17th-20th low day temp
14. 2022 Dec 18th-26th low day temp

Data Interpretation:

One notable characteristic of the camera video is that some computer vision technologies have been applied in cameras to detect cars entering and leaving zones in the intersections. Some of these camera detectors have visual indicators represented by red and green boxes (for the interaction zones) along with tiny red circle indicators (for entering and leaving) (Figure 1). Other factors (e.g., weather conditions) could affect these detectors' performance. Below are some examples of how the performance is affected by different weather conditions: 1) Camera is affected by heavy snow.

Figure 1: Image of camera affected by heavy snow.

When the cameras encounter some issues (e.g., poor conditions caused by bad weather) and cannot work, all the detected areas (red rectangles and red dots) stay red consistently until the poor conditions resolve. When the cameras function well, the (green) rectangle area will be activated once cars enter the area. Simultaneously, a red dot (e.g., CH20 in the left plot of Figure 9) is activated and remains on as long as a car remains in the area. If a car leaves this area, another red dot (e.g., CH41) will be activated temporarily. Corresponding traffic lights can also be observed.

2) Camera is affected by fog

All the camera detections fail due to the fog interference on the perception ability in Figure 2.

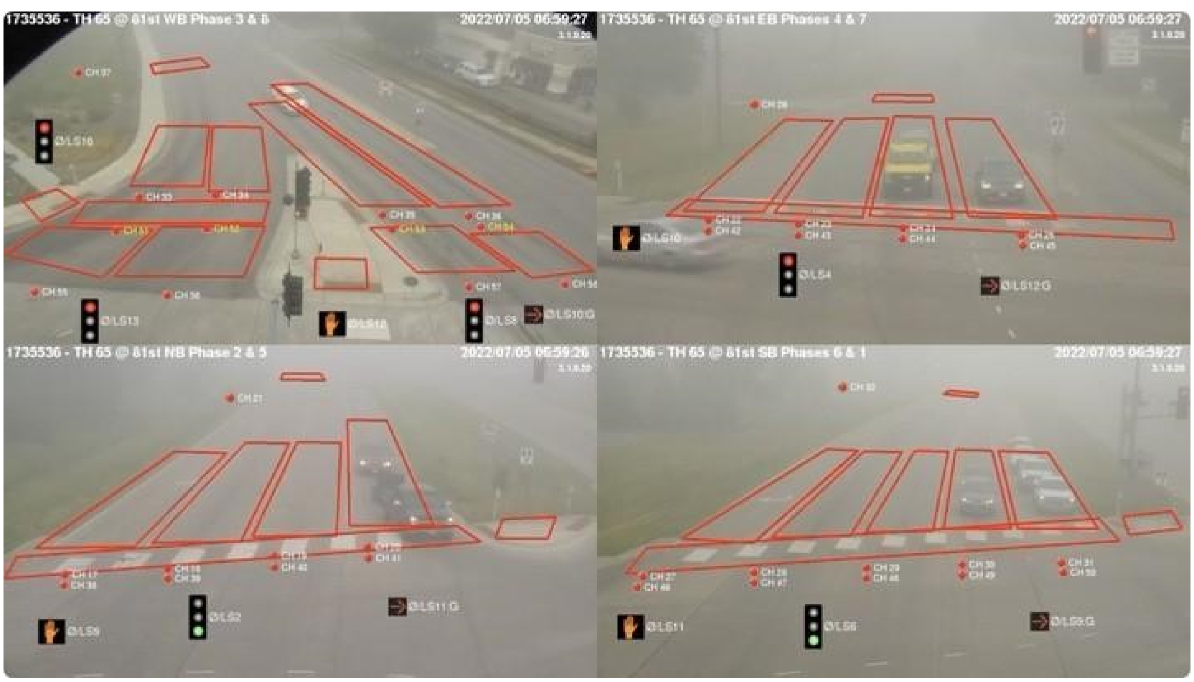


Figure 2: Image of camera affected by fog.

3) Camera is affected by heavy rain

The detection areas marked by the green boxes are not activated due to the raindrop (Figure 3). The raindrop occluding the camera's view of this area so that no cars are detected, even though cars appear in the detection areas.

Figure 3: (a) Camera image without rain.   (b) Camera image affected by rain.

Another notable aspect of the data is that we can observe other boxes farther away from some intersections (CH 37, CH 21, CH 26, and CH 32 in Figure 2). These boxes represent loop detectors installed in the road. These methods of detecting cars are more reliable than computer vision methods because they are not affected by camera occlusion or image quality issues.

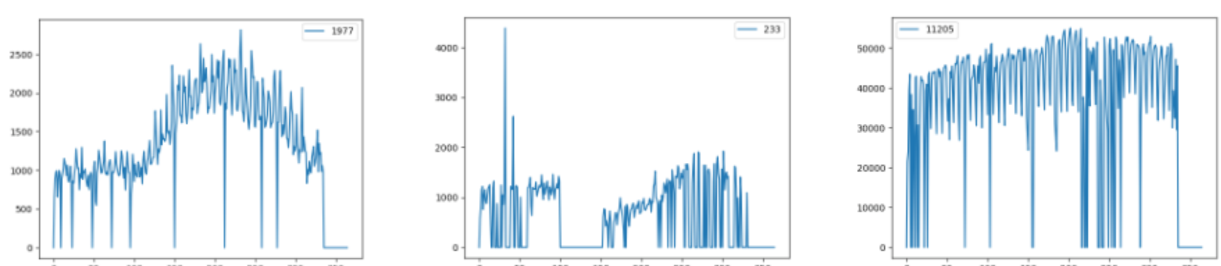
Data missing:

1. Not all cameras explicitly show the computer-vision-based detection results (e.g., the green and red boxes).
2. The collected video streams could have missing videos for many days. The recorded dates are in Appendix I.
3. Some cameras do not have accurate timestamps, making it difficult to analyze them.

1.1.2: Traffic Volume Data

Analysis process:

We collect daily traffic volumes to find trends over time using the traffic volume data, as shown in Figure 4 (a-c).



(a) Station 1977 (b) Station 233 (c) Station 11205

Figure 4 (a-c): Daily traffic volume for 2022 from different stations.

To better capture the normal trends of traffic volumes, we conduct a Univariate Time Series Clustering using the K-Means method with DTW as distance. We set the sliding window width as 24 hours and the sliding window step as 48 hours, meaning that by sampling the traffic volume data series every 48 hours, each data series consists of 24 hours of data. In this way, we generate 7103-time sequences from the original traffic volume data of 2022. The setting of the number of clusters was 12. The clustering result is in Figure 5.

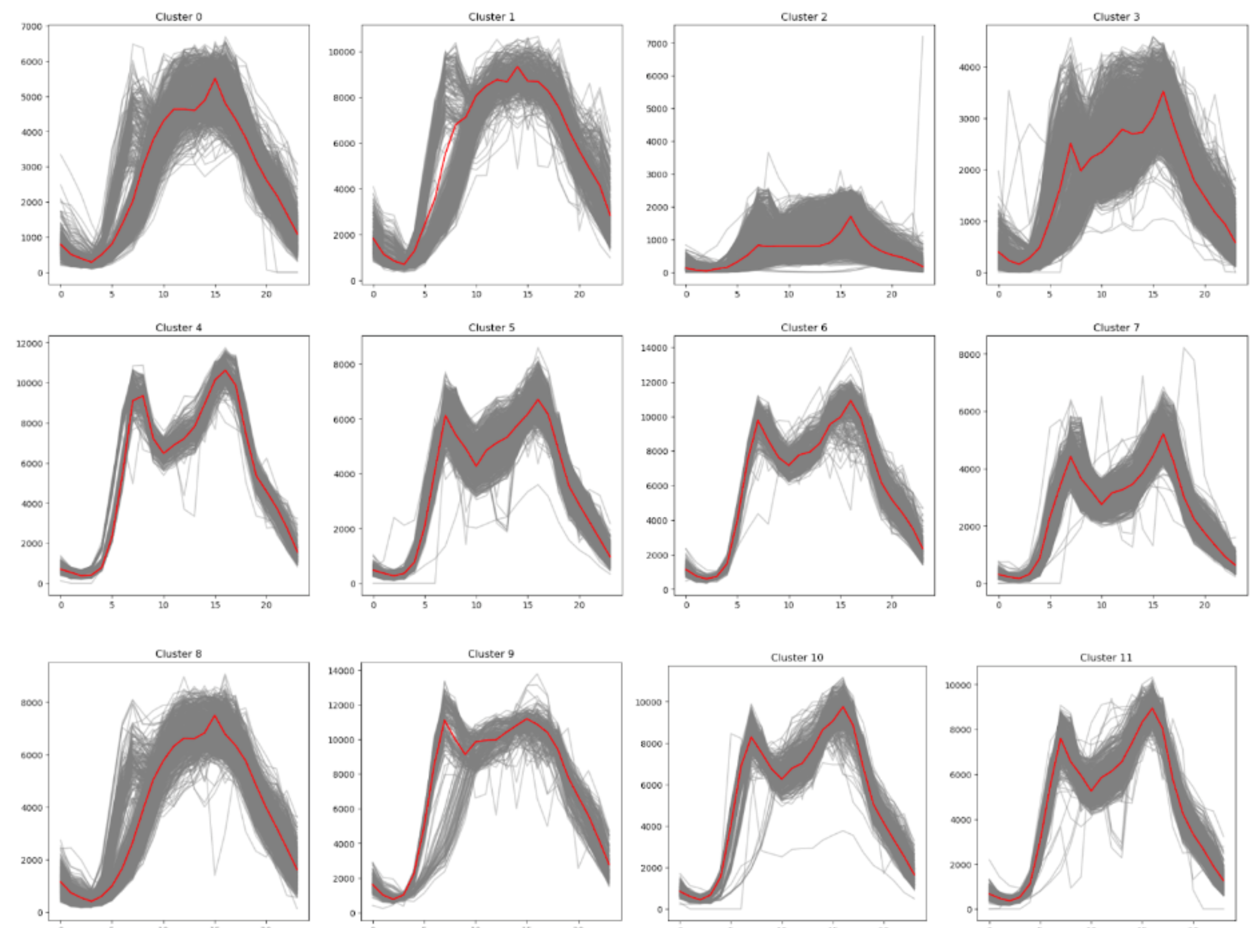


Figure 5. The 12 clusters of daily traffic volume of 2022. The red line is the DTW Bary Center Averaging.

Data Interpretation:

Observing Figure 5, we can see the red line is the DTW Bary Center Averaging, which is a good representation of the average shape of all time series in each cluster. Each of the 12 clusters of the daily traffic volume shows different trends and characteristics, representing the different daily traffic volume scenarios in the Twin Cities Metropolitan Area over an entire year. Time series in each category whose overall shape differs from the red line indicate potential abnormal traffic conditions.

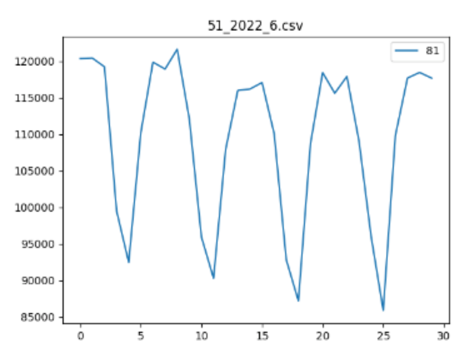
1.1.3: Actuated Signal Data – detector on/off phases

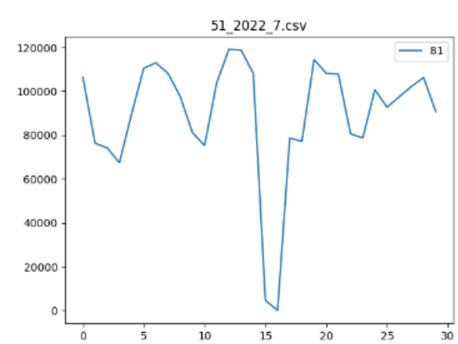
Analysis process:

The initial analysis of the actuated signal data consists of two parts: the aggregated analysis and the separated analysis. The aggregated analysis considers all on/off phases together without differentiating their sensor types (camera sensors and inductive loops). In the aggregated analysis, we checked the general trends. We investigated their patterns at different temporal granularities (e.g., second-level patterns, hourly-level patterns, daytime and nighttime patterns, daily patterns, weekly patterns, and seasonal patterns). Also, we align the signal data with the camera video to study abnormal behaviors. We explore how we could discover abnormal behaviors based on the analysis of Actuated Signal Data. We plan to develop methods to monitor how the signal data behaves in normal conditions (i.e., the detected number of cars in this signal data is expected to be close enough to the number detected by object detection tech from the video we are going to develop) and abnormal conditions (i.e., the detected number of cars is inconsistent with the ground truth number observed in the video, which usually occurs in the frigid days) in Task 8. In a separate analysis, we analyze the behavior of sensors belonging to the same type. We particularly focus on analyzing inductive loop and camera sensor behaviors separately.

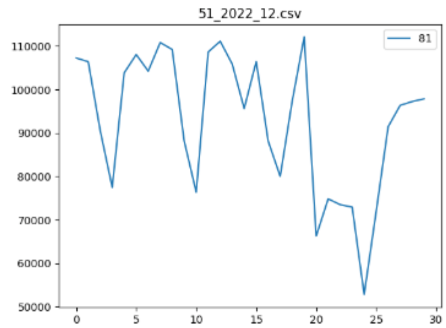
Data Interpretation:

A. Aggregated analysis: We focus on the records with the detector on/off (Event Codes 82/81) phases representing a car entering and leaving a specific lane (indicated by the event parameter) at an intersection. Figure 6 (a-d) below shows the daily frequency of on-phase 82 (off-phase 81 results in the same plot) at location 51. We could observe weekly patterns (higher volume on weekdays and lower volume on weekends), seasonal patterns (higher volume in summer and lower volume in winter), sudden decrease patterns in big holidays (e.g., Christmas and new year) and frigid days (i.e., a snowstorm on Jan 3rd-4th). We also confirm the daily patterns (higher volume in the daytime and lower volume in the nighttime). Most of these patterns are consistent with the general trend in the traffic volume data in section 1.1.2.

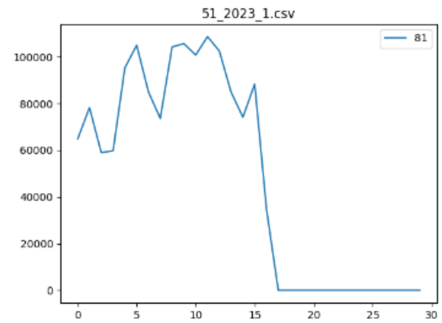




(a) Daily volume in June (b) Daily volume in July



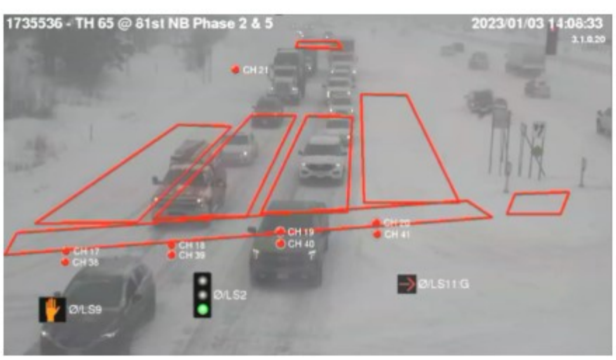
(c) Daily volume in Dec.

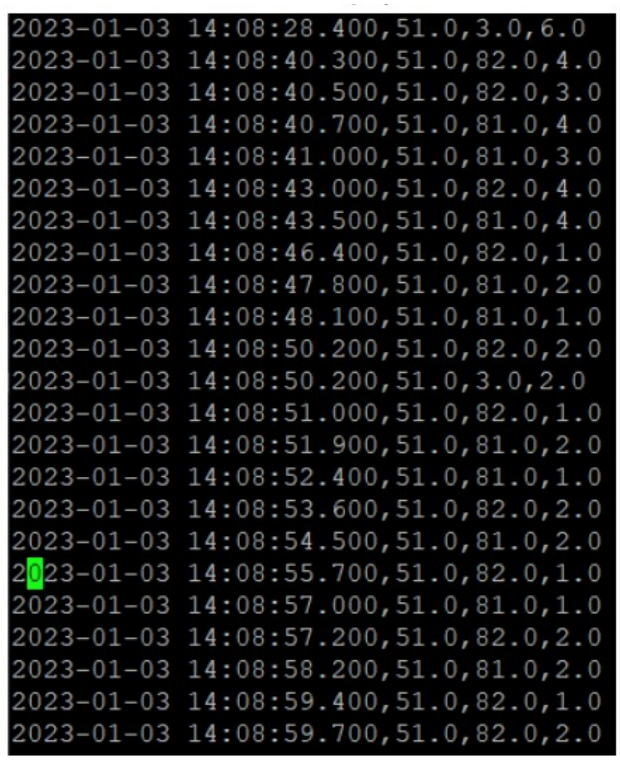


(d) Daily volume in Jan.

Figure 6: Daily detected traffic (frequency) volumes in different months at interaction 51.

When an intersection experiences heavy snow, the detectors would not be sensitive enough to detect all the cars passing through. Figure 7 (a) below is an example of an intersection on 81st facing south. Cars are seen moving through one way of the intersection (with green light) from 14:08:28-14:08:40, but there is no record in the actuated signal data (Figure 7 (b)). This indicates the failure of all sensors (e.g., camera sensors and inductive loops).




```
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2023-01-03 14:08:40.500,51.0,82.0,3.0
2023-01-03 14:08:40.700,51.0,81.0,4.0
2023-01-03 14:08:41.000,51.0,81.0,3.0
2023-01-03 14:08:43.000,51.0,82.0,4.0
2023-01-03 14:08:43.500,51.0,81.0,4.0
2023-01-03 14:08:46.400,51.0,82.0,1.0
2023-01-03 14:08:47.800,51.0,81.0,2.0
2023-01-03 14:08:48.100,51.0,81.0,1.0
2023-01-03 14:08:50.200,51.0,82.0,2.0
2023-01-03 14:08:50.200,51.0,3.0,2.0
2023-01-03 14:08:51.000,51.0,82.0,1.0
2023-01-03 14:08:51.900,51.0,81.0,2.0
2023-01-03 14:08:52.400,51.0,81.0,1.0
2023-01-03 14:08:53.600,51.0,82.0,2.0
2023-01-03 14:08:54.500,51.0,81.0,2.0
2023-01-03 14:08:55.700,51.0,82.0,1.0
2023-01-03 14:08:57.000,51.0,81.0,1.0
2023-01-03 14:08:57.200,51.0,82.0,2.0
2023-01-03 14:08:58.200,51.0,81.0,2.0
2023-01-03 14:08:59.400,51.0,82.0,1.0
2023-01-03 14:08:59.700,51.0,82.0,2.0
```
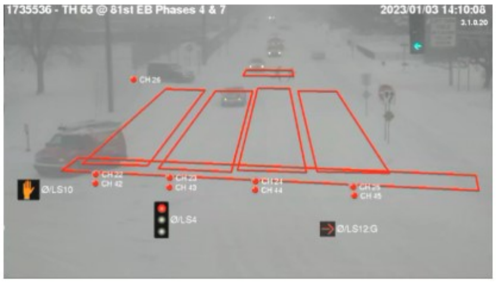
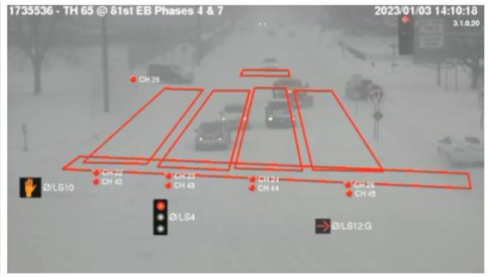

Figure 7: (a) A camera image with heavy snow. (b) The corresponding actuated signal data.

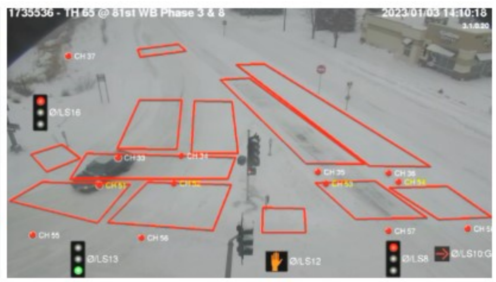
Other malfunctions indicate partial failure where some but not all cars are detected. Below is an example of this type of behavior (Figure 8). At least three cars entered the intersection in Figure 8 during 14:10:08-14:10:18, but only two 82 (on) phases are observed in the actuated signal data. Note that we only show two ways of the intersection in Figure 8(a)-(d), while the signal data records four ways. Even without another two ways, we could still observe more cars are passing than the detected cars in Figure 8(a)-(d). This implies that several car entrances were not detected.





(a) EB way image at 14:10:08

(b) EB way image at 14:10:18



(c) WB way image at 14:10:08

(d) WB way image at 14:10:18

```
2023-01-03 14:10:07.100,51.0,82.0,2.0
2023-01-03 14:10:08.500,51.0,81.0,2.0
2023-01-03 14:10:08.500,51.0,3.0,8.0
2023-01-03 14:10:09.700,51.0,81.0,1.0
2023-01-03 14:10:13.000,51.0,7.0,3.0
2023-01-03 14:10:13.000,51.0,6.0,8.0
2023-01-03 14:10:13.000,51.0,8.0,8.0
2023-01-03 14:10:13.000,51.0,8.0,3.0
2023-01-03 14:10:13.000,51.0,63.0,6.0
2023-01-03 14:10:13.000,51.0,6.0,3.0
2023-01-03 14:10:13.000,51.0,7.0,8.0
2023-01-03 14:10:13.900,51.0,82.0,4.0
2023-01-03 14:10:14.500,51.0,81.0,4.0
2023-01-03 14:10:16.000,51.0,65.0,6.0
2023-01-03 14:10:16.000,51.0,10.0,3.0
2023-01-03 14:10:16.000,51.0,9.0,3.0
2023-01-03 14:10:16.300,51.0,82.0,1.0
2023-01-03 14:10:16.500,51.0,9.0,8.0
2023-01-03 14:10:16.500,51.0,10.0,8.0
2023-01-03 14:10:19.500,51.0,11.0,3.0
2023-01-03 14:10:19.500,51.0,12.0,3.0
2023-01-03 14:10:19.900,51.0,81.0,1.0
2023-01-03 14:10:20.000,51.0,31.0,2.0
```

(e) The corresponding actuated signal data

Figure 8: More cars passing than the detected cars

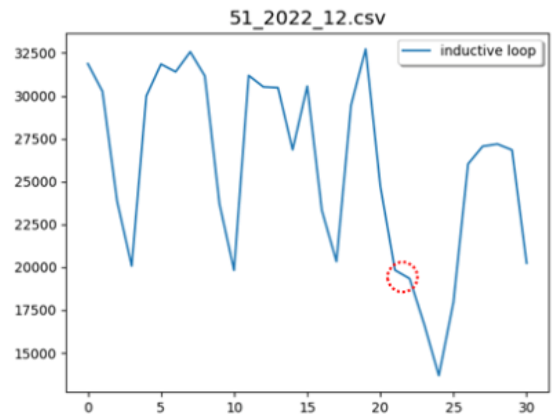
Observations:

1. Based on Jun.-Jul. and Dec.-Jan. records obtained from MnDOT, we confirmed that there are more detected cars in the summer than in other seasons.
2. Weekly traffic patterns (Weekdays vs. Weekends) could be observed on days/weekends with no major holidays.
3. Religious and National holidays are often associated with a sudden decrease in traffic.
4. Heavy snow is associated with a sudden decrease in traffic.
5. The detector performance is affected by heavy snow. Further analysis is necessary on cold days without snow before a determination about temperature affecting performance can be made.

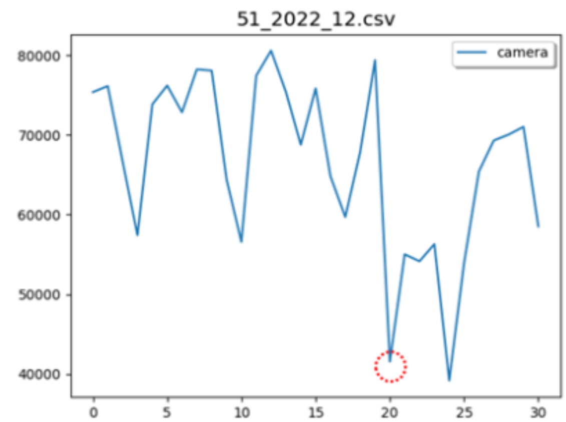
Missing data:

1. We will be able to collect the majority of the requested actuated signal data from MnDOT. Therefore, the research team expects missing data will not be a significant problem.
2. There are days or hours of data missing in July around the 15th-16th. We will continue investigating to identify other durations with missing data

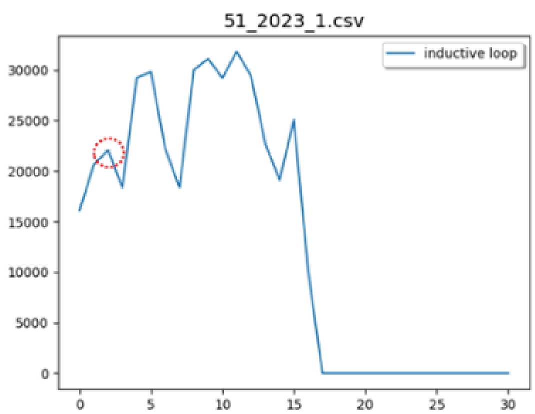
B. Separated analysis: We investigate the behaviors of the inductive loop and camera sensors separately. The initial results for our analysis are on the detected volume of on-phase (event code 82) on June.-July. 2022 and Dec. 2022, and Jan. 2023. Notably, we count the on-phase with parameters 1-4 as the inductive loop detection behavior and the on-phase with parameter 17+ as the camera detection behavior. Since the camera has more detected lanes than an inductive loop, the detected on-phase volume of a camera is much higher than the counterpart of an inductive loop. Nevertheless, their general trend is similar over time. Thus, in this analysis, we compare their relative volume trend (i.e., the local volume change) instead of the real volume for a fair comparison. However, their abnormal behaviors show distinct patterns. For example, there are more sudden drops on Dec. 21st, 2022, and Jan. 3rd, 2023, in camera detection (marked by red circles in Figure 9(a)-(d)). We observe heavy snow on both days, which significantly affects the visibility and results in a camera malfunction, while the inductive loop doesn’t suffer from this. Even though we can usually observe that the camera could encounter more sudden drops than an inductive loop, it does not mean an inductive loop always performs better than a camera. According to *The Basics of Loop Detection* [7], the high temperature could also negatively impact the inductive loop and cause fake detections. As a result, an inductive loop may have a larger volume than reality. On Jun. 21st and Jul. 19th, even though the camera had less relative volume (marked by red circles in Figure 9(e)-(h)), we cannot say the camera performed poorly. Instead, the marked days are sunny (visibility is excellent), and the temperature is very high. The inductive loop may produce fake detections. To confirm this, we need additional analysis by integrating analysis from video in the future.



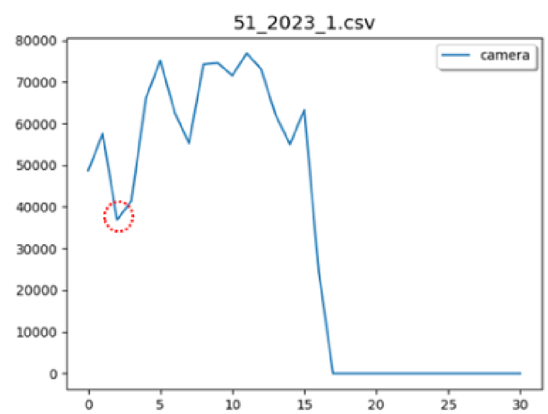
(a) inductive loop in Dec. 2022



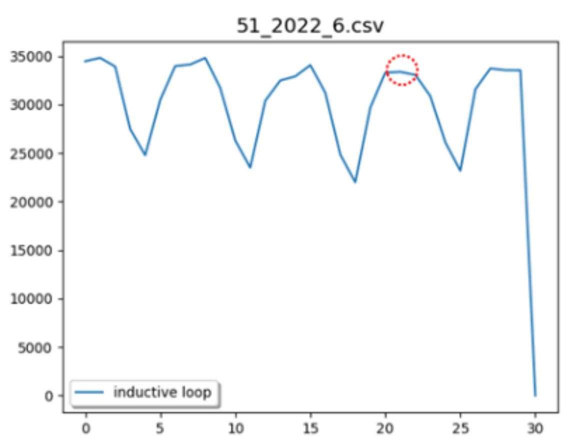
(b) camera in Dec. 2022



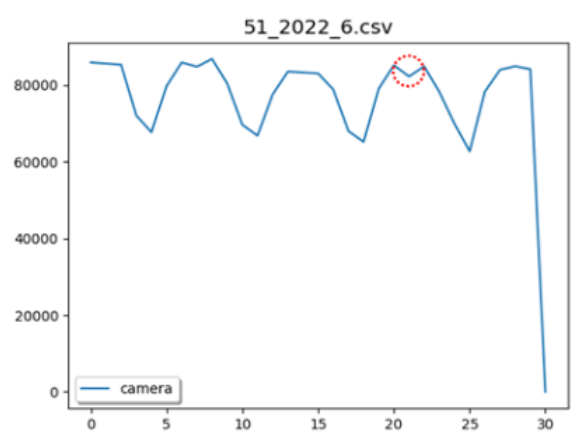
(c) inductive loop in Jan. 2023



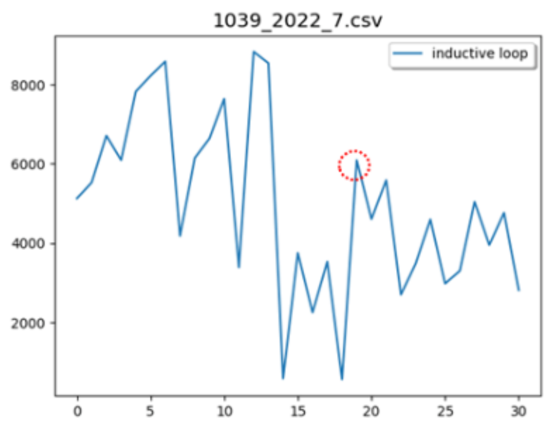
(d) camera in Jan. 2023



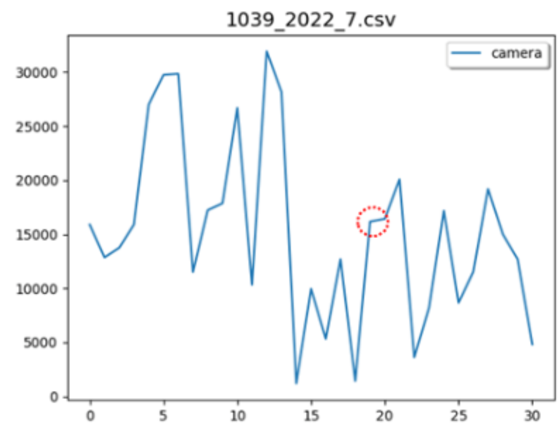
(e) inductive loop in June. 2022



(f) camera in June. 2022



(g) inductive loop in July. 2022



(h) camera in July. 2022

Figure 9: Separated analysis on daily detection behaviors of inductive loop and camera.

Observations:

1. Based on Jun.-Jul. and Dec.-Jan. records obtained from MnDOT, we confirmed that there are more detected cars in the summer than in other seasons.
2. Weekly traffic patterns (Weekdays vs. Weekends) can be observed when there are no major holidays/events.
3. Religious and National holidays are often associated with a sudden decrease in traffic.
4. Heavy snow affects the camera more than the inductive loop due to the visibility issue.
5. High and low temperatures could have negative (but different) impacts on the inductive loop, requiring additional confirmation with integrated analysis from video.

Missing data:

1. We will be able to collect the majority of the requested actuated signal data from MnDOT. Therefore, the research team expects missing data will not be a significant problem.
2. There are days or hours of data missing in July around the 15th-16th. The research team will continue investigating to identify other durations with missing data

Weather Data

1.2.1: Weather Station Data

Analysis process: The dataset includes 11 weather attributes (visibility, humidity, precipitation rate, wind speed, max temperature, min temperature, wet bulb temperature, dew point, surface temperature, subsurface temperature, and air temperature) collected at ten weather stations. We first divide the dataset by season and then generate descriptive statistics to capture the general situation of the weather. Table 1 and Table 2 are examples of the descriptive statistics of all of the weather attributes in summer and winter. “Count” is the number of not null data records in the dataset, “mean” is the average of all data records, “std” is the standard deviation of all data records, “min” is the minimum number of all data records, “25%” is the lower quartile number of all data records, “50%” is the median number of all data records, “75%” is the upper quartile number of all data records. At the same time, “max” is the maximum number of all data records.

	VISIBILITY (mi.)	**HUMIDITY**	**PRECIP RATE**	**WIND SPEED** (MPH)	**MAX TEMP** (° F)
count	53510	58528	59423	59427	59468
mean	12.01	0.64	0.30	4.51	85.71
std	1.72	0.18	6.32	3.74	5.92
min	0.10	0.21	0.00	0.00	61.00
25%	12.40	0.50	0.00	2.00	82.00
50%	12.40	0.65	0.00	4.00	85.00
75%	12.40	0.78	0.00	7.00	89.00
max	12.40	1.00	397.80	20.00	100.00
MIN TEMP (° F)	**WET BULB TEMP** (° F)	**DEW POINT** (° F)	**SURFACE TEMP** (° F)	**SUBSURFACE TEMP** (° F)	**AIR TEMP** (° F)
59468	59468	59468	36080	42087	59468
64.34	66.84	61.05	87.21	82.21	73.79
5.57	6.79	7.82	14.38	4.89	8.46
48.00	47.00	39.00	60.00	72.00	50.00
61.00	62.00	55.00	76.00	77.00	68.00
64.00	67.00	62.00	84.00	83.00	74.00
68.00	71.00	67.00	97.00	86.00	80.00

79.00	98.00	81.00	130.00	94.00	100.00

Table 1. General descriptive statistics of weather attributes data collected in summer (June 20, 2022, to July 10, 2022).

	VISIBILITY (mi.)	**HUMIDITY**	**PRECIP RATE**	**WIND SPEED** (MPH)	**MAX TEMP** (° F)
count	62796	61096	62802	62594	62802
mean	8.20	0.81	0.17	5.15	20.57
std	4.52	0.11	1.50	4.34	13.38
min	0.10	0.48	0.00	0.00	-11.00
25%	3.70	0.72	0.00	2.00	9.00
50%	10.20	0.82	0.00	4.00	25.00
75%	12.40	0.91	0.00	7.00	32.00
max	12.40	1.00	94.00	28.00	40.00
MIN TEMP (° F)	**WET BULB TEMP** (° F)	**DEW POINT** (° F)	**SURFACE TEMP** (° F)	**SUBSURFACE TEMP** (° F)	**AIR TEMP** (° F)
62802	62802.00	62802	37642	43858	62798
6.53	13.27	9.33	18.05	27.10	13.90
14.10	14.28	16.27	12.76	6.22	14.47
-16.00	-16.00	-22.00	-14.00	12.00	-16.00
-6.00	0.00	-6.00	7.00	23.00	1.00
4.00	17.00	12.00	22.00	28.00	17.00
20.00	26.00	24.00	29.00	33.00	26.00

34.00	36.00	38.00	43.00	37.00	40.00

Table 2. General descriptive statistics of weather attributes data collected in winter (December 20, 2022, to January 10, 2023).

Data Interpretation: We attempt to find trends in all the weather attributes over two time ranges, three weeks in summer and three weeks in winter. This data could provide information to study how the behaviors of detection technologies are affected by different weather attributes at the high-resolution level. Our initial analysis focuses on the temporal patterns in the original time-series weather dataset. After we confirm the detection technologies are affected by extreme weather events, we are interested in quantifying the weather events and seeing which level of weather conditions are specified by various weather attributes that could affect the detection technologies. The research team plots all the weather attributes. Below are examples of a sample three-week weather attribute at ten stations (Figure 10-19).

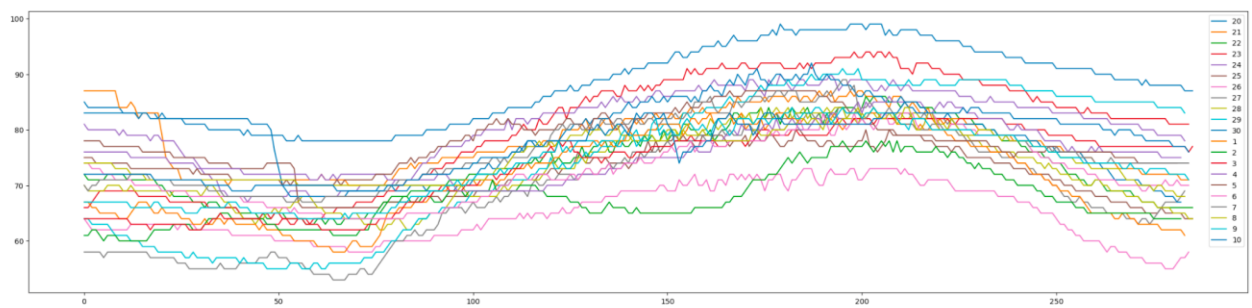


Figure 10: Average Air Temp across ten weather stations by date.

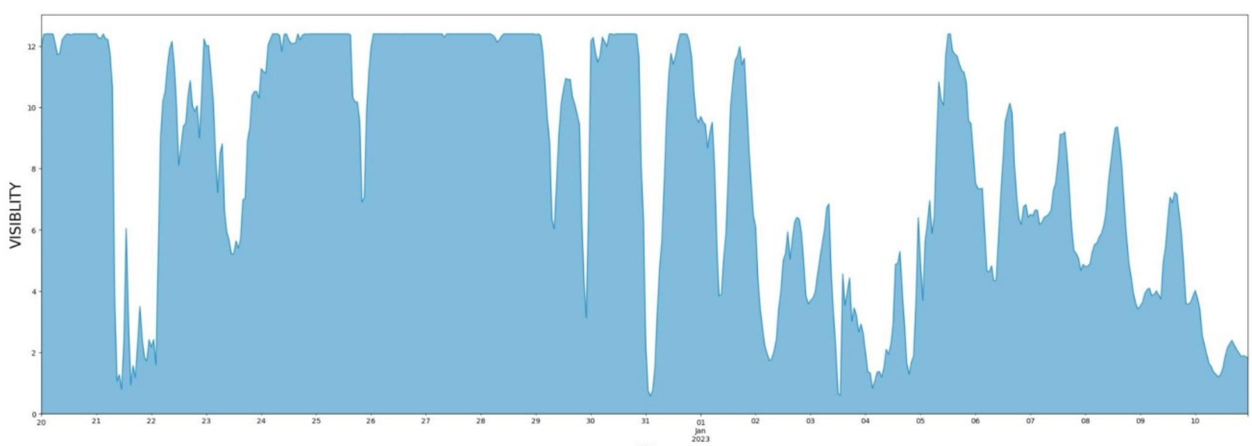


Figure 11. Average visibility trend across ten weather stations in winter.

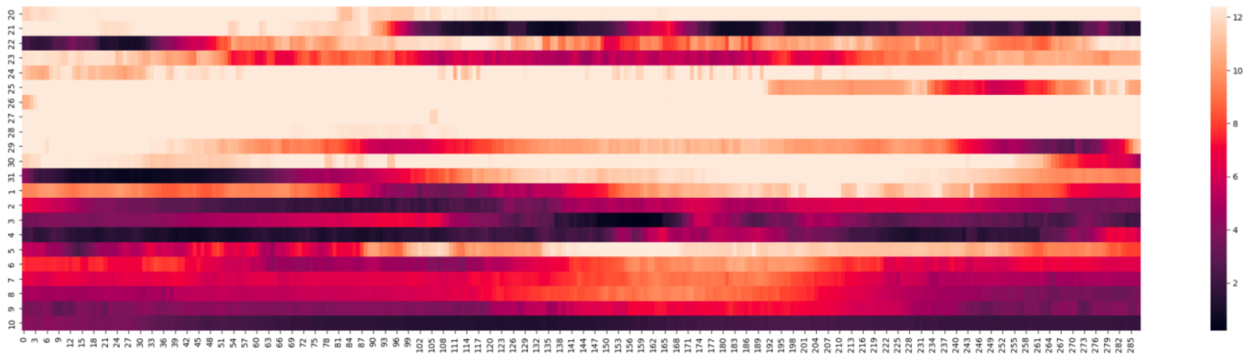


Figure 12. Heatmap of the average visibility across ten weather stations in winter.

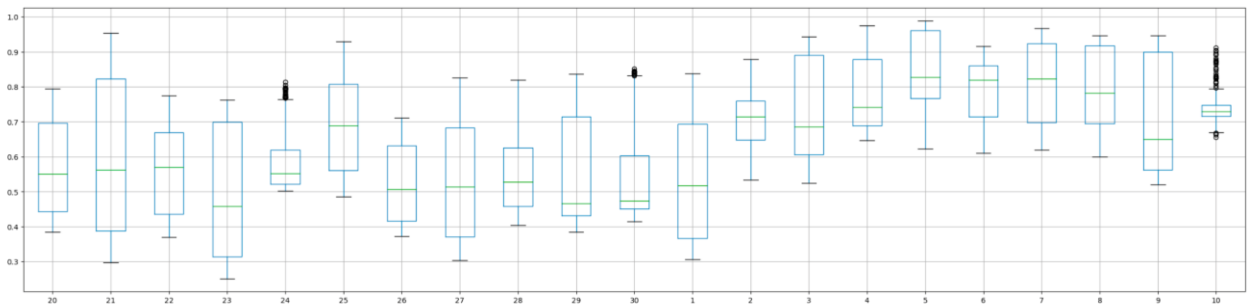


Figure 13. Box plot of the average humidity across ten weather stations in summer.

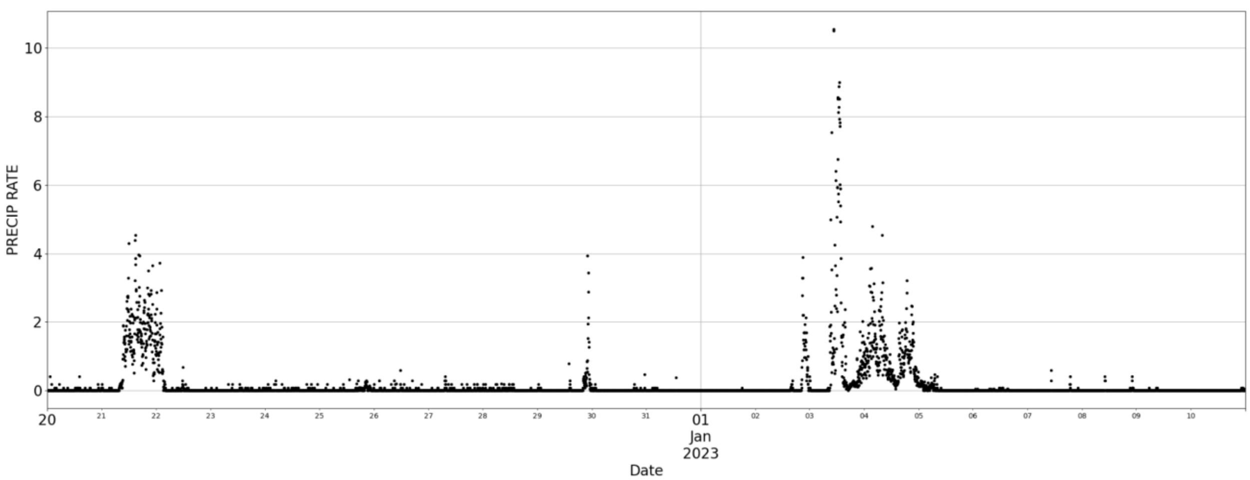


Figure 14. Scatter plot of the average precipitation across ten weather stations in winter.

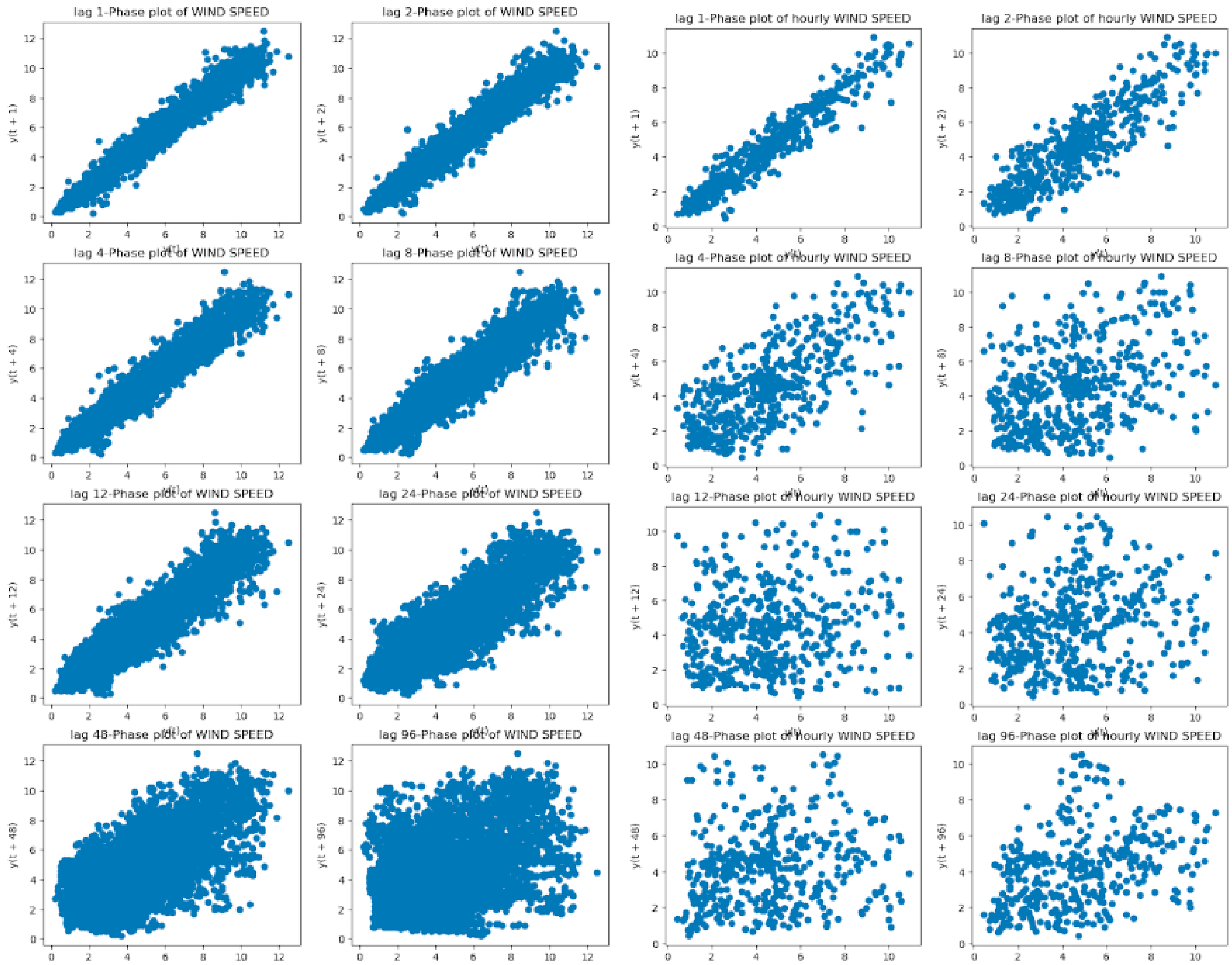


Figure 15. Lag plots of the average wind speed across ten weather stations in summer.

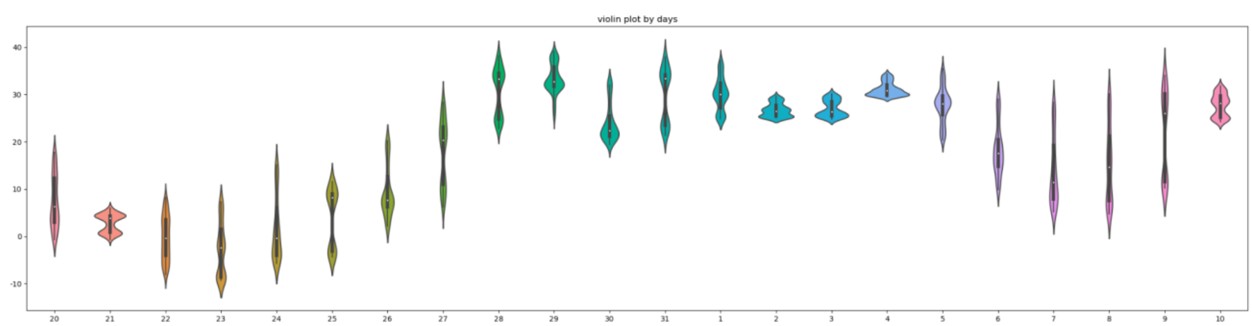


Figure 16. Violin plot of the average surface temperature across ten weather stations in winter.

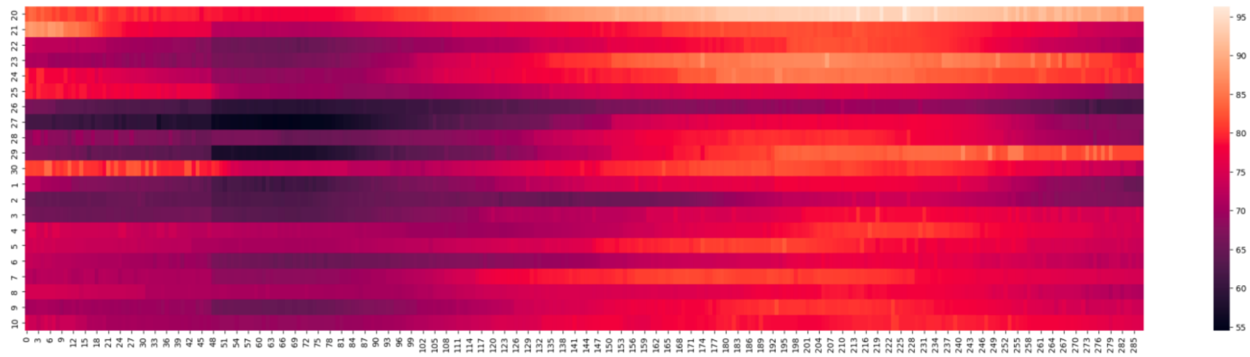


Figure 17. Heatmap of average air temperature across ten weather stations in summer.

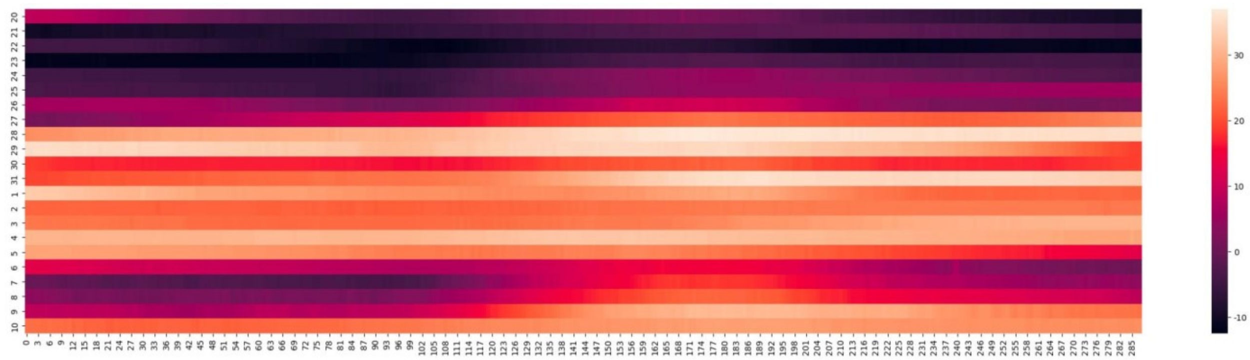
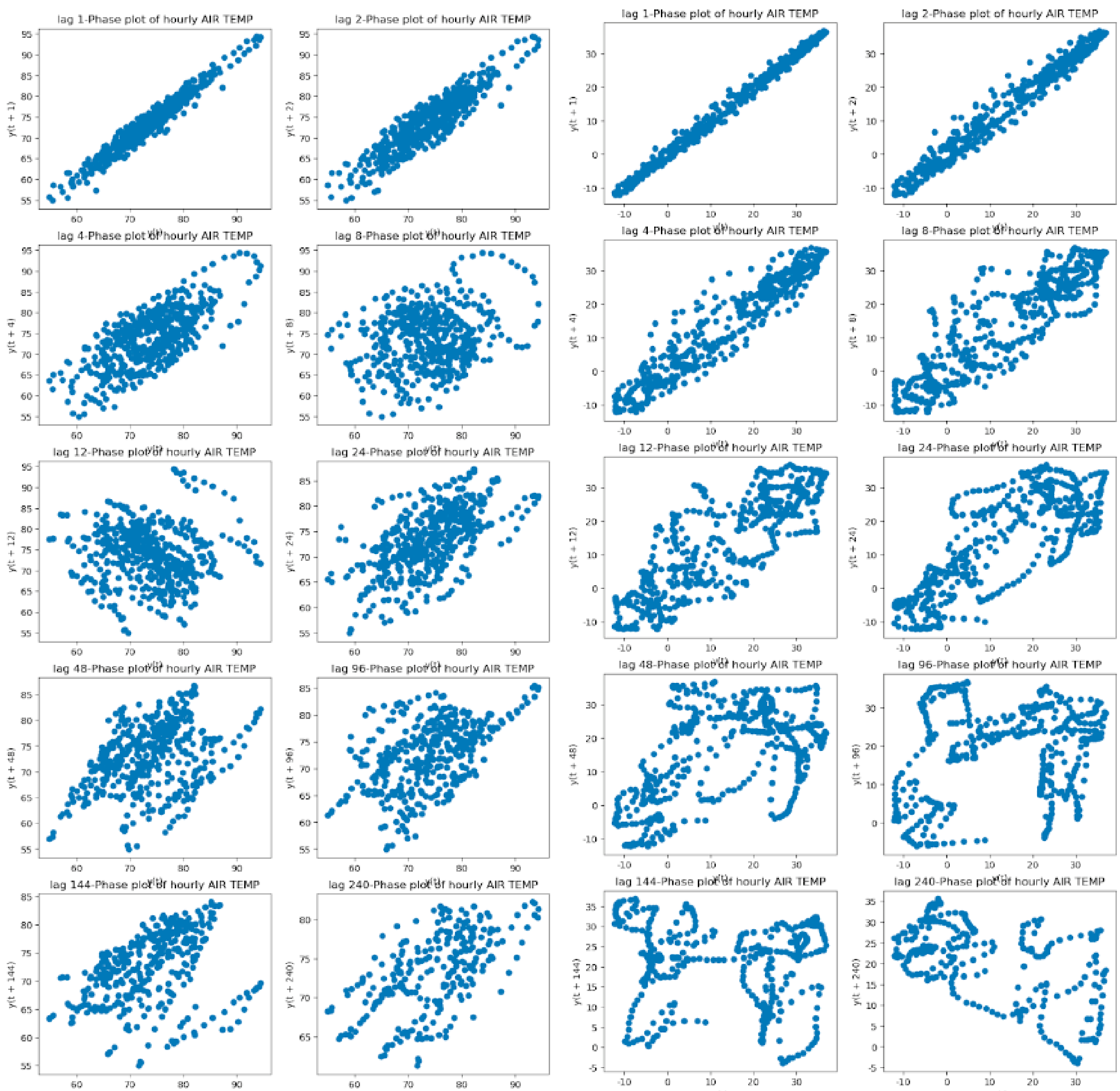


Figure 18. Heatmap of the average air temperature across ten weather stations in winter.



(a) Summer (b) Winter

Figure 19. Lag plots of average air temperature across ten weather stations in (a) summer and (b) winter.

Observations:

The heatmap explicitly shows how data changes over time and shows very high and low data. The box plot shows the descriptive statistics of each weather variable. The scatter plot shows the general trend of each weather variable and the outliers. The violin plot shows the distribution and range of each weather variable. The lag plot shows the degree of auto-correlation. The closer the data distribution is to the upper right and lower left diagonal, the stronger the n-phase lag autocorrelation of the data.

1. In all temperature variables (max temperature, min temperature, wet bulb temperature, dew point, surface temperature, subsurface temperature, and air temperature), the standard deviation in winter is larger than that in summer. The range of temperature also varies more in winter.
2. There is clear autocorrelation in humidity, max temperature, min temperature, wet bulb temperature, dew point, surface temperature, and air temperature. The smaller the interval lag, the more pronounced the autocorrelation.
3. The autocorrelation is limited in visibility, precipitation rate, wind speed, and subsurface temperature.
4. In summer, the daily temperature rises and falls in a similar trend, while in winter, the temperature varies every few days depending on special weather events such as cold snaps and snowstorms.

Geographic Data

Analysis process: In task 6, we generated a buffer with a radius of 2,000 meters and 5,000 meters for each camera location to represent the environmental features of cameras in vector space. Next, we split all the point, line, and polygon geographic layers by attributes and values of attributes. We traversed the split layers and calculated the number of points, the total length of lines, and the total area of polygons located in each buffer circle. Table 3 lists 66 buffer statistical attribute results from this procedure.

To study how the environment of the camera location impacts the camera performance, the research team clusters the 66-dimension feature data of 31 cameras using the Hierarchy Cluster Analysis method. The result of the Hierarchy Cluster Analysis is shown in Figure 20. As we decide to have six classes for the 31 cameras, each red bounding box represents one camera class. The numbers in the horizontal axis represent the camera IDs, which could refer to Table 4 for the camera names.

Data source type	Data source layer	Feature generated within buffer	Buffer radius	
			2000 m	5000 m
Polygon	OSM_building_a	Building area (m^2)	✓	✓
	OSM_water_a	Water area (m^2)	✓	✓
	OSM_pofw_a	Religious place area (m^2)	✓	✓
	OSM_pois_a	Points of Interest area (m^2)	✓	✓

	OSM_traffic_a	Parking lot area (m^2)	✓	✓
	OSM_landuse_a	Grass area (m^2)	✓	✓

Point	OSM_pois	Point of Interest number	✓	✓
	OSM_transport	Bus stop number	✓	✓
	OSM_traffic	Road crossing number	✓	✓
		Motorway junction number	✓	✓
		Turning circle number	✓	✓
		Traffic signal number	✓	✓
		Stop number	✓	✓
		Street lamp number		✓
		Parking number		✓
		Bicycle Parking number		✓
Polyline	OSM_railways	Total railway length (m)	✓	✓
	OSM_roads	Total cycleway length (m)	✓	✓
		Total motorway length (m)	✓	✓
		Total motorway link (m)	✓	✓
		Total service road length (m)	✓	✓
		Total residential road length (m)	✓	✓

		Total footway length (m)	✓	✓
		Total primary road length (m)		✓
		Total primary link length (m)		✓
		Total bridleway length (m)		✓
Polyline	OSM_roads	Total secondary road length (m)	✓	✓
		Total secondary link length (m)	✓	✓
		Total tertiary road length (m)	✓	✓
		Total tertiary link length (m)	✓	✓
		Total track road length (m)	✓	✓
		Total path road length (m)	✓	✓
		Total steps road length (m)		✓
		Total trunk road length (m)	✓	✓
		Total trunk link length (m)	✓	✓
		Total pedestrian road length (m)		✓
		Total unclassed road length (m)	✓	✓

Table 3: Table of 66 buffer statistical attributes retrieved from OSM.

Data Interpretation: The six classes from the Hierarchy Cluster Analysis are in Figure 20 and Table 5. The difference between classes 1-3 and 4-6 is that classes 1-3 are cameras in more built areas, while classes 4-6 are in more open and natural areas. The evidence in the 66 buffer statistical attributes is that the built area and length (e.g., parking lot area, building area, POIs area) for classes 1-3 are much more than classes 4-6.

To represent the environmental features of cameras in vector space, we generate a buffer with a radius of 2,000 meters and 5,000 meters for each camera location. Next, we split all the point, line, and polygon geographic layers by attributes and values of attributes. We traversed the split layers and calculated the number of points, the total length of lines, and the total area of polygons located in each buffer circle. Below is the list of 66 buffer statistical attribute results from this procedure (Table 3). The number of bus stops, the length of the footway, the length of the cycleway, and the resident population clearly impact classes 1, 2, and 3 or classes 4, 5, and

6.

ID	Camera Name	ID	Camera Name	ID	Camera Name
0	494_flyingcloud_sramp_gridsmart	11	s_65_viking_nuturn_gridsmart	21	s_cr144_james_vision
1	494_pilotknob_nramp_iteris	12	s_65_viking_wside_gridsmart	22	s_cr144_rogershighscool_vision
2	62_france_nramp_vision	13	35e_cliff_eramp_iteris	23	s_12_carlson_sramp_vision
3	62_france_sramp_vision	14	35e_cliff_wramp_iteris	24	s_12_carlson_nramp_vision
4	65_41st_gridsmart	15	36_whitebear_sramp_iteris	25	CR81_industrial_visions_stream
5	694_eriver_nramp_vision	16	36_whitebear_nramp_iteris	26	CR81_deere_visions_stream
6	694_eriver_sramp_vision	17	47_85th_Iteris_Stream1	27	CR81_memorial_visions_stream
7	77_cliff_eramp_vision	18	47_Mississippi_Movision_Stream3	28	s_12_csah101_sramp_vision
8	77_cliff_wramp_vision	19	51_crc2_iteris	29	s_12_csah101_nramp_vision
9	s_65_viking_suturn_gridsmart	20	s_cr144_northdale_vision	30	65_81st_Vision_Stream1
10	s_65_viking_eside_gridsmart				

Table 4. The camera IDs used in Figure 20's horizontal axis and its corresponding camera names.

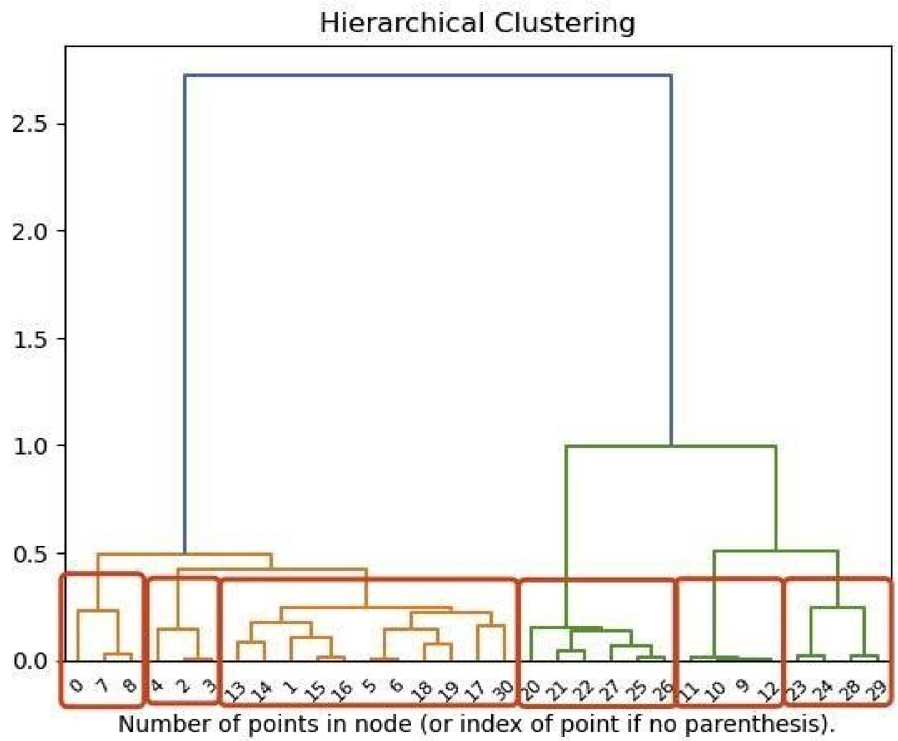


Figure 20. Hierarchy Cluster Analysis result of all 31 cameras' 66 environmental features.

Camera Class ID	Camera IDs
1	0, 7, 8
2	4, 2, 3
3	13, 14, 1, 15, 16, 5, 6, 18, 19, 17, 30
4	20, 21, 22, 27, 25, 26
5	11, 10, 9, 12
6	23, 24, 28, 29

Table 5. Table of camera IDs in each camera class from The Hierarchy Cluster Analysis (a clarification of Figure 20).

Methods for NIT Performance Evaluation

Our proposed methods aim to provide insight into how we can evaluate the performance of the NIT. We will use the results of our initial analysis to inform how we design our evaluation methods and the guidelines. Primarily we will focus on what conditions contribute to poor camera performance and develop models that can determine if poor performance is likely. By using methods to evaluate the physical conditions of the camera and observing the broader weather and traffic patterns, we intend to create a system that can notify operators if poor performance is likely and/or currently occurring. We sampled our test data from December 20, 2022, to January 10, 2023, to evaluate our methods. We use this time range because it is one of the few date ranges that include many winter storms that would provide adverse weather conditions for our models to detect drops in the NIT performance. This date range also includes two major holidays, which allows us to observe abnormal traffic patterns.

Computer Vision

2.1.1: Occlusion Detection

Motivation: Often, we run into instances where the cameras are occluded by dirt, snow, rain, etc. Figure 3-b shows an example of a camera occluded by rain, and Figure 21 shows an example of a camera occluded by snow. These issues present immediate performance problems for the NIT as they cannot determine if cars are present at the intersection. Consequently, not only does this affect the performance of the NIT, but it also affects our ability to adequately diagnose other issues that the camera may face due to temperature, humidity, wind, etc.

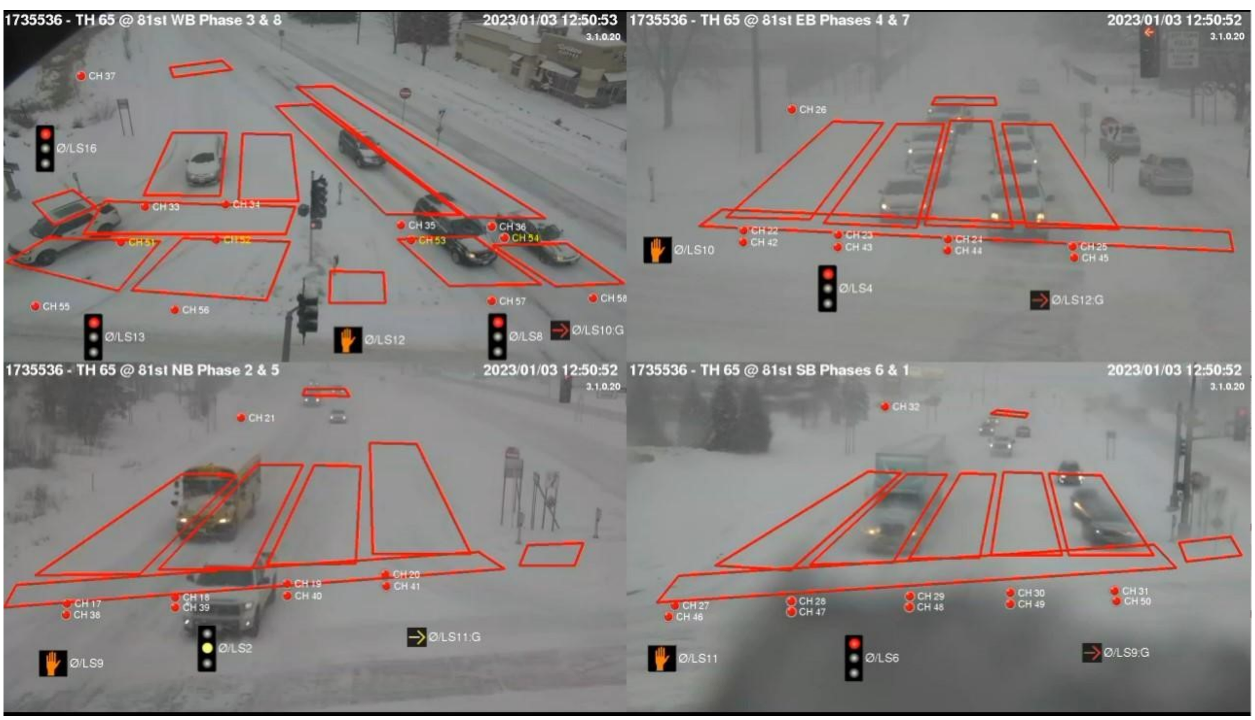


Figure 21: Camera occluded by snow

Purpose: We implement this method to 1) detect whether a camera is occluded and 2) provide data for a broader analysis of which camera types and placements are more prone to being affected by conditions that cause occlusions. Determining whether a camera is occluded will provide immediate benefits as it will notify operators if someone needs to be sent to the location to clear the blockage. It will also provide information if a blockage persists or if it will resolve itself (e.g., snow accumulating on a lens during the night and melting during the day). The data from analyzing broader occlusion patterns between camera types and environmental conditions will allow us to provide recommendations to MnDOT on which conditions result in cameras requiring more consistent maintenance. This will allow us to make recommendations to MnDOT to aid in reducing maintenance costs and improving overall camera performance. For example, in Figure 21, only one camera is severely affected by snow. If this issue persists for certain camera types or a pattern is found correlating higher occlusion rates with certain environmental features, it would indicate other intersections with those same features would face similar issues. However, because we are only analyzing a small set of cameras, it will be difficult to draw broader conclusions from this mode of analysis.

Method: We implement a model based on PFENet (Prior Guided Feature Enrichment Network) [1], an image segmentation model that uses supporting images during runtime. The specific model implemented uses Pytorch's Resent50 [2] model as a backbone which is pretrained using the COCO dataset [3]. We then fine-tune the PFENet model using the Woodscape dataset [4], an open-source dataset of fisheye lens camera views from cars, for training image segmentation models for soil and dirt detection on the lens. The model is trained for 90 epochs with a base learning rate of 0.0025.

After training, we tested the model on the recordings we collected during the data collection period. The model could accurately predict camera occlusion due to snow and water during our sample time range. As a consequence of this model having to evaluate a live video and the model taking ~0.1 seconds to process a single frame, we recommend an implementation only be run on every second or every third frame so the model can keep up with the live video.

A) Preprocessing

There are only two preprocessing steps required for the PFENet model. The first is the creation of a custom support image from our dataset. We used an image editing software called GIMP to create the mask for the image displayed in Figure 22.

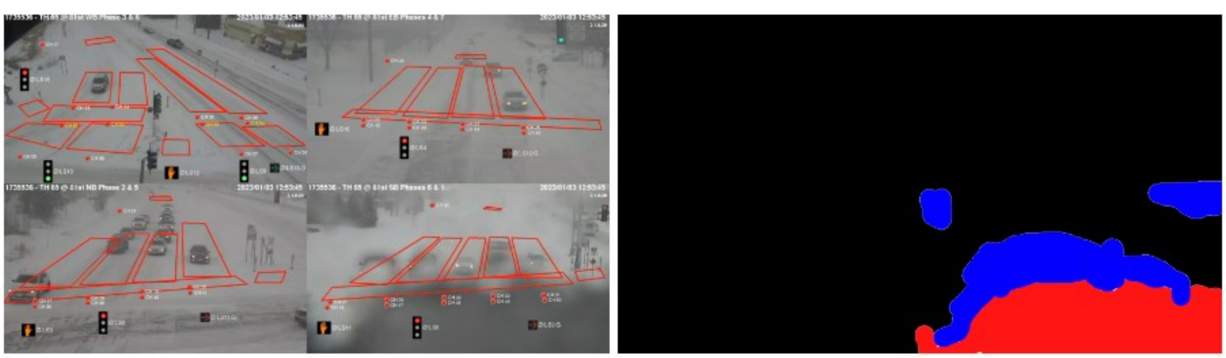


Figure 22: Image and mask of the supported image for PFENet

The second preprocessing step is to take the video files, read them using OpenCV, and convert them to crop them to specific cameras. For example, in Figure 22, the image is a composition of four different camera perspectives. We crop each image to be a composition of four separate images and process them separately to improve accuracy. Once we have completed these steps for images and labels, we convert the labeled dataset to grayscale. Cropping is unnecessary during training time because the training set is not presented in the four frames in one format.

B) Testing

Once preprocessing steps are completed, we pass our images into our PFENet model. For each image, the model outputs a matrix of the size of the image with labels for each pixel of the image indicating whether it is occluded or not. We then sum the result and divide it by the total size of the image. This gives us a percentage value for the amount of the occluded image. We can then plot these results to see the amount of occlusion that occurs for a specific lens over a span of time. Figure 23 shows the results of this procedure for cameras at location 51 between December 20, 2021 and January 10, 2023. We can observe several instances where occlusion is detected.

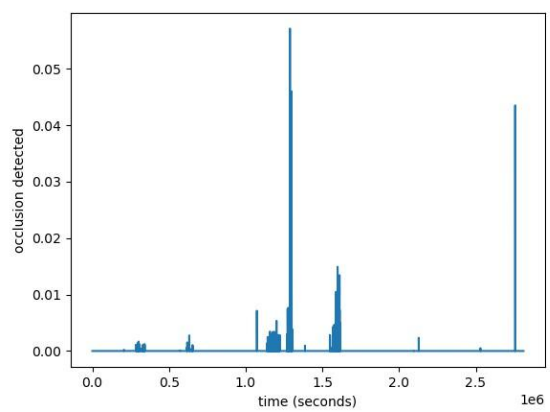


Figure 23: Time-series plot of occlusion detected on cameras at location 51

Figure 24 shows us a sample frame from one of the peeks we observe in the graph in Figure 23. While the occlusion is not severe and does not affect the performance of the NIT, further accumulation will cause issues to become present later.

Figure 24: Example of detected occlusion at location 51

C) Evaluation

There is no systematic way to evaluate the occlusion detection because our test data is unlabeled. Therefore, we have had to manually check frames where occlusion is detected to determine how accurate our model is. Through manual observation, we have found that while our model is good at detecting occlusion, it gives many false positive results, see Figure 25.

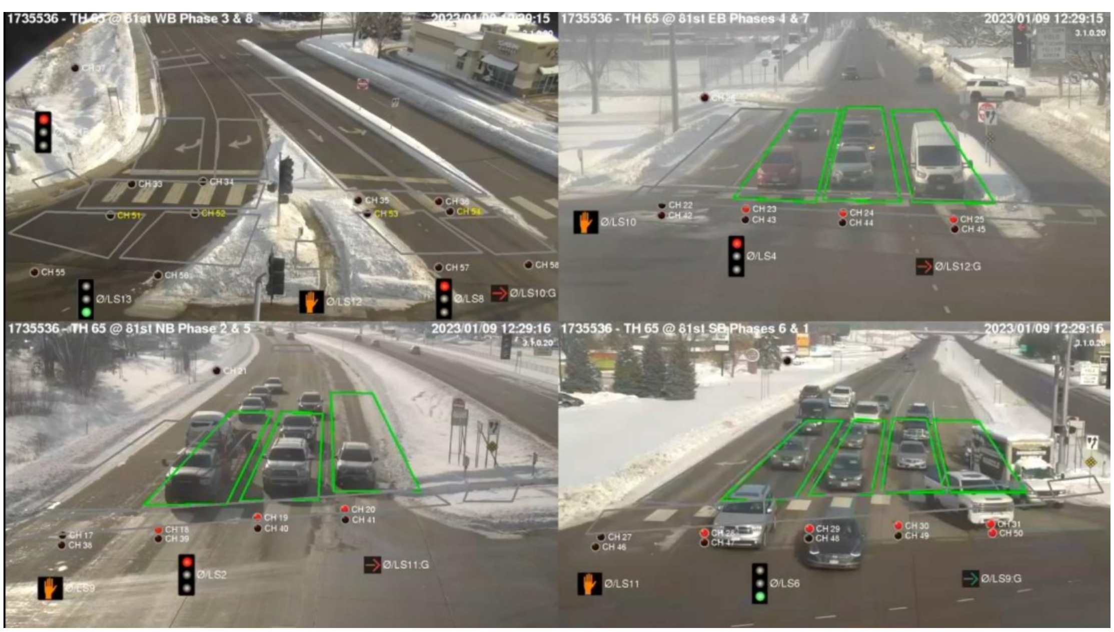


Figure 25: Example of a false positive result for PFENet at location 51

More training epochs on the PFENet model may help alleviate these issues; however, in the immediate term, we plan on implementing threshold values to the occlusion detection method.

This would require a minimum percentage of the lens occluded before operators are notified. This is supported by evidence from our observations that many false positive results have lower occlusion percentages than their counterparts where occlusion is truly present.

2.1.2: Car Detection

Motivation: Currently, we have no baseline for evaluating the performance of the NIT technologies in determining if a car is present in the detection areas as described in section 1.1.1. Manually checking the video for a long time (e.g., one year) is not possible. This does not allow us to directly observe performance drops due to factors outside of lens occlusion like temperature, wind, faulty parts, etc.

Purpose: The purpose of this model is to provide a proper baseline to measure the ongoing capabilities of the NIT in vehicle detection. Once this baseline has been established, we can compare the NIT technologies' performance to the car detection model to determine if there are any performance lags or drops that indicate the NIT is degrading somehow. Once a significant discrepancy is detected, operators will be flagged that there is an issue so proper diagnostic procedures can be made to resolve the issue. Additionally, we want to determine if any specific camera types have more consistent and long-lasting performance drops to support our recommendation for different camera types that do not show those issues.

Method: We implement a YOLO v5 model [5], a popular object detection model loaded using Pytorch. It was pre-trained using the COCO dataset [3], containing 50 labels, including various vehicle types, cars, bikes, trucks, etc. We use this model out of the box on the video data to determine if a vehicle is inside one of the detection zones. We then compare the results from YOLO to the Acctuated Signal data to determine if there is a significant difference to indicate an issue with the NIT.

Like occlusion detection, the model will take ~0.1 seconds to process a single frame when performing detection on a live video feed. This will require the model to be run on every second or third frame for the model to keep up with the live video feed.

A) Preprocessing

Actuated Signal Data: We focus on 81/82 calls as they indicate whether a car has entered a detection volume. Additionally, the actuated signal data is initially unordered, so we take steps to order it temporally.

Video Data: To preprocess the video data, we crop the video to a section immediately before one of the detection zones in a single lane (Figure 26). This reduces noise and allows us to focus on a single signal code for analysis. We chose a section before the detection zone because, through experimentation, we found that the colored detection zones interfere with the YOLO model resulting in lower accuracy.

Figure 26: Sample of cropped video data

B) Testing

We run the YOLO model on the video data and output the detection results for each second of the video data to a .csv file for evaluation. During runtime, we implement a text reader model on the video data section containing the timestamp to automatically determine if a car has been detected moving into a detection zone at that timestamp. We then export these results for an entire video to a .csv file for evaluation. While the text reading models tend to be reasonably accurate, we have noticed some minor issues in reading the timestamp code, this can be resolved in the live version by simply tracking the real-time, but for now, we will expect some small drop in the accuracy of our model due to these errors.

We take the results in the .csv file and compare them with the actuated signal data results to show an accurate comparison. We also plot the results of our YOLO detection over time (Figure 27). We can observe fairly regular night/day patterns with intersections. Promisingly, we can observe that time ranges in Figure 23, where occlusion is detected, often line up with sections in Figure 27, where no cars are detected, indicating that the occlusion detected affects the camera's ability to detect cars.

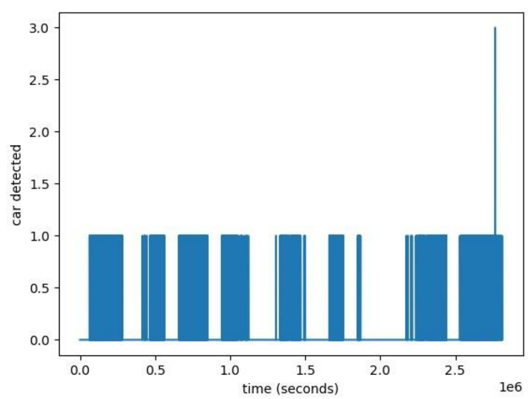


Figure 27: Time-series plot of car detection on cameras at location 51

C) Evaluation

We evaluate the results of our YOLO model by comparing them to the actuated signal data. Using the obtained time-stamped .csv files from the YOLO model, we look at the time stamps where cars were detected and compare them to the 81/82 calls in the actuated signal data. We include a 20-second buffer to account for the time it takes for cars to enter and leave the detection area. We hope to improve the selected time span to fine-tune our accuracy and minimize false negatives. With the 20-second buffer, our current accuracy results for the selected time span is 12.8% which is surprisingly low. Our initial explanation for these poor results is that YOLO often fails in low-light conditions. At the same time, it seems the NIT switches over to headlight detection in those conditions, making it so they can operate as night as well as day under certain circumstances. We intend to investigate further ways to improve the accuracy of our YOLO metrics for our future analysis

Anomaly Detection

Motivation: The detailed actions of sensors could be recorded in the actuated signal data. Thus the actuated signal data contains the aggregated information about different kinds of sensors in an intersection. Sensor malfunctions cause abnormal detection behaviors. Correspondingly, abnormal patterns could be observed in actuated signal data. Based on this, if we can detect the abnormal patterns in the actuated signal data, we can get the reference to reflect the potential malfunctions of sensor detection. As it is hard to enumerate all the possible malfunctions due to the diversity of detection technology and cause conditions, an unsupervised method that can automatically detect abnormal signals is preferred. Thus, we plan to apply unsupervised anomaly detection on actuated signal data to detect the abnormal patterns which could correspond to potential sensor detection malfunctions.

Purpose: The goal is to detect abnormal patterns with an unsupervised time series anomaly detection method. Once an anomaly is detected by our method, we can check related information to finalize the exact issues. The related information could be the root causes (e.g., environment and weather conditions) of the abnormal patterns (which would be introduced in detail in the method description) or domain knowledge (according to the judgment of maintenance staff). The possible final issues could be: 1) abnormal patterns caused by actual sensor detection malfunctions, 2) abnormal patterns caused by unusual events (e.g., holidays) beyond sensor functionality, and 3) unexpected sudden changes in the traffic flow (e.g., sudden traffic accidents).

Method: We propose to apply VAE[6] for time series anomaly detection to detect abnormal patterns in actuated signal data and develop root cause analysis to identify the cause of the abnormal patterns for helping finalize the potential abnormal patterns into actual sensor detection malfunctions. Thus, we first preprocess all the related data (e.g., actuated signal data, weather metrics, and dates over time) into time series (i.e., an time series is a sequence of values with temporal order). Below are some strategies we use to preprocess these data.

A. Preprocessing:

(1) Actuated signal data: We focus on the 81/82 phases (off/on actions for all detectors). We aggregate all the phases within a specific time span (e.g., an hour or a day) and count the frequency as the value for a time step. Currently, we focus on a daily level. Each time step in our following preprocessing and initial results represents a day if not specified. 81 and 82 appear as a pair simultaneously, so we only need to count one phase. Thus, the data is processed into *phase volume time series*.

(2) Weather metrics: Our initial analysis of failure cases shows that bad weather conditions can cause the failure of detection technology. Thus, we preprocess the weather metrics into a similar resolution corresponding to actuated signal data and apply root cause analysis between weather metrics time series and phase volume time series. Due to the diversity of weather metrics, the preprocessing for different weather metrics could be classified into two categories: when the weather metrics are numeric type, we aggregate the metrics values over a specific time span with the mean or median operation; When the weather metrics are categorical type, we aggregate the metrics values over a specific time span with a majority voting strategy (i.e., the most frequent value is the winner value for the time step).

(3) Dates over time: Our initial analysis of traffic volume data implies that the traffic volume has various temporal patterns related to dates: daily pattern (e.g., high volume in the daytime and low volume in the night), weekly pattern (e.g., high volume in the weekdays and low volume in the weekend), seasonality pattern (e.g., high volume in the summer and low volume in the winter), festival pattern (e.g., traffic volume drops suddenly in big festival). Thus, the 81/82 phases in actuated signal data should have similar patterns as the phase volume corresponds to the traffic volume, which could be reflected by the dates over time. Currently, we focus on modeling the weekly pattern and festival pattern. Particularly, we encode each day within a week as 1–7 correspondingly if there is no holiday. Otherwise, we encode a holiday (i.e., Christmas) as 10. Thus, the dates over time become time series with possible values of 1–7 and 10 at each time step.

B. Anomaly detection on phase volume time series:

At any given time step t, a target snippet (of window size k for recent k time steps in) from the phase volume time series, the VAE anomaly detection method could predict if there is an abnormal pattern. In our initial study, we set k=14. Under the recent 14 days as the context, it implies that the target time step t is an abnormal pattern.

C. Root cause analysis:

We build a causality graph (i.e., a directed edge indicates the causality relation) between phase volume time series and other root cause time series (e.g., weather metrics and dates over time). The graph edge weight is a dynamic weight representing the root cause's impact over time. Once the abnormal pattern is detected, the root cause (i.e., the time series with the highest impact) could help interpret the possible cause.

D. An case study

Here, we provide an example from our initial results to better show the B and C steps. Figure 28 presents anomaly detection results for the phase volume time series between Dec. 14th, 2022 – Jan. 17th, 2023. The smallest predicted value is the 20th time step, which corresponds to Jan. 4th, 2023, with the second lowest volume value (the lowest value is on Christmas). According to the weather report, a snowstorm occurred on the 3rd-4th of 2023. Our recorded video also verifies this. The corresponding weather metrics time series are shown in Figure 23. We can observe significantly low visibility and a precipitation type 10 (mapping to

frozenPrecipitationSlight). Assume we learn causality relations between weather metrics time series and phase volume time series for this time step (Figure 24). We can speculate bad weather conditions likely caused the abnormal pattern. The low visibility suggests that the heavy snow could affect the camera detection and result in the consequent decrease in the phase volume. As for the 11th time step (with the lowest volume value), even though the predicted likelihood is small (the 7th smallest) and could be a potentially abnormal pattern, we may not speculate a snowstorm caused it as the visibility is excellent. Instead, both the Christmas festival and the low temperature could affect the volume decrease. To further confirm that low temperature affects the detection of the inductive loop, we have analyzed in section 1.1.3 for Fig. 7 and Fig. 8. And we can observe that during the very low-temperature days, the inductive loop fails to detect all the cars (i.e., the parameter representing inductive loop phases are not shown as expected) even though the cars can be observed in the video. This observation is consistent with the report [7] that explains how very low/high temperature affects the performance of the inductive loop from the working principle of the inductive loop.

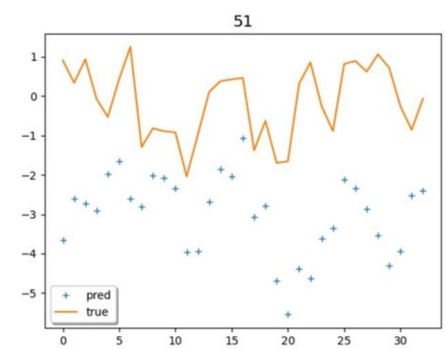
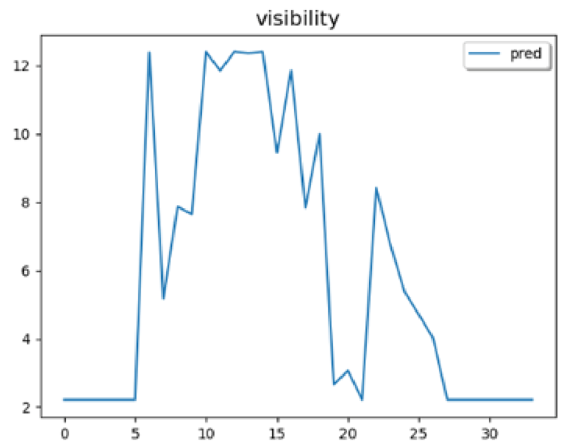
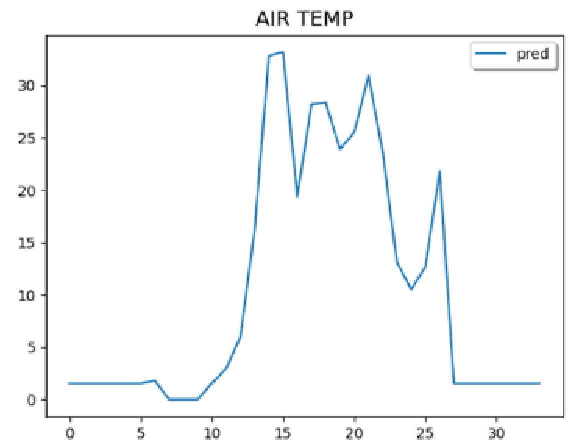


Figure 28. anomaly detection example for phase volume time series from intersection 65_81st.

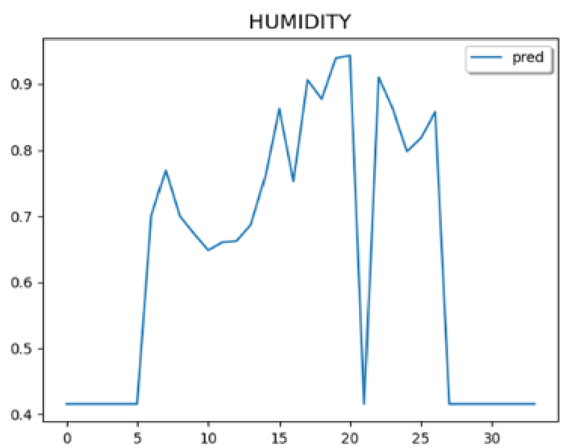
Each x-axis time step represents a daily record. The orange line is the phase volume time series over time. The blue crosses will likely be a normal pattern for all the corresponding time steps. The lower the predicted likelihood is, the more likely the time step is abnormal.



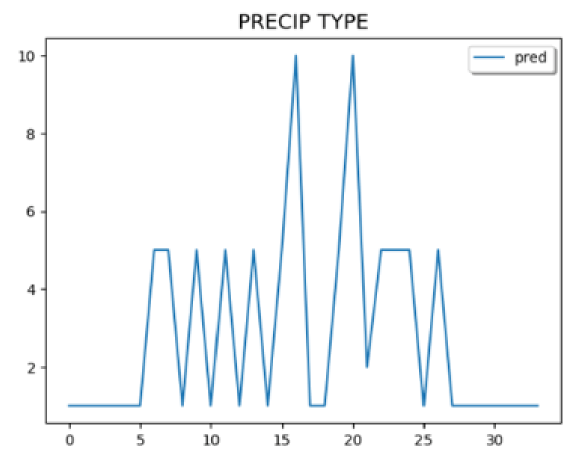
(a) visibility



(b) air temperature



(c) humidity



(d) precipitation type

Figure 29. Four examples of weather metrics time series. For the categorical metrics precipitation type, we have the following mapping: 'noPrecipitation'=1, 'rainSlight'=2,

'rainModerate'=3, 'rainHeavy'=4, 'snowSlight'=5, 'snowModerate'=6, 'snowHeavy'=7, 'other'=8,

'frozenPrecipitationSlight'=10

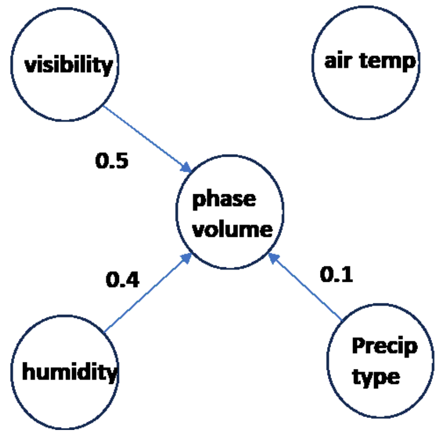


Figure 30. An example of a learned root cause analysis graph for time step 20th.

Summary and Next Steps

In this task, we performed several analyses on the traffic camera data, traffic volume data, actuated signal data, weather station data, and geographic data. Our analysis shows useful patterns for characterizing when and how various environmental factors (e.g., weather events) could impact the NIT performance. We also developed several machine learning methods to facilitate the NIT performance evaluation. The machine learning methods include computer vision models for detecting camera occlusion (e.g., raindrops on the camera lens) and counting cars for traffic camera data and time series anomaly detection models for traffic volume data and actuated signal data. The lessons learned from the analysis results and the machine learning method serve as the basis for developing the guidelines for the next task.

We plan to integrate the analysis results with the machine learning methods in the next step to produce a final memorandum detailing the scenarios (e.g., the surrounding built environment of a camera, camera types, camera directions, and weather events) linked to anomalies in the NIT performance. We will also document the limitations of the proposed technique using evaluation results from manually verified data at sampled locations.

Appendix:

I. Video data recorded:

'2021-11-22', '2021-11-23', '2021-11-24', '2021-11-25', '2021-11-26', '2021-11-27', '2021-11-28',

'2021-11-29', '2021-11-30', '2021-12-01', '2021-12-02', '2021-12-03', '2021-12-04', '2021-12-05',

'2021-12-06', '2021-12-07', '2021-12-08', '2021-12-09', '2021-12-10', '2021-12-11', '2021-12-12',

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'2021-12-27', '2021-12-28', '2021-12-29', '2021-12-30', '2021-12-31', '2022-01-01', '2022-01-06', '2022-01-07', '2022-01-08', '2022-01-09', '2022-01-10', '2022-01-11', '2022-01-12', '2022-01-13',

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'2022-02-04', '2022-02-05', '2022-02-06', '2022-02-07', '2022-02-08', '2022-02-09', '2022-02-10', '2022-02-11', '2022-02-12', '2022-02-13', '2022-02-14', '2022-02-15', '2022-02-16', '2022-02-17',

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'2022-08-29', '2022-09-14', '2022-09-15', '2022-09-16', '2022-09-17', '2022-09-18', '2022-09-19',

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'2022-09-27', '2022-09-28', '2022-09-29', '2022-09-30', '2022-10-01', '2022-10-02', '2022-10-03',

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'2022-12-02', '2022-12-03', '2022-12-04', '2022-12-05', '2022-12-06', '2022-12-07', '2022-12-08', '2022-12-09', '2022-12-10', '2022-12-11', '2022-12-12', '2022-12-13', '2022-12-14', '2022-12-15',

'2022-12-16', '2022-12-17', '2022-12-18', '2022-12-19', '2022-12-20', '2022-12-21', '2022-12-30',

'2022-12-31', '2023-01-01', '2023-01-02', '2023-01-03', '2023-01-04', '2023-01-05', '2023-01-06', '2023-01-07', '2023-01-08', '2023-01-09', '2023-01-10', '2023-01-11', '2023-01-12', '2023-01-13',

'2023-01-14', '2023-01-15', '2023-01-16', '2023-01-17', '2023-01-18', '2023-01-19', '2023-01-20',

'2023-01-21', '2023-01-22', '2023-01-23', '2023-01-24', '2023-01-25', '2023-01-26', '2023-01-27',

'2023-01-28', '2023-01-29', '2023-01-30', '2023-01-31', '2023-02-01', '2023-02-02', '2023-02-03',

'2023-02-04', '2023-02-05', '2023-02-06', '2023-02-07', '2023-02-08', '2023-02-09', '2023-02-10',

'2023-02-24', '2023-02-25', '2023-02-26', '2023-02-27', '2023-02-28', '2023-03-01', '2023-03-02',

'2023-03-03', '2023-03-04', '2023-03-05', '2023-03-06', '2023-03-07', '2023-03-08', '2023-03-09', '2023-03-10', '2023-03-11', '2023-03-12', '2023-03-13', '2023-03-14', '2023-03-15', '2023-03-16',

'2023-03-17', '2023-03-18', '2023-03-19', '2023-03-20', '2023-03-21', '2023-03-22', '2023-03-23',

'2023-03-24', '2023-03-25', '2023-03-26', '2023-03-27', '2023-03-28', '2023-03-29', '2023-03-30',

'2023-03-31', '2023-04-01', '2023-04-02', '2023-04-03', '2023-04-04', '2023-04-05', '2023-04-06',

'2023-04-07', '2023-04-08', '2023-04-09', '2023-04-10', '2023-04-11', '2023-04-12', '2023-04-13', '2023-04-14'

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Appendix G: Task 8 Deliverable

Performance Evaluation of Different Detection Technologies for Signalized Intersections in Minnesota

Task 8 Deliverable:

Final Memorandum on Research Benefits and Implementation Steps

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Executive Summary

Modern intersection control primarily relies on the actuated systems that respond to traffic at the intersection. MnDOT and many local MN agencies have traditionally used embedded loop detectors in the pavement for detecting vehicles. Although the performance of a well-placed loop detector has yet to be matched by any other method, changes in the vehicle fleet (higher use of non-ferrous material), as well as increased need for more comprehensive detection (vulnerable road users, all lanes individual advance and stop line detection), has resulted in the increased use of Non-Intrusive detection Technologies (NIT). There are studies evaluating the performance of NIT detection. Still, all have been racing against obsolescence given the rapid developments in the market, and generally do not provide the necessary results to evaluate performance in specific environments. This report shows the results of year-round observation and recording of the performance of selected real deployments of major products used in Minnesota. We select several sites within the Twin Cities Metropolitan area and analyze their performance when subjected to different environmental conditions.

To evaluate the performance of NIT in different conditions, our methodology uses signal data to determine failure rates for different NIT devices, video data to determine what type of failure has occurred, and weather data to determine the conditions that lead to the failure. In our research, failure rates are determined by comparing NIT and baseline detector controller data to averages from the surrounding two weeks using the Pearson correlation. If there is a significant deviation in the NIT controller data and not the baseline controller data, we classify this as a failure. Using an optical flow algorithm, our pipeline then looks for any signs of lens occlusion on the camera through the video data. Finally, weather variables are correlated with NIT failures in our method by using the Local Correlation metric to determine how strongly the weather conditions relate to the controller data. If a weather variable strongly correlates with the controller data, we say it has caused the failure.

We construct a pipeline to accomplish this goal and evaluate the data over 10 days from

January 1-10 2023. Using our pipeline's results, failure rate statistics are calculated for different detection technologies and what types of weather conditions they occur under. In evaluating both Iteris and Vision NITs, our results show neither detection technology outperforms the other in all conditions. However, when observing the performance of both Iteris and Vision detection technologies under intense winter storms, we find that the Vision detection technology is less susceptible to long-term failures that require on-site maintenance (e.g., snow, dirt, rain, etc., blocking the camera lens). Additionally, the Iteris detection technology is uniquely susceptible to failures caused by humidity, and while it may experience fewer overall malfunctions, it experiences more malfunctions during intense winter storms.

Problem Description

The Minnesota Department of Transportation (MnDOT) worked to deploy Non-Intrusive Detection Technologies (NIT) for vehicle detection at signalized intersections to detect cars, bikes, and pedestrians. They are used to alert other drivers and allow the traffic signal to modify timing to better serve the immediate traffic needs. This project aims to evaluate the operational performance and costs of the various technologies deployed by MnDOT at intersections in the Twin Cities Metropolitan Area. We accomplish this goal by evaluating the performance of these NITs under various conditions.

In this report, we present a final memorandum that documents the methodology we use to calculate the benefits of our proposed approach for evaluating NIT and outlines key steps that MnDOT can take to implement the results of our research. The outline methods that were employed in our research to evaluate the performance of NIT under various conditions, along with some preliminary results from our analysis. This report is broken into three sections, each outlining essential steps in the methodology and evaluation of our research and any assumptions we make.

The report is structured as follows. Section 2 outlines the methodology for our proposed approach to evaluating NIT, including a flow chart that describes how our approach utilizes the provided data to generate results. The section presents the results of our proposed methodology and the benefits it offers to MnDOT. It also explains the process for selecting NIT technologies using this methodology. Section 3 provides a pointer to the code repository for implementing the methodology described in Section 2 and instructions for running it.

Methodology

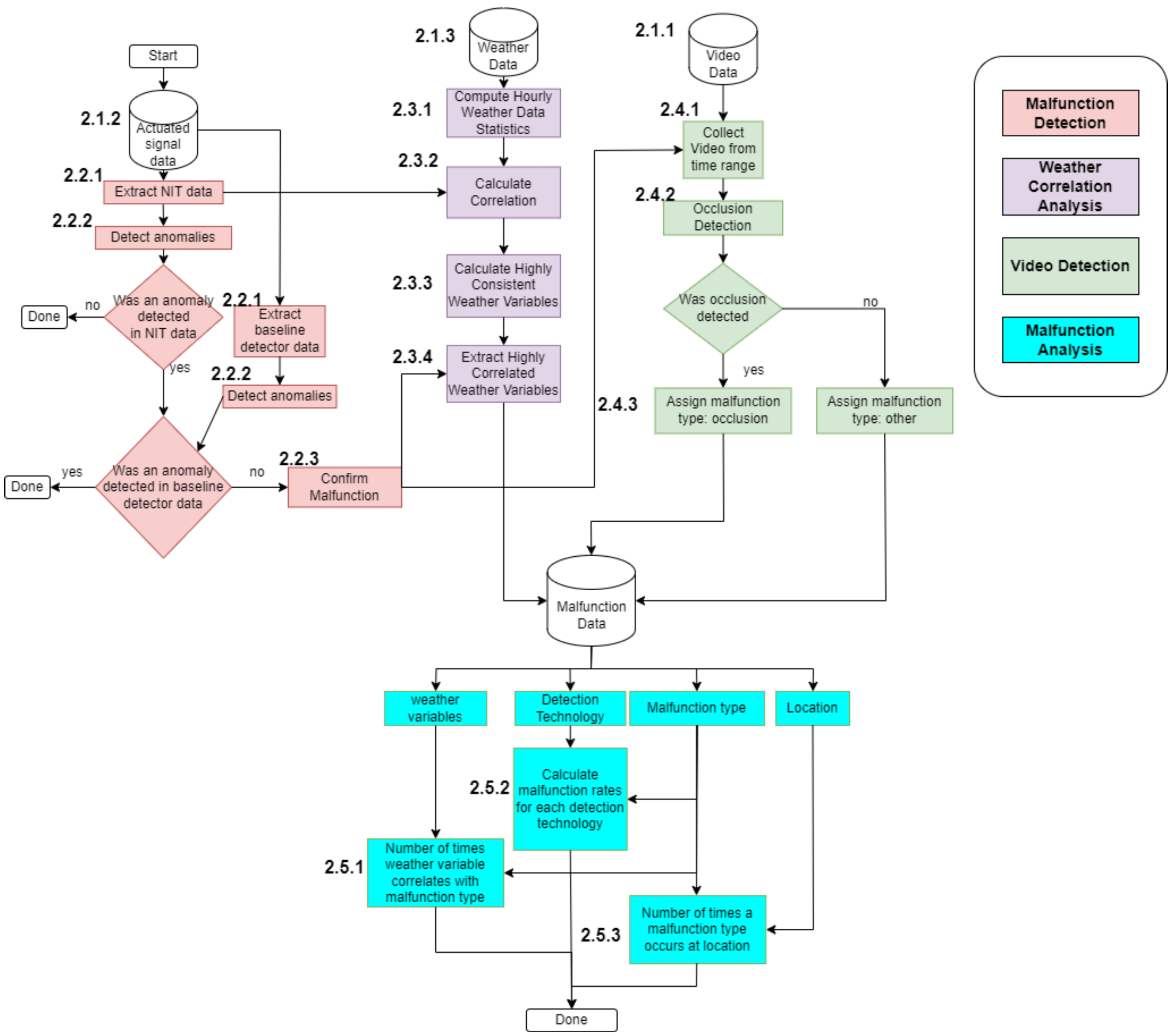

Figure 1: Flowchart of our proposed methodology broken down into color-coordinated sections.

In our methodology, signal controller (2.1.2), weather (2.1.3), and video data (2.1.1) are used to detect, categorize, and perform a correlation analysis of malfunctions of NIT detection technologies. Figure 1 shows an overview of the methodology through a flow chart with color-coordinated sections for each sub-task in evaluating NIT performance. In the Malfunction Detection section (2.2), our methods detect when malfunctions in NIT occur. In the Weather Correlation Analysis (2.3) and Video Detection (2.4) sections, we describe the possible causes of malfunctions. We generate example results for January

2023 at six road intersections using this method. We have chosen this period because January 2023 had severe snow storms that affected NIT's performance. Evaluating which technologies performed better over this period will give insight into which technologies perform better in the worst of a Minnesota winter. Before continuing to the in-depth description of each section, we need to define important terms and give a brief overview of each subsection.

Evaluation Data

We evaluate our methods using signal controller and video data from six intersections around the Twin Cities Metropolitan area. These intersections are 65_81st_Vision_Stream1, 51_crc2_iteris, 47_85th_Iteris_Stream1, 77_cliff_eramp_vision, 694_eriver_nramp_vision, and 694_eriver_sramp_vision, with respective locations in Table 1. For analysis, these cameras are split into two groups, one of which uses the Iteris Vantage Next detection system (shortened to ITERIS) and the other which uses the Autoscope Vision detection system (shortened to VISION). We have 4 detection systems using the Autoscope Vision detection system and 2 using the Iteris Vantage Next detection system. The focus is on these detection systems as they are the most widely used video detection technologies within the study area defined by the Task 4 and 5 deliverables documents.

Important Terms

- *Pattern*: When referring to patterns in the signal controller data, we refer to predictable changes in the number of cars detected at an intersection over a specified period.
- *Anomaly*: When referring to anomalies, we describe patterns in the signal controller data that do not align with historical trends.
- *Performance*: When referring to the performance of NIT devices, we refer to their accuracy and *Malfunction Rate*.
- *Malfunction*: A Malfunction is defined by the differences in the vehicle count profiles that exceed a certain threshold between NIT and baseline data.
- *Lens Occlusion*: When referring to lens occlusion, we describe snow, ice, dirt, or other particles that can accumulate on a NIT camera lens, preventing detections.
- *Baseline Detector*: When referring to a baseline detector, we describe devices placed at intersections meant to detect cars passing through an intersection that is not NIT. These include loop detectors, lidar, radar, etc. As per the recommendation in the Task 1 deliverable, our methodology uses these as baselines to evaluate NIT performance.
- *Pearson Correlation*: The Pearson correlation is a statistical measure that quantifies the degree and direction of a linear relationship between two continuous variables, ranging from perfect positive correlation (1) to perfect negative correlation (-1), with 0 indicating no linear relationship.
- *Local Correlation*: The local correlation [5] tracks non-linear relationships between time series locally using eigen-analysis of auto-covariance matrices. Unlike the Pearson correlation, it can capture complex, non-linear relationships between time series.

Performance Measures

- Malfunction Rate: Using our method, the performance of NIT is evaluated by observing the number of times a NIT device experiences a *Malfunction* over a period. As our pipeline uses a temporal resolution of one hour for malfunction detection, each day has a maximum of 24 possible malfunctions. We expect to see some malfunctions on every device during the night when, due to low-light conditions, performance drops. Therefore,

  our analysis focuses on days with 8 or more malfunctions. Additionally, when comparing different detection technologies, the performance of each detection technology is measured by comparing its malfunction rate on a given day.

- *High Correlation Rate*: In our methodology, weather features correlate with NIT device malfunctions (see *Local Correlation* in the **Important Terms** section for more information). For a given detection technology or malfunction type, we calculate the number of times our pipeline determines a weather feature is highly correlated with malfunctions out of the total number of malfunctions. We use this measure to analyze the effect that weather feature has on the detection technology/malfunction type. If a weather feature appears in a third of all malfunctions of a given detection technology/malfunction type, we consider this significant for our analysis.

Section Overview

Data (2.1): This section includes an overview of the data used in our pipeline.

Malfunction detection (2.2): In the flow chart, the red-colored module uses the signal controller data to detect malfunctions in NIT technologies. Our methods detect malfunctions by independently evaluating the performance of NIT and baseline detectors. We accomplish this by comparing the signal controller data from a specified period to historical averages to generate a

list of anomalous periods (see section 2.2.2). This task is performed twice, once for the controller data from the baseline detectors and again for the controller data from the NIT. We then compare the anomalous periods our methods detect in NIT data and the baseline detector data to define malfunction (see section 2.2.3). <u>If our methods detect an anomalous period from the NIT data, not the baseline detector data, we classify this as a malfunction</u>. In cases where an anomalous period is detected in either device or an anomalous period in both devices, we do not classify this as a malfunction. This is the purpose of the two "Was anomaly detected" blocks, as our methodology detects anomalies in the NIT controller data and the baseline detector controller data. Through this process, our methodology returns the locations, dates, and times of the malfunctions it detects. We exclude anomalous periods that appear in both NIT and baseline detectors from the set of malfunctions to focus our evaluation on NIT failure cases exclusively. **Weather Correlation Analysis (2.3):** In the flow chart, the purple-colored module uses the weather data and results from the malfunction detection step to perform a correlation analysis of the malfunctions. We compare time series trends in signal controller data to those in several weather variables and calculate a local correlation value for each hour for every weather variable using a sliding window of 5 hours (see 2.3.2). The local correlation score measures the similarity between the two time series over the 5-hour window. However, the individual scores cannot capture the global similarity between the two time series trends. We introduce the consistency score to measure this value (see 2.3.3). In our research, the consistency score is calculated using the local correlations for a given weather variable. The consistency score measures how much a weather variable's local correlation score fluctuates over the entire period covered by the weather and signal controller data. We extract the weather variables with high consistency and local correlations during each malfunction (see 2.3.4). Using the local correlation and consistency scores ensures our methodology only extracts weather variables with high global and local similarity to the signal controller data.

Video Detection (2.4): In the flow chart, the green-colored module uses the video data to determine the type and direct cause of the malfunction (e.g., lens occlusion, blur, glare, etc.).

This process returns the type of malfunction based on the video data analysis.

Malfunction Analysis (2.5): In the flow chart, the blue-colored module uses the Malfunction Database to analyze the data we collect on malfunctions. This process outputs the overall results of our pipeline and provides statistics on malfunctions for different NIT technologies, locations, and weather conditions.

2.1: Data:

This section briefly outlines the data used directly in our methodology. We use Traffic Camera Data (2.1.1), Signal Controller Data (2.1.2), and Weather Data (2.1.3).

Traffic Camera Data

Summary: The Traffic Camera Data is video data we collect from the traffic cameras around the Twin Cities Metropolitan Area. MnDOT provides the data which contains the video recordings from traffic cameras in *.mp4 format. Our research uses the video data to look for camera detection failures and help confirm failures in NITs.

Data Source: MnDOT provides 39 cameras in the Twin Cities Metropolitan Area, with traffic camera names assigned to each camera.

Attributes: Camera Name, Latitude, Longitude, Link (Google Maps) (Table 1). The camera name is a designation given by MnDOT and contains information about the intersecting streets, the camera technology used, and the ramp direction (if next to a highway). We identify the Latitude, Longitude, and the Google Maps URL that reference the location of each camera (our process is outlined in the Spatial Coverage section below) using Google Maps. **Spatial Coverage:** MnDOT provides 39 cameras named after camera locations and types covering the Twin Cities Metropolitan Area, including four counties or 13 cities. We collect the point geographic coordinates of each camera location by searching the road intersection on

Google Maps. Take “35e_cliff_eramp_iteris” as an example. We search “I-35E” and “Cliff” on Google Maps, find the road intersection of “I-35E” and “Cliff Rd,” and acquire the geo-coordinates on the east ramp. “Iteris” refers to the camera type. After removing the cameras that cannot be located using this process, we then record the 31 individual identifiable cameras (No.1- No.31 in Table 1) with their associated geographic coordinates for further sampling and analysis (Figure 2).

Date Captured: We collect camera recordings from 11/22/2021 to 05/20/2023 and from

08/09/2023 to 10/07/2023

Collected Spatial Coverage: Twin Cities Metropolitan Area, covering four counties

Use Case: We use the Traffic Camera Data to help categorize detected malfunctions. Detecting malfunctions in the camera data by reviewing all video data would take an incredibly long time and be computationally expensive. Therefore, we focus on video sections where our methods determine a malfunction in the NIT device using the Signal Controller Data (2.2). Our research then uses Video Detection (2.4) to determine the type of malfunction.

Point Locations:

No.	Camera Name	Type	Latitude	Longitude	Link (Google Maps)
1	35e_cliff_eramp_iteris	iteris	44.790136	-93.198956	https://goo.gl/maps/24skT2KbrnrMoU1JA
2	35e_cliff_wramp_iteris	iteris	44.790131	-93.205099	https://goo.gl/maps/HZ2SHM65K83eTTog77
3	36_whitebear_nramp_iteris	iteris	45.012665	-93.020928	https://goo.gl/maps/KieTBYXEXENGR6dY9
4	36_whitebear_sramp_iteris	iteris	45.010636	-93.022571	https://goo.gl/maps/zgHTW9FXs4WwYts988
5	47_85th_Iteris_Stream1	iteris	45.125053	-93.264553	https://goo.gl/maps/A48DyvcpYnLMF29p8
6	47_Mississippi_Movision_Stream 3	movision	45.086136	-93.263535	https://goo.gl/maps/kV5jmgUQ26DopU9q7
7	494_flyingcloud_sramp_gridsmart	gridsmart	44.861405	-93.425593	https://goo.gl/maps/hjjbYwgqjXQGMmkD6
8	494_pilotknob_nramp_iteris	iteris	44.861479	-93.167119	https://goo.gl/maps/KTBLqUaRBo45sv9V7
9	51_crc2_iteris	iteris	45.027917	-93.167081	https://goo.gl/maps/1VwBnov8FEq7tvkS77
10	62_france_nramp_vision	vision	44.887507	-93.328961	https://goo.gl/maps/AA2CmQ5MdAqmbCRh9
11	62_france_sramp_vision	vision	44.886547	-93.328982	https://goo.gl/maps/P31VNKuaC9LCvqnn7

12	65_41st_gridsmart	gridsmart	45.042744	-93.247337	https://goo.gl/maps/SEp3jd6vY7UHZvCKA
13	65_81st_Vision_Stream1	vision	45.11504	-93.241732	https://goo.gl/maps/vTJozXz3D2wy8GLY9
14	694_eriver_nramp_vision	vision	45.069585	-93.278772	https://goo.gl/maps/LAGPMU2MyM6Soepk7
15	694_eriver_sramp_vision	vision	45.068929	-93.279158	https://goo.gl/maps/ZKiHcteNBToFauu47
16	77_cliff_eramp_vision	vision	44.790226	-93.21963	https://goo.gl/maps/cnTfPvzrihw4eEgm9
17	77_cliff_wramp_vision	vision	44.790237	-93.223347	https://goo.gl/maps/Nbewbfn3NogrT8R18
18	CR81_deere_visions_stream	vision	45.190296	-93.550583	https://goo.gl/maps/PfWNoeWpfnirCQmh9
19	CR81_industrial_visions_stream	vision	45.192302	-93.55264	https://goo.gl/maps/2eonYzcRxoWLQRNw7
20	CR81_memorial_visions_stream	vision	45.188553	-93.547743	https://goo.gl/maps/Et7H17RuUAnQBNZN7
21	s_12_carlson_nramp_vision	vision	44.972593	-93.469741	https://goo.gl/maps/hQ4cu5LSTH5XYPc36
22	s_12_carlson_sramp_vision	vision	44.969558	-93.469776	https://goo.gl/maps/uLjGo5sdCg9u8k7v9
23	s_12_csah101_nramp_vision	vision	44.976979	-93.50213	https://goo.gl/maps/FMrxWoYBbAR7uFB98
24	s_12_csah101_sramp_vision	vision	44.975039	-93.502106	https://goo.gl/maps/f1bJe7qj2vRihaX1A
25	s_65_viking_eside_gridsmart	gridsmart	45.319684	-93.235698	https://goo.gl/maps/VqgHYCqXZBmjtcac8
26	s_65_viking_nuturn_gridsmart	gridsmart	45.322122	-93.236216	https://goo.gl/maps/Si6BYYFV3nM7Cb9dA
27	s_65_viking_suturn_gridsmart	gridsmart	45.317065	-93.235865	https://goo.gl/maps/DW8TqZkE1ttYz2X56
28	s_65_viking_wside_gridsmart	gridsmart	45.319638	-93.236458	https://goo.gl/maps/UWS7Cc5PyAj7gRh58
29	s_cr144_james_vision	vision	45.210298	-93.550016	https://goo.gl/maps/i8dBxffTY6PUi6SJA
30	s_cr144_northdale_vision	vision	45.210364	-93.55579	https://goo.gl/maps/sQxo359WMDgVNAXj8
31	s_cr144_rogershighscool_vision	vision	45.210303	-93.546439	https://goo.gl/maps/L2e4wecC3rcx93kf9
32	169_main_gridsmart	gridsmart			
33	47_Roselawn_Gridsmart_Stream 1	gridsmart			
34	494_tamarack_eramp_gridsmart1	gridsmart			

35	494_tamarack_eramp_gridsmart2	gridsmart			
36	65_Blake_Vision_Stream1	vision			
37	97_hornsby_gridsmart1	gridsmart			
38	97_hornsby_gridsmart2	gridsmart			
39	s_12_carlson_twelveoaks_vision	vision			

Table 1: Traffic camera names, locations (latitude, longitude), address, and Google Maps link. The locations used in evaluating our methodology are highlighted in yellow.

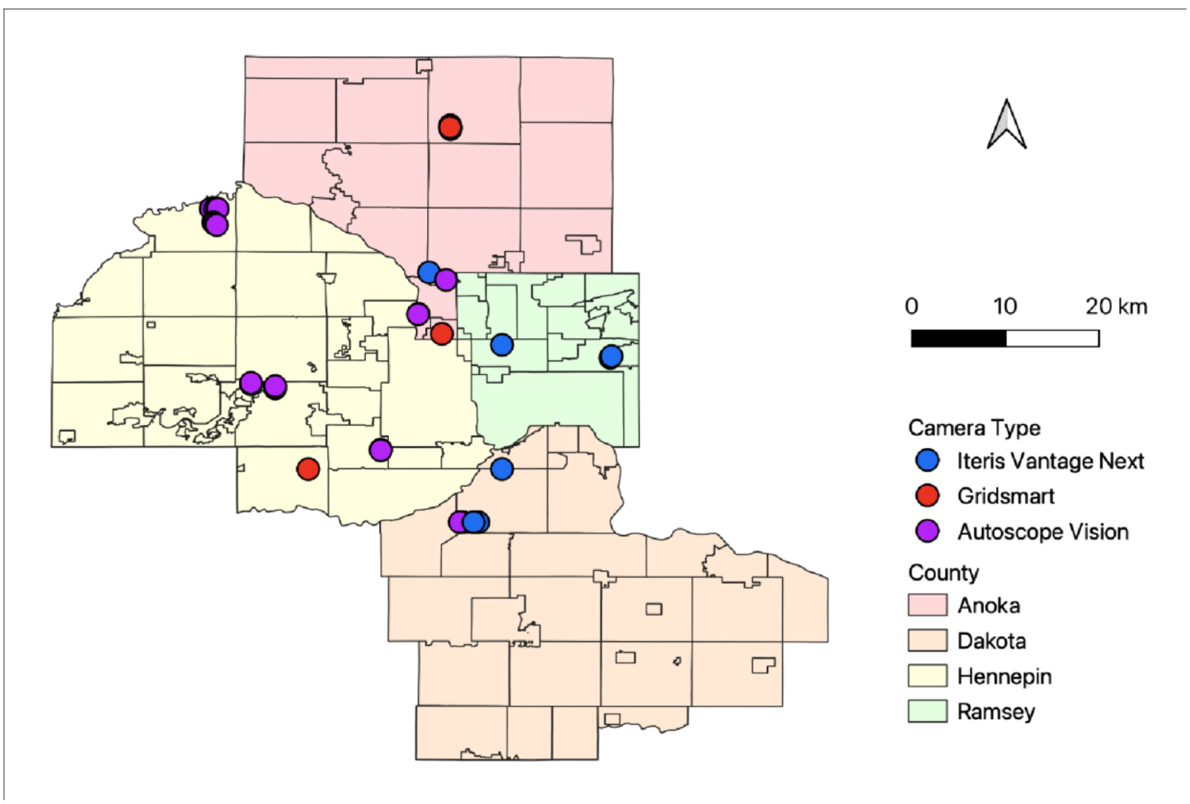

Figure 2: Locations of cameras colored by type overlaid on the county map of the Twin Cities Metropolitan Area

Signal Controller Data

Summary: MnDOT provides some data in the Comma-separated values (CSV) format as a downloadable link. However, MnDOT has since updated how they store and display signal controller data. We download all records from the MnDOT website in CSV format. The signal controller contains temporal event data on signal changes, maintenance, and traffic passing through the intersection. We use this data to evaluate the performance of NIT in detecting traffic moving through an intersection.

Data Sources: MnDOT; we retrieve data when needed.

Attributes: Time (Year, Month, Day, Hour, Minute, Second, Millisecond), Camera ID, Event Code, and Event Parameter [3]. Table 2 displays an example sequence of the Signal Controller Data.

Temporal Resolution: The record updates every time a traffic-related event occurs at an intersection (0 milliseconds-10 seconds). The time interval is irregular and varies depending on traffic.

Temporal Coverage: MnDOT collects the data continuously starting on 11/2021.

Spatial Resolution: We sample six cameras out of the original 31 to cover more cases of location distribution, camera types, environmental features, and intersection types. Figure 3 displays the locations of the six cameras. The selected six cameras are:

1. 694_eriver_nramp_vision
2. 694_eriver_sramp_vision
3. 65_81st_Vision_Stream1
4. 47_85th_Iteris_Stream1
5. 51_crc2_iteris
6. 77_cliff_eramp_vision

Collected Temporal Coverage: December 20, 2022 - January 10, 2023

Why we collected these data: We sample these six cameras out of the 31 to cover various types of camera location distribution (from urban to suburban) and two camera types (Iteris Vantage Next, Autoscope Vision). This signal data gives precise timestamps for many types of traffic events, such as red lights, green lights, car detection, pedestrian detection, maintenance signals, etc., at a very high temporal resolution, allowing us to accurately describe the signals' behavior at intersections. We focus on event codes 82/81 because they directly correspond to vehicle counts based on detector activation, and use these codes to evaluate traffic detector performance. This time period is ideal as it covers a period of heavy snow and cold weather and allows us to evaluate the performance of NIT in extreme weather conditions. In addition to capturing data from NIT detections, the signal controller data also contains data from the baseline detectors. MnDOT assigns Event Parameters 1-4 to baseline detectors and all other Event Parameters to NIT (see Table 2 for Event Parameter examples) to differentiate baseline detectors from NIT detectors in the signal controller data.

Data Preparation: MnDOT provides the data in the CSV format. The data is partially unordered and has to be ordered by timestamps using Pandas [4]. We also remove any unnecessary event codes that do not pertain to evaluating camera performance. The outcome of this preprocessing is a Pandas DataFrame.

Example:

Time	Camera ID	Event Code	Event Parameter
2022-12-01 04:03:12.400	596	10	3
2022-12-01 04:03:12.400	596	9	3
2022-12-01 04:03:14.900	596	11	3
2022-12-01	596	12	3
04:03:14.900			
2022-12-01 04:03:14.900	596	0	6
2022-12-01 04:03:14.900	596	31	2
2022-12-01 04:03:14.900	596	0	2
2022-12-01 04:03:14.900	596	1	2
2022-12-01 04:03:15.000	596	1	6

2022-12-01 04:03:15.000	596	3	2
2022-12-01 04:03:29.900	596	3	6
2022-12-01 04:03:29.900	596	2	6
2022-12-01 04:03:36.200	596	7	6
2022-12-01 04:03:36.200	596	8	6
2022-12-01 04:03:41.700	596	4	6

Table 2: Sample of Signal Controller Data

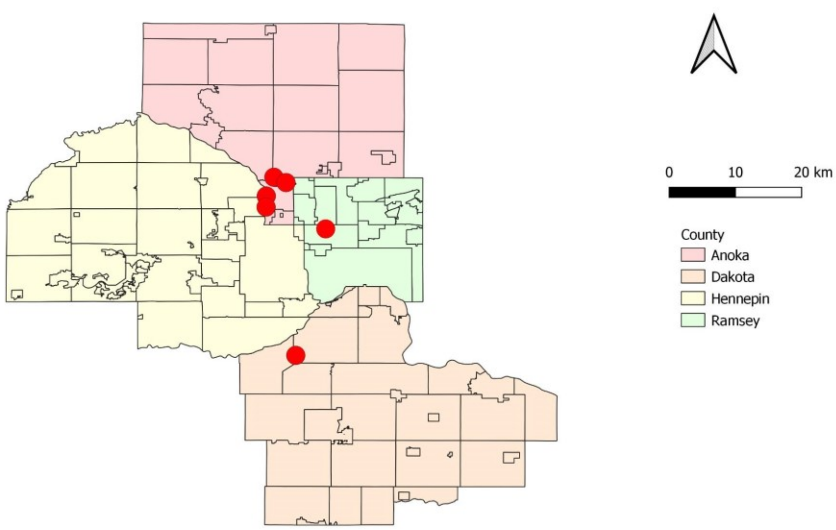

Figure 3: The locations of the six cameras used in the methodology overlaid on the county map of the Twin Cities Metropolitan Area.

2.1.3: Weather Data

Summary: We collect the weather data from MDSS (www.webmdss.com). MDSS records 50 types of weather features for many areas inside the U.S. in real-time with a 5-minute resolution. Our methodology utilizes the weather data to help interpret the malfunctions detected by the Malfunction Detection section. Through our research, we find that weather conditions are often the leading cause of NIT malfunctions.

Data Source: As our focus is on the intersections of interest, we only collect the data from the weather stations whose locations are the closest to the intersections listed in the Spatial Resolution section of 2.1.2.

Attributes: [EVENTDATE, WEATHERSENSOR, VISIBILITY, HUMIDITY, PRECIP RATE, WIND

DIR, WIND SPEED, MAX TEMP, MIN TEMP, WET BULB TEMP, DEW POINT, FRICTION,

SURFACE TEMP, SURFACE STATUS, SUBSURFACE TEMP, AIR TEMP, PRECIP TYPE]

Spatial Coverage: We focus on the Twin Cities Metropolitan area. Figure 5 shows the relevant weather stations.

Figure 4: Weather station locations

Date Captured: We collect weather records from 11/22/2021 to 09/10/2023

Collected Spatial Coverage: Currently, we focus on weather stations Maple and Little Canda as they are the closest stations to the intersections of interest.

Use Case: We use weather data to help interpret the detected malfunctions. By comparing the dynamic relations between weather variables and the signal controller data with correlation analysis (2.3), we can determine the leading cause (weather conditions) of each malfunction.

Example:

EVENTDATE	WEATHERSENSOR	VISIBILITY	HUMIDITY	PRECIP RATE
1/1/2023 0:00	WS0089	11.4 mi.	97%	0
1/1/2023 0:05	WS0089	11.3 mi.	96%	0
1/1/2023 0:10	WS0089	11.0 mi.	95%	0
1/1/2023 0:15	WS0089	12.4 mi.	93%	0
1/1/2023 0:20	WS0089	12.4 mi.	92%	0

WIND DIR	WIND SPEED	MAX TEMP	MIN TEMP	WET BULB TEMP
SW	5 MPH	35□F	17□F	34□F
SW	3 MPH	35□F	18□F	33□F
SW	6 MPH	35□F	18□F	33□F
SW	5 MPH	35□F	18□F	33□F
SW	6 MPH	35□F	18□F	33□F

DEW POINT	SURFACE TEMP	SURFACE STATUS	SUBSURFACE TEMP	AIR TEMP	PRECIP TYPE
33□F	34□F	N/A	29□F	34□F	None
33□F	34□F	N/A	29□F	34□F	None
33□F	34□F	N/A	29□F	34□F	None
32□F	34□F	N/A	29□F	34□F	None
32□F	34□F	N/A	29□F	34□F	None

Table 3: Sample of Weather Data

Malfunction Detection

Summary: The process described in this section evaluates the performance of NIT for each hour within a specified time range of seven consecutive days. From this range, our methodology identifies the hours during which NIT devices experience performance drops (i.e., malfunctions). We accomplish this by using the Pearson correlation to compare the signal controller data from a particular hour to averages calculated from the two weeks before and two weeks after the specified time range. The Pearson Correlation is helpful as it is a widely used and understood method for measuring linear relationships between time series. It efficiently calculates correlation over large datasets and is well-suited for measuring the linear relationships between two time series. If the signal controller data from the hour deviates from the average by more than a pre-defined threshold (see **Method** in section 2.2.2), we define this as an anomaly. We then determine if an anomaly can be classified as a malfunction if no corresponding anomaly exists in the baseline detector (e.g., loop detector, Radar, Lidar, etc.).

Assumptions: We make several assumptions during this process. We assume that anomalies detected in NIT are not unique to NIT if an anomaly is also detected an anomaly in the baseline detector. Additionally, we assume that the 4-week average values of the signal controller data describe normal NIT/baseline detector operation.

2.2.1: Extract NIT/Baseline Detector Data

Goal: In this step, our pipeline transforms the signal controller data into hourly information, which we can use to describe the traffic flowing through an intersection.

Input Schema: A CSV file of the same format as Table 2, where each row with an Event Code of 82/81 represents a car detected as entering/leaving a detection volume.

Method: For each Event Parameter in the signal controller data, we calculate the difference between 82 and 81 events and track how many 81 events occur. This step then use these values to calculate the cumulative time a detector is on, the number of times the detector turns on, and the average amount of time a detector stays on each event parameter every hour. An example of the output of this process is shown in Appendix 1.

Output Schema: This process outputs the cumulative amount of time a detector stays on, the number of times a detector turns on, and the average amount of time a detector stays on for each detection volume at an intersection for each hour in the signal controller data.

2.2.2: Detect Anomalies

Goal: This step determines how much the signal controller data from the selected seven-day period deviates from the historical averages. We calculate this deviation for each hour of data in the dataset. If the signal controller data deviates significantly, this indicates that either the detector is detecting cars passing through an intersection where there are none, or the detector fails to detect cars as they pass through the intersection. We classify these cases as anomalies.

Input Schema: The pipeline uses the results of section 2.2.1 as input for this section. **Method:** We compute the mean values for the cumulative duration a detector is active (X), the frequency of detector activations (Y), and the average duration a detector remains active (Z) for each hour throughout the week. We base the calculation on data from the two weeks preceding and following the chosen 7-day time range. Subsequently, for each hour within the selected 7-day period, our methods determine the Pearson correlation between the historical averages of X, Y, and Z and the values observed during the 7 days. We compute the Pearson correlation using a 13-hour sliding window centered on the specified hour. The Pearson correlation quantifies the linear relationship between the 13-hour window's average values and those of the selected 7-day period. If, for a sliding window centered on hour h, the Pearson correlation is below the threshold of -0.6, this indicates that traffic patterns surrounding hour h deviate significantly from historical norms. We choose the threshold of -0.6 to ensure a strong negative correlation between the historical averages and the selected 13-hour window. Doing this ensures that we only capture traffic anomalies that deviate significantly from the historical norms. We classify these cases as anomalies occurring on hour x.

Output Schema: The output of this step is the location and time of the anomalies and the type of detector, either NIT or baseline detector.

2.2.3: Confirm Malfunction

Goal: This step extracts anomalies unique to NIT devices by filtering the results of step 2.2.2. We do this to ensure that our analysis focuses only on conditions that lead to failure in NIT devices. Our pipeline then classifies these anomalies as malfunctions in NIT.

Input Schema: Using the output of section 2.2.2, we split the detected anomalies into two groups, one for NIT and one for baseline detectors. We then compare these anomalies in the methods section below.

Method: Using the results from the previous section, this step compares the anomalies detected in NIT to those detected in the baseline detector. If an anomaly is detected in a NIT detector and not the baseline detector, we classify it as a malfunction. If an anomaly appears in both NIT and the baseline, we exclude it from our analysis.

Output Schema: This step outputs the location and time of the malfunctions (Figure 6).

```
{"intersection": 51.0, "date": "2023-1-1", "hour": 0.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 1.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 2.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 3.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 4.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 5.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 6.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 7.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 8.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 9.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 10.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 11.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 13.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 17.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 18.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 19.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 20.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 21.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 22.0}
{"intersection": 51.0, "date": "2023-1-1", "hour": 23.0}
{"intersection": 51.0, "date": "2023-1-2", "hour": 0.0}
{"intersection": 51.0, "date": "2023-1-2", "hour": 1.0}
```


Figure 6: Example output of detected malfunctions. Each line in this image is an example of a detected malfunction

Weather Correlation Analysis

Summary: Our analysis results from Task 7 provide a foundation that bad weather conditions are a common cause of the failure of NIT technologies. In this section, we implement a correlation analysis method for determining which weather conditions present at a given time have high correlation with NIT performance drops. To accomplish this, our method calculates the local correlation between reported weather conditions and the signal controller data. We use the local correlation instead of the Pearson correlation because the local correlation can describe non-linear relationships between two time series. Describing non-linear relationships is advantageous for comparing the signal controller data and the weather variables, as they may have more complex relationships than a simple linear relationship can describe. The sections below outline this process in detail.

Assumptions: We make two major assumptions in this section. First, we assume that a high local correlation between the signal controller data and weather variables indicates a strong relationship between the weather variables and the signal controller data. For example, if temperature fluctuations are highly correlated with fluctuations in traffic flow, we assume that temperature fluctuations have a strong relationship with the traffic flow. Our second assumption is that temperature and visibility affect the performance of NIT, and are therefore consistently correlated with the performance of NIT. We assume visibility is correlated with NIT performance because it affects the camera's ability to see, and assume temperature is correlated with NIT performance because temperature fluctuations are known to affect the performance of electronic components.

2.3.1: Compute Hourly Weather Data Statistics

Goal: This step calculates hourly statistics for weather data. Hourly statistics are calculated from the weather data for each weather variable (all variables in the **Attributes** section of 2.1.3 excluding EVENTDATE and WEATHERSENSOR). We compare these statistics with those calculated in section 2.2.1 to determine the local correlation in section 2.3.2.

Input Schema: The weather data comes in a CSV file of the same format as in Table 5, with weather values reported every 5 minutes.

Method: This step computes the average of each weather variable to calculate the hourly statistics for the weather data.

Output Schema: This step outputs hourly averages for each weather variable.

2.3.2: Calculate Correlation Between Signal Data and Weather Variables

Goal: This step calculates the correlation between the signal controller data and each weather variable. Calculating the correlation helps determine which weather variables affect the detected traffic flow.

Input Schema: Using the output of sections 2.2.1 and 2.3.1, we compare the statistics calculated from the signal controller data and the hourly averages for each weather variable. **Method**: Using the method for calculating the local correlation outlined in [5], we compute the local correlation between the signal controller data and each weather variable. The local correlation is computed for each hour of the dataset in this step, employing a 5-hour sliding window centered on the specified hour. We choose a 5-hour sliding window as it is large enough to capture relationships between time series data while being small enough to enable a fine-grained analysis of the temporal patterns within the data. Because correlation analysis requires continuous, numerical values, we exclude discrete variables such as precipitation type, wind direction, and surface status. The abovementioned method generates local correlation scores for each weather variable over each sliding window centered around an hour h. A sample output of this process is shown in Appendix 2.

Output Schema: This step outputs hourly correlation scores for each weather variable where the hour represents the hour h the sliding window was centered.

2.3.3: Calculate which Variables are Consistently Correlated with the Signal Controller Data

Goal: Our goal with this method is to extract weather variables with consistent correlation values over the entirety of the input data. If a weather variable has consistent local correlation scores

for each sliding window, the relationship between that weather variable and the signal controller data is strong.

Input Schema: Using the output of section 2.3.2, we analyze the local correlation values for each weather variable and take a list of known highly correlated variables as input (described in the **Assumptions** section of 2.3).

Method: To calculate the ratio between high and low-correlated time steps for each weather variable, we define two groups of correlation scores for each weather variable: a high-correlation group and a low-correlation group. These groups follow a

percentage/(100%-*percentage*) split, with the highest *percentage* of values assigned to the high-correlation group and the lowest 100%-*percentage* assigned to the low-correlation group. We then compute average values for the high-correlation and low-correlation groups and compute their ratio. This ratio describes how consistent the local correlation scores are over the entirety of the input data. If the ratio is close to 1, then the consistency is high. Then taking the ratios of the known highly correlated variables, this step compares them to the other ratios. If the ratio of another variable falls within a pre-defined ratio *radius range* of any of the ratios of the known highly correlated variables, we then extract this variable as another highly correlated variable. To tune the hyperparameters *percentage* and *ratio radius*, we try different values in the range (0, 1) until the consistency ratio can make the known relevant weather variables close to each other and known irrelevant weather variables far from each other. In other words, when sorting all the consistency ratios in ascending order, we expect to see the ratio difference between consecutive variables in relevant variables is significantly smaller than the ratio difference between the consecutive variables in irrelevant variables. Below is an example output. We know HUMIDITY and VISIBILITY are causes for some malfunctions while WET BULB TEMP is not. After tuning hyperparameters, we can observe that the consistency ratio difference (i.e., less than 0.1) of consecutive variables in the bold font is much smaller than the difference (i.e., more than 0.1) between consecutive variables between consecutive variables beyond the bold font area. The consistency ratio behaviors of SUBSURFACE TEMP, SURFACE TEMP, WIND SPEED, and MAX TEMP are similar to those of known relevant variables, so we should also consider these variables as relevant, while others are deemed irrelevant variables. **Example Output of Consistency Ratio: ('SUBSURFACE TEMP', 1.0448035431937792),**

('HUMIDITY', 1.078791988521441), ('SURFACE TEMP', 1.0970805959902372), ('WIND SPEED', 1.1738984861599309), ('VISIBILITY', 1.1964599746902513), ('MAX TEMP', 1.2808760737728937), ('AIR TEMP', 1.4181559845100764), ('WET BULB TEMP', 1.4370509159635703), ('MIN TEMP', 1.849867709823101), ('DEW POINT', 2.001827953145505), ('PRECIP RATE', 2.2338439241972194)

Output Schema: The output of this step is a list of variables with consistency scores within a 0.1 range of the consistency scores of the known highly correlated variables.

2.3.4: Extract Highly Correlated Weather Variables

Goal: Our method links weather variables to the malfunctions identified in Section 2.3.3. To achieve this, we leverage the outcomes of Section 2.3.3 and focus solely on weather variables exhibiting strong consistency with the signal controller data. Focusing on weather variables exhibiting strong consistency with the signal controller data ensures the selection of weather variables consistently correlated with the signal controller data. This step extracts weather variables exhibiting high local correlation during the malfunction period for each malfunction event. In alignment with our initial assumption, we consider weather variables with elevated local correlation as having a causal relationship with signal controller performance. This approach allows us to assess performance drops (i.e., malfunctions) in the signal controller data using weather variables with consistent correlations.

Input Schema: This step uses the list of consistently correlated variables from section 2.3.3, the hourly averages for the weather variables from section 2.3.1, the local correlation scores from section 2.3.2, and the list of malfunctions in section 2.2.3.

Method: Using the output of section 2.3.2, this step iterates over the correlation scores for each sliding window centered on an hour. We check the correlation score of each variable returned by the results of section 2.3.3 and check if it is greater than a specified threshold. In most cases, 0.8 is a reasonable threshold to use as it indicates a strong correlation between the weather variables and the signal controller data. However, we have observed that this method may fail during sudden significant changes in the data patterns; when this method returns nothing, this step defaults to using the three variables with the highest correlation scores. Once the highly correlated variables are obtained, we retrieve the average values of the highly correlated variables from the output of step 2.3.1. Finally, we iterate through the list of detected malfunctions output by step 2.2.3 and obtain the names and average values of the highly correlated variables.

Output Schema: This step outputs a list of malfunctions with associated weather variables and average values. An example output of this process is shown in Appendix 3.

Video Detection

Summary: We perform Video Detection to categorize detected malfunctions returned by the Malfunction Detection section (2.2). Our method retrieves a specific video from our database of video files and uses an optical flow algorithm to determine if there is lens occlusion on the lens of any of the cameras at an intersection. We then assign a malfunction type based on the results of the analysis and pass the results into the Malfunction Database.

2.4.1: Collect Video

Goal: Our goal with this method is to assign video files to a specific malfunction based on the detected time of the malfunction and the video's timestamp.

Input Schema: this step uses the list of detected malfunctions from section 2.2.3 as input (Figure 6).

Method: We retrieve the video for each malfunction at the given date and hour. For clarity, we assign a *malfunction ID* to each malfunction case

Output Schema: The output of this step a list of malfunctions with video files corresponding to the location and time the malfunction occurred.

2.4.2: Occlusion Detection

Goal: This step determines whether lens occlusion is present in the video. We use the detected lens occlusion to help classify the malfunction and determine if the camera requires maintenance to clear the occluded lens.

Input Schema: The input to this step is the list of malfunctions with corresponding video files (section 2.4.1).

Method: We iterate through each malfunction case, read the files associated with that malfunction, check the video frames for each video file, and calculate points of interest using Shi-Tomasi corner detection [1]. This step uses Lucas-Kanade optical flow [2] on the subsequent read frame to track the points from the original frame to the new one. Figure 7 shows the results of this process. For each read frame, we calculate the magnitude of the distance that each point of interest has traveled from the previous read frame and calculate the sum of the magnitudes for all identified points of interest for each read frame of the video. After reading all the video frames, we calculate the average magnitude across all the retrieved frames. Lens occlusion is present if the average magnitude is lower than a pre-defined threshold.

This method can effectively track movement on a video. For a normally operating traffic camera, we expect to observe cars moving across the video and higher values for the magnitude of optical flow calculations as cars are tracked between frames. In cases where a camera lens is occluded, we expect to see no cars moving as they would be blocked by whatever is occluding the camera lens. Lower optical flow magnitudes result from this lens occlusion, as cars are not detected and tracked throughout the video. Figure 8 shows an example of an occluded camera where lens occlusion was successfully detected.

Figure 7: Results of optical flow analysis on a sequence of frames. The colored dots represent points of interest, and the colored trailing lines are the distance and direction traveled from the previous frame.

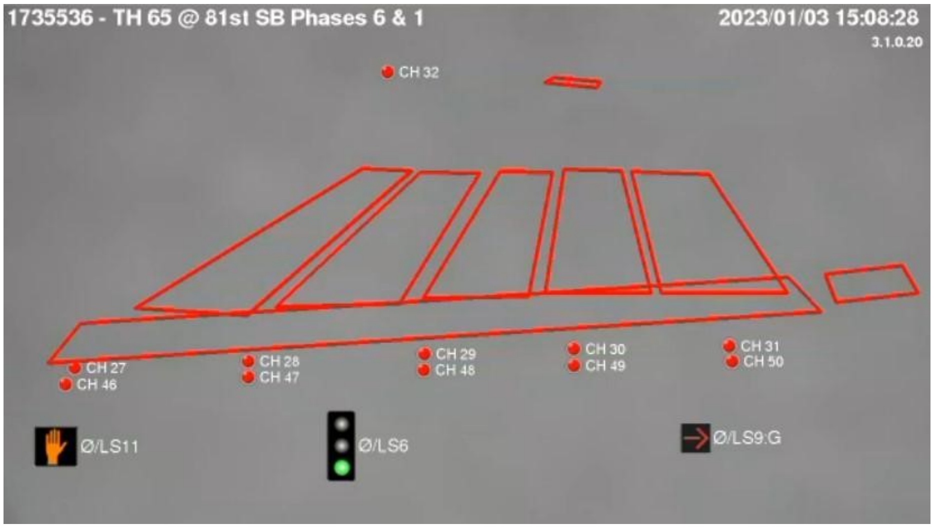

Figure 8: Example frame from a video where lens occlusion has been detected.

If this step detects lens occlusion in a video, it returns 'True' for lens occlusion and 'False' otherwise. This step also returns a random frame from the video as a snapshot. This process allows us to quickly confirm if lens occlusion is present.

Output Schema: This step outputs the list of malfunctions and whether or not lens occlusion was detected in the video during the malfunction. Snapshot files containing a frame from the video are also returned by this step.

2.4.3: Assign Malfunction Type

Goal: Our goal is to assign a malfunction type based on whether or not lens occlusion is detected in the video.

Input Schema: We use the output of section 2.4.2, the list of malfunctions with values indicating whether or not lens occlusion was detected.

Method: This step iterates over all malfunctions and sets the malfunction type based on the type of malfunction detected. We set the type to 'occlusion' if lens occlusion is detected during the malfunction. Otherwise, it is set the type to 'other'.

Output Schema: This step outputs a list of malfunctions with associated types based on whether or not lens occlusion was detected.

Malfunction Analysis

Summary: Our above methods can detect, categorize, and extract weather features for malfunctions. In this step, we compile our results into a single table and analyze the results generated to determine specific trends relating to malfunctions in NIT. We split this analysis into three sections. In section 2.5.1, our methods generate data on how weather conditions relate to specific malfunction types and locations. In section 2.5.2, our methods generate data on how many malfunctions of different types occur for different detection technologies. In section 2.5.3, our methods generate data on how many malfunctions of different types occur at different locations.

Malfunction Database: Using the results of sections 2.3 and 2.4, we iterate through the detected malfunctions and extract the *malfunction ID*, *camera name*, *date*, *hour*, *detection technology*, and *malfunction type*. We then look up the *date* and *hour* for the specific *camera name* from the results of 3.2 and retrieve the names, means, and standard deviations of all weather variables highly correlated with the malfunction at that time. A sample from the malfunction database is shown in Appendix 4.

Evaluation: We use the evaluation metric *Malfunction Rate* specified in the **Performance**

2.5.1: Weather Variable, Malfunction Type, and Detection Technology Correlation

Goal: Our goal in this section is to determine which weather features correlate with our identified malfunction types/detection technologies and provide value ranges where we can expect malfunctions. This information will help determine maintenance schedules for camera cleaning and upkeep and guide MnDOT on when to check cameras for specific malfunctions and which camera technologies perform better in different weather conditions. We focus mainly on malfunctions with the malfunction type 'occlusion' instead of the malfunction type 'other', as these cases require on-site cleaning to resolve.

Input Schema: The input schema to this step is the Malfunction Database described in the **Malfunction Database** section and linked in Appendix 4.

Method: We count the number of times a weather variable appears in the list of highly correlated weather variables for all entries of the same malfunction type and again for all entries of the same detection technology. Then, by dividing the count by the number of malfunctions of that type, we obtain the rate. Figures 9 and 10 show the output of this process. Note that the sum of the rates across all weather variables for the same detection technology does not sum up to 1 because many weather variables can be highly correlated with a single malfunction (Appendix 4). The rate at which weather variables appear in the list of highly correlated variables for all malfunctions of the same detection technology lets us analyze what weather features are determined to be more highly correlated to malfunctions in each detection technology. The rate at which weather variables appear in the list of highly correlated variables for all malfunctions of the same malfunction type lets us analyze what weather features lead to malfunctions that will require maintenance to resolve. We then calculate each weather variable's mean and standard deviation across each malfunction type/detection technology. The output of this process can be found in Figures 11-19. We use these results and the calculated malfunction rates to decide what weather conditions lead to malfunctions in each detection technology. We also use these results to decide what weather conditions lead to malfunctions that require maintenance to resolve, allowing us to recommend informed and targeted maintenance on cameras that experience similar conditions.

Analysis: Analyzing malfunctions from different detection technologies, wind speed, air temperature, and humidity are often heavily correlated with malfunctions in cameras using the Iteris detection technology. Wind speed shows the strongest correlation of the three listed, appearing in 49% of all malfunctions in cameras using the Iteris detection technology. Referencing Figure 11a, we observe that malfunctions due to wind speed in cameras using the Iteris detection technology often occur at 5-7 mph wind speeds. Contrasting this, malfunctions in cameras using the Vision detection technology are caused by wind speed at a much lower rate, roughly 20%, but occur at slightly lower wind speeds of 3-5.5 mph. While malfunctions in cameras using the Vision detection technology occur at lower wind speeds than those using the Iteris detection technology, the difference is minimal, with both value ranges only describing a light breeze [6]. These results indicate that the Iteris detection technology can tolerate more wind than the Vision detection technology, as malfunctions in Vision detection technologies occur at lower wind speeds.

Humidity shows a slightly weaker correlation, appearing in 30% of all malfunctions in cameras using the Iteris detection technology, but more significantly, no malfunctions in cameras using the Vision detection technology are highly correlated with humidity. These results indicate that humidity, more specifically humidity values of around 65% (Figure 12a), uniquely affects the performance of cameras using the Iteris detection technology.

Air temperature, while showing the weakest correlation of the three, appearing in only 22% of all malfunctions in cameras using the Iteris detection technology, affects cameras using the Iteris detection technology far more than those using the Vision detection technology, appearing in only 5% of those malfunctions. Referencing Figure 13a, we observe that malfunctions due to air temperature in cameras using the Iteris detection technology often occur at temperatures below 20°F. In contrast, malfunctions in cameras using the Vision detection technology are caused by air temperatures below 26°F. While air temperature may have a more substantial effect on cameras using the Iteris detection technology compared to cameras using the Vision detection technology, our results show that cameras using the Vision detection technology often experience malfunctions at higher temperatures than the malfunctions experienced by cameras using the Iteris detection technology. These results indicate that cameras using Vision technology may be slightly more robust to changes in air temperature. However, there are specific cases where it may fail, often at slightly higher temperatures than we would expect cameras using the Iteris detection technology to fail.

Figure 9 shows that minimum temperature, surface temperature, and wet bulb temperature are more highly correlated with malfunctions in cameras using the Iteris detection technology when compared to malfunctions in cameras using the Vision detection technology. Wet bulb temperature shows the strongest correlation of the three listed, appearing in 28% of all malfunctions in cameras using the Iteris detection technology. Figure 14a shows that malfunctions due to wet bulb temperature in cameras using the Iteris detection technology often occur at 23°F. Contrasting this, malfunctions in cameras using the Vision detection technology are caused by wet bulb temperatures below 19°F. These results support our prior analysis that cameras using the Iteris detection technology are uniquely affected by humidity as cameras using the Vision detection technology as wet bulb temperature measurements are affected by both baseline temperature and humidity [7].

While showing a slightly higher correlation in malfunctions experienced by cameras using the Iteris detection technology, surface temperature and minimum temperature show a similar correlation rate in malfunctions experienced by cameras using the Vision technology. Figure 15a shows that malfunctions due to surface temperature in cameras using the Iteirs detection technology are caused by surface temperatures of 29°F. Contrasting this, malfunctions in cameras using the Vision detection technology are caused by surface temperatures of 20°F. We see an opposite trend in minimum temperature, however. Observing Figure 16a, we can see that malfunctions due to minimum temperature experienced by cameras using the Iteris detection technology occur at 11°F while those experienced by cameras using the Vision detection technology occur at 13°F.

In figure 9, we find that maximum temperature and subsurface temperature are more highly correlated with malfunctions in cameras using the Vision detection technology when compared to malfunctions in cameras using the Iteris detection technology. Maximum temperature shows the larger correlation between the two, appearing in 45% of all malfunctions in cameras using the Vision detection technology. Figure 17a shows that malfunctions due to maximum temperature in cameras using the Vision and Iteris detection technologies occur at very similar values, 30°F for Vision and 28°F for Iteris. Referencing Figure 18a, we observe the same trend for subsurface temperature. There were malfunctions in cameras using the Vision detection technology at subsurface temperatures of 30°F and cameras using the Iteris detection technology at subsurface temperatures of 28°F.

Observing the results from all temperature values – air temperature, minimum temperature, surface temperature, subsurface temperature, maximum temperature, and wet bulb temperature – we find contradictory results. Cameras using the Vision detection technology experience malfunctions at higher air temperatures, subsurface temperatures, and minimum temperatures, while cameras using the Iteris detection technology experience malfunctions at higher surface temperatures, maximum temperatures, and wet bulb temperatures. While our analysis of wet bulb temperatures explains humidity's unique effect on cameras using the Iteris detection technology, this does not explain differences seen in the other temperature variables. As these are all temperature measurements, we would expect to see similar correlation scores and consistent temperature values between them, but this is not the case. We need to conduct further analysis on how these temperature values are measured and what environmental factors influence the values they measure before interpreting these results further.

Analyzing both detection technologies, we find that visibility is the weather variable most often correlated with malfunctions, appearing in 70% of malfunctions experienced by cameras using the Vision detection technology and 62% of malfunctions experienced by cameras using the Iteris detection technology. Figure 19a shows that cameras using the Iteris detection technology experience malfunctions at wind speeds of 6.8 miles or higher, and cameras using the Vision detection technology experience malfunctions at wind speeds of 3-5.5 mph. These results confirm our baseline assumption that fluctuations in visibility correlate with malfunctions and demonstrate that even relatively moderate visibility values can cause issues with NIT technologies.

To summarize our analysis of the different detection technologies concerning weather conditions, we find that cameras using the Iteris detection technology are broadly more susceptible to malfunctions caused by weather conditions than cameras using the Vision detection system, except for wind impact. The malfunctions experienced by cameras using the Iteris detection technology are highly correlated with more weather variables than those experienced by cameras using the Vision detection system, and humidity has a unique effect on them.

Analyzing malfunctions with the ‘occlusion’ malfunction type (Figure 10), we find that these malfunctions correlate highly with visibility and wind speed. Specifically, malfunctions with the ‘occlusion’ malfunction type have visibility as a highly correlated weather variable 60% of the time and wind speed as a highly correlated weather variable 40% of the time. Consequentially, we recommend using visibility and wind speed as metrics to decide when camera cleanings should occur. Visibility values between 6.5 and 7.5 miles (Figure 19b) and wind speeds between 5 and 7 mph (Figure 11b) should be a particular cause for concern, as many malfunctions caused by lens occlusion appear within these ranges. These malfunctions are primarily caused by wind blowing snow or dust onto the camera lens, causing lens occlusion. We recommend checking cameras for occluded lenses after periods with visibility and wind speeds within this range, as winds with these speeds can cause snow or dust to cover the lens.

The temperature values in Figure 10 show that only surface and wet bulb temperatures correlate more with malfunctions with the ‘occlusion’ malfunction type. We also observe similar contradictory results to those found when analyzing camera type. Figure 13b, Figure 15b, and Figure 16b show that malfunctions with the ‘occlusion’ malfunction type occur at higher temperatures than malfunctions with the ‘other’ malfunction type. In Figure 14b displays the opposite trend, with malfunctions of the ‘occlusion’ malfunction type occurring at a lower temperature than malfunctions of the ‘other’ malfunction type. Figure 17b and Figure 18b show that malfunctions with the ‘other’ and ‘occlusion’ malfunction types occur at the same temperatures. These results confirm our conviction that we need to further analyze the methods used when measuring the different temperature values before interpreting these results. The analysis should also include a list of cameras using heated casings and lenses referenced in the Task 2 deliverable, as these have a substantial effect on camera performance, as noted by operators.

Output Schema: This process produces statistics on the rate at which weather variables highly correlate with malfunctions of a specific type and malfunctions from specific detection technologies (Figure 9 and Figure 10). Additionally, it outputs average values with standard deviations for weather variables used in our analysis (Figures 11-19).

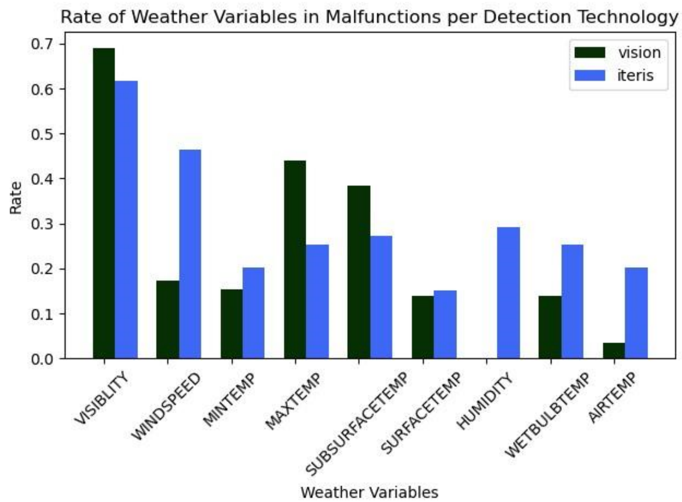

Figure 9: The rate at which weather variables are highly correlated to malfunctions per NIT device.

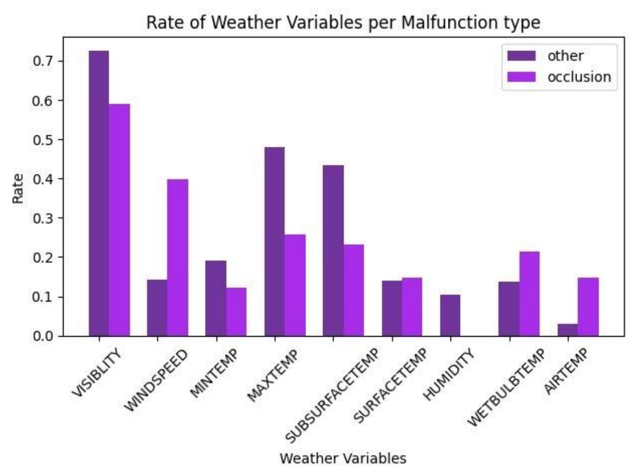

Figure 10: The rate at which weather variables are highly correlated to malfunction per malfunction type.

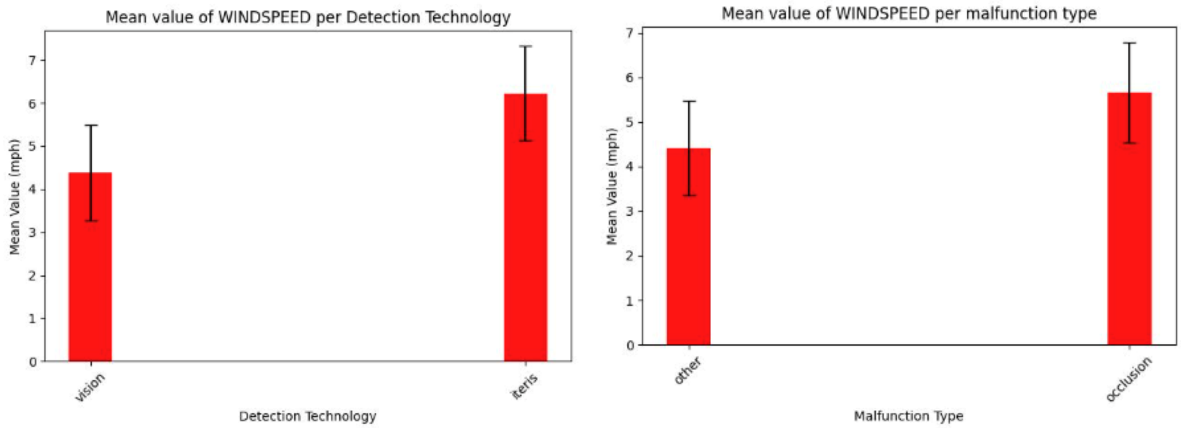

Figure 11: (a) left is the mean and standard deviation values of wind speed for malfunctions of each detection technology; (b) right is the same calculation for malfunctions of each malfunction type

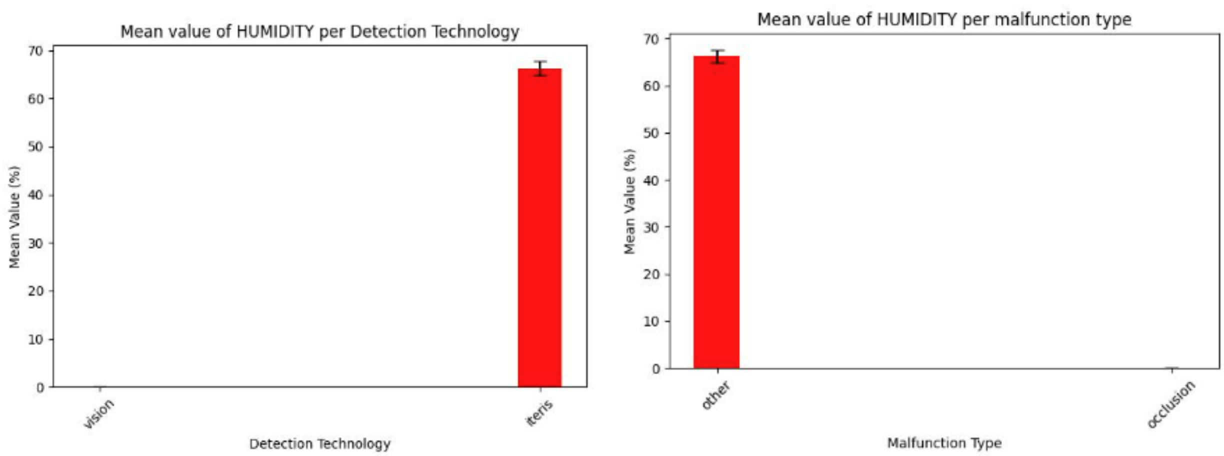

Figure 12: (a) left is the mean and standard deviation of humidity for malfunctions of each detection technology; (b) right is the same calculation for malfunctions of each malfunction type.

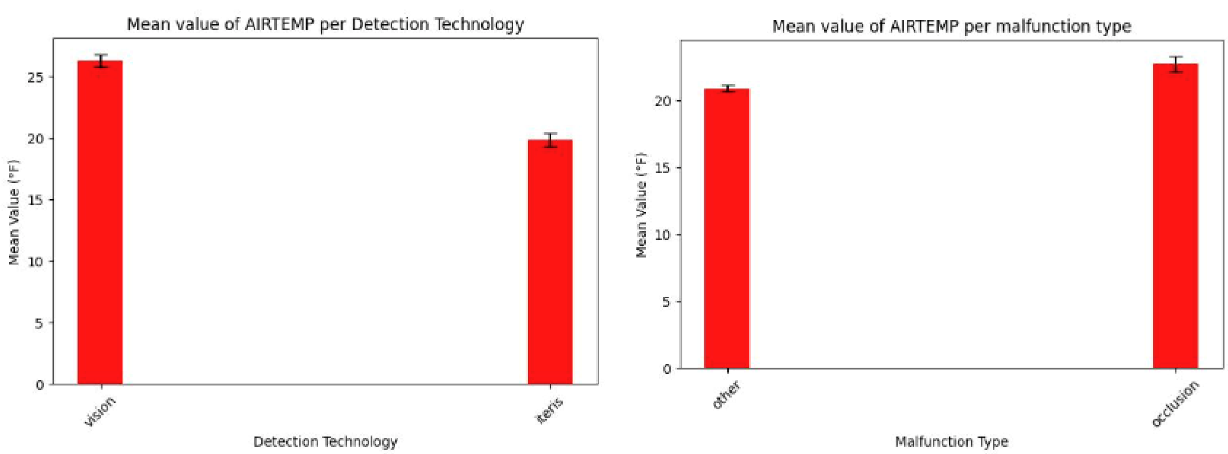

Figure 13: (a) left is the mean and standard deviation of air temp. for malfunctions of each detection technology; (b) right is the same calculation for malfunctions of each malfunction type

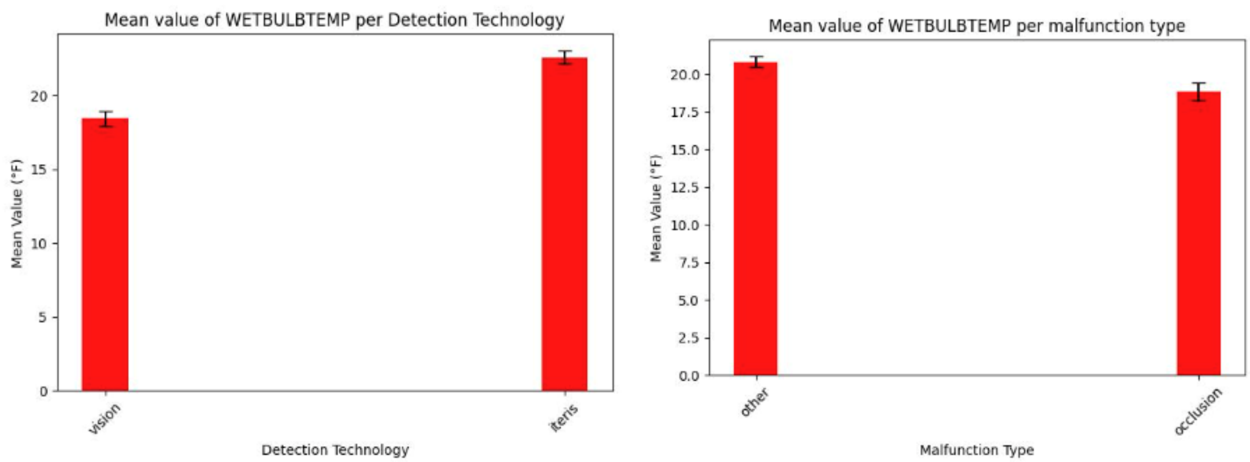

Figure 14: (a) left is the mean and standard deviation values of wet bulb temp. for malfunctions of each detection technology; (b) right is the same calculation for malfunctions of each malfunction

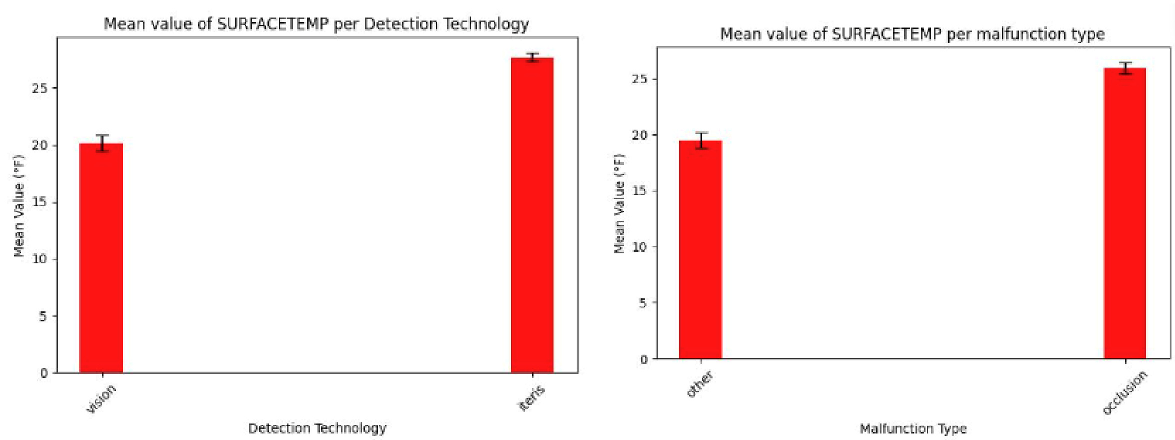

Figure 15: (a) left is the mean and standard deviation values of surface temp. for malfunctions of each detection technology; (b) right is the same calculation for malfunctions of each malfunction

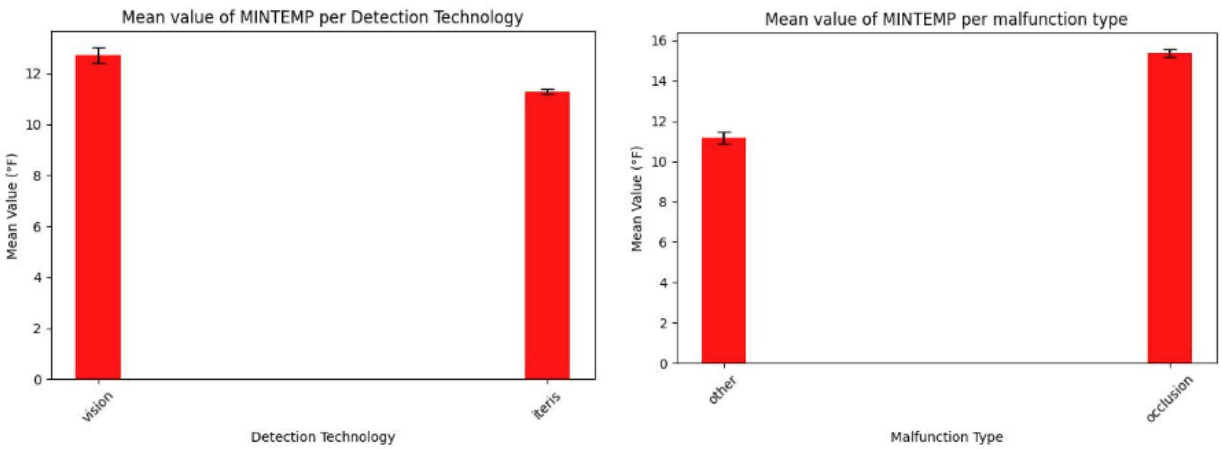

Figure 16: (a) left is the mean and standard deviation values of min. temp. for malfunctions of each detection technology; (b) right is the same calculation for malfunctions of each malfunction type

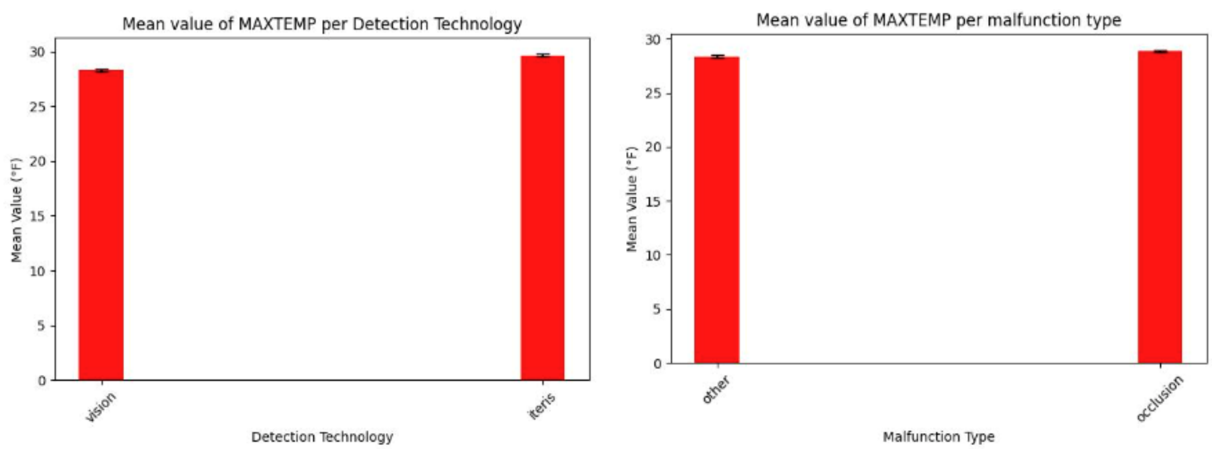

Figure 17: (a) left is the mean and standard deviation values of max. temp. for malfunctions of each detection technology; (b) right is the same calculation for malfunctions of each malfunction

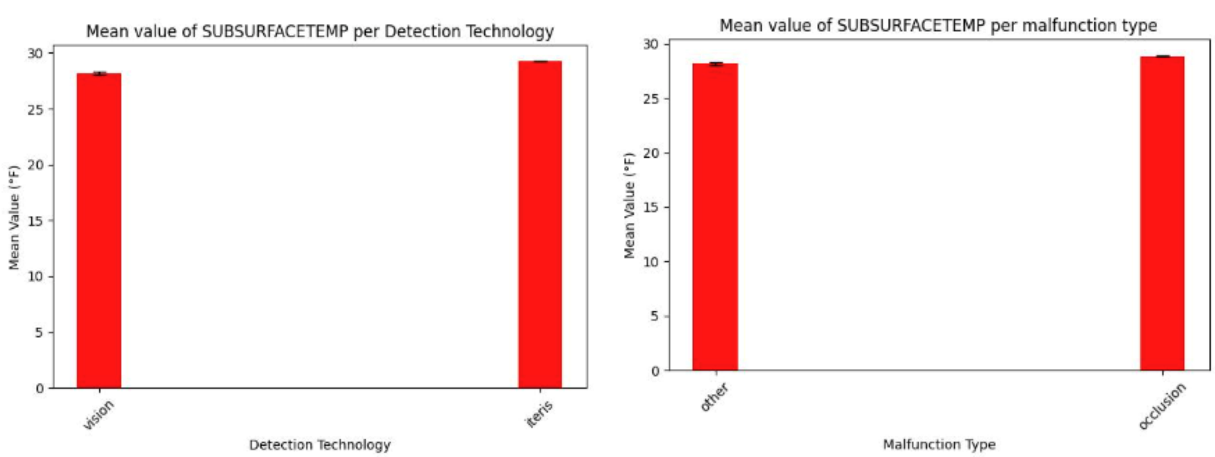

Figure 18: (a) left is the mean and standard deviation values of subsurface temp. for malfunctions of each detection technology; (b) right is the same calculation for malfunctions of each malfunction

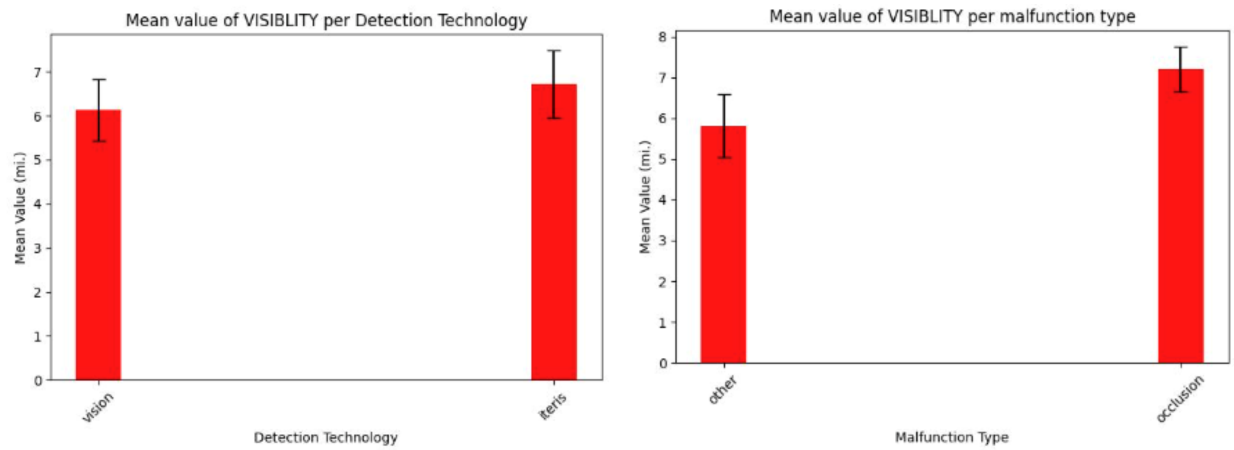

Figure 19: (a) left is the mean and standard deviation values of visibility for malfunctions of each detection technology; (b) right is the same calculation for malfunctions of each malfunction type

2.5.2: Detection Technology Malfunction Rates

Goal: This section compares the detection technologies within our study area to help determine their relative performance.

Input Schema: The input schema to this step is the Malfunction Database described in the **Malfunction Database** section and linked in Appendix 4.

Method: We compute the sum of malfunction instances for each unique date and detection technology combination. This process returns daily counts for the number of malfunctions experienced by all cameras with the same detection technology over our study period. Because the number of cameras with the Vision detection technology (4) and those with the Iteris detection technology (2) are unequal, we need to normalize the values to compare them. This is accomplished by dividing the daily counts of malfunctions for the Vision detection technology by 4 and the daily counts of malfunctions for the Iteris detection technology by 2.

Analysis: Figure 20 shows how malfunction rates fluctuate over our study period and we can observe a noticeable spike in malfunctions in both detection technologies on January 4, 2023. This is expected, as through manually reviewing video and weather data on January 4th, we find a period of intense snow storms and cold temperatures many malfunctions in all NIT are expected. We also observe that cameras using the Iteris detection technology experience fewer overall malfunctions than cameras using the Vision detection system, particularly between January 1 and January 3, 2023, when cameras using the Iteris detection system experience no malfunctions. However, observing January 4, 2023, we find that cameras using the Iteris detection system experience malfunctions more than those using the Vision detection system. These results indicate that cameras using the Iteris detection system may experience fewer overall malfunctions but are prone to increased malfunction rates during periods of severe weather.

Output Schema: The output of this process is normalized values for the number of malfunctions experienced by different detection technologies for each day of our study period.

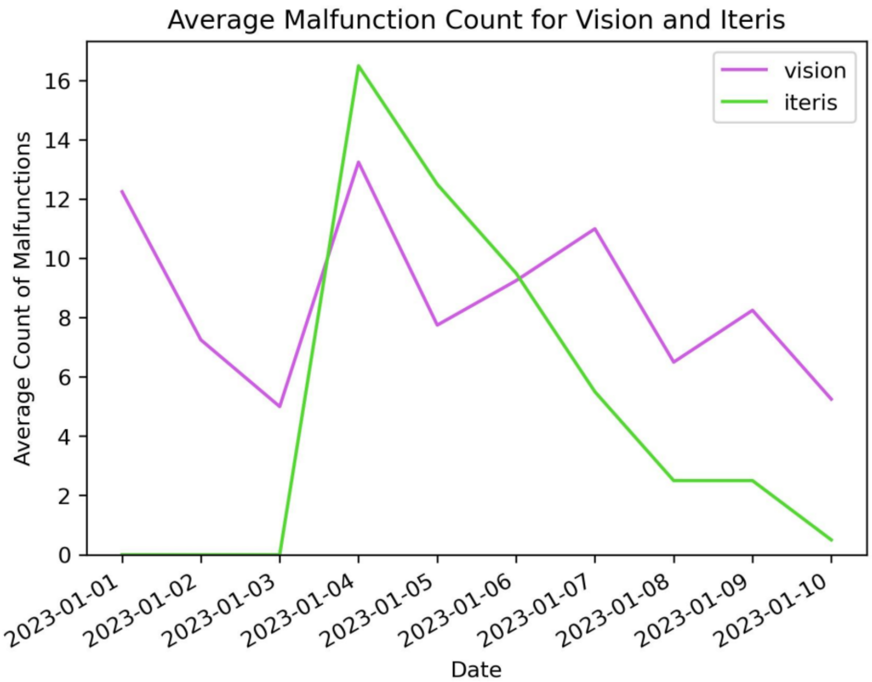

Figure 20: A graph of the average number malfunctions over time for each detection technology.

2.5.3: Location Malfunction Rates

Goal: Our goal with this analysis method is to compare different intersections and the number of malfunctions they experience.

Input Schema: The input schema to this step is the Malfunction Database described in the **Malfunction Database** section and linked in Appendix 4.

Method: Compute the sum of all malfunction instances for each unique combination of malfunction type and camera name.

Analysis: Figure 21 shows that the intersection at 65_81st experiences more malfunctions than any other intersection in our study. 47_85th experienced more 'occlusion' type malfunctions than any other intersection.

Output Schema: This step outputs statistics on the number of malfunctions of specific types experienced at the different intersections in our study area.

intersection	malfunction_type	malfunction_count
77_cliff_eramp_vision	other	5
77_cliff_eramp_vision	occlusion	47
694_eriver_nramp_vision	other	66
694_eriver_nramp_vision	occlusion	11
51_crc2_iteris	other	37
694_eriver_sramp_vision	other	40
694_eriver_sramp_vision	occlusion	21
47_85th_Iteris_Stream1	other	31
47_85th_Iteris_Stream1	occlusion	76
65_81st_Vision_Stream1	other	100
65_81st_Vision_Stream1	occlusion	8

Figure 21: Malfunction rates for each location and malfunction type

Implementation Steps

To implement this pipeline, run the code in our GitHub repository. The readme gives an in-depth guide on how to run the code and what to do with the outputs.

Appendix:

1. A sample of hourly signal controller data statistics. The "Cumu_sec" column gives the cumulative time the parameter was active for the hour in seconds; the "count" column gives the number of times the parameter turned on/off for the hour, and the 'avg_sec' column gives the average amount of time the parameter is turned on in seconds.

intersection	parameter	phase	date	hour	cumu_sec	count	avg_sec
51	1	81	2023-01-01	0	283	8	35.37
51	19	81	2023-01-01	0	30999	88	352.26
51	29	81	2023-01-01	0	4121	81	50.87
51	1	81	2023-01-01	1	35506	128	277.15
51	19	81	2023-01-01	1	32134	95	338.25
51	29	81	2023-01-01	1	35024	52	673.53

2. A sample of correlation scores between the signal controller data and each weather variable. The date and hour show when the sliding window used to calculate the local correlation was centered; all scores range from 0 to 1.

Date	hour	VISIBILITY	HUMIDITY	PRECIP RATE	WIND SPEED	AIR TEMP	MIN TEMP	MAX TEMP	WET BULB TEMP	DEW POINT	SURFACE TEMP	SUBSURFACE TEMP
1/1/2023	0	0.901	0.969	0.580	0.788	0.950	0.989	0.820	0.949	0.953	0.938	0.843
1/1/2023	1	0.901	0.947	0.650	0.644	0.870	0.976	0.743	0.846	0.884	0.849	0.751
1/1/2023	2	0.937	0.936	0.684	0.591	0.789	0.960	0.708	0.761	0.828	0.756	0.663
1/1/2023	3	0.954	0.922	0.708	0.561	0.693	0.945	0.672	0.678	0.796	0.658	0.701
1/1/2023	4	0.951	0.904	0.703	0.560	0.592	0.912	0.637	0.617	0.762	0.597	0.656

3. A sample of detected malfunctions and the associated highly correlated weather variables with average and standard deviation values.

date	hour	location	variables	average	Standard deviation
1/2/2023	0	65_81st	VISIBILITY, MAX TEMP, SUBSURFACE TEMP	10.80, 33.08, 30.0	0.55, 0.27, 0.0
1/2/2023	1	65_81st	VISIBILITY	5.10	1.24

1/2/2023	2	65_81st	VISIBILITY	3.44	0.23
1/2/2023	3	65_81st	VISIBILITY	3.05	0.13
1/2/2023	4	65_81st	VISIBILITY	3.25	0.14

4. A sample of the malfunction database. It contains a list of detected malfunctions with associated dates and locations. We assign malfunction types based on the outputs of section 2.4.3, and we assign weather variables with associated mean and standard deviations based on the outputs of section 2.3.4.

Malfunction id	Camera name	date	hour	Detection technology	Malfunction type
122	694_eriver_nramp_vision	1/4/2023	2	vision	other
123	694_eriver_nramp_vision	1/4/2023	3	vision	other
124	694_eriver_nramp_vision	1/4/2023	4	vision	other
125	694_eriver_nramp_vision	1/4/2023	5	vision	other
126	694_eriver_nramp_vision	1/4/2023	7	vision	occlusion

Weather variables	Weather variable averages	Weather variable standard deviations
MAX TEMP	30.0	0

MAX TEMP, SUBSURFACE TEMP, VISIBILITY	30.0, 29.0, 0.96	0.0, 0.0, 0.159
MAX TEMP, SUBSURFACE TEMP, VISIBILITY	30.0, 29.0, 0.61	0.0, 0.0, 0.05
MAX TEMP, SUBSURFACE TEMP, VISIBILITY	30.0, 29.0, 0.63	0.0, 0.0, 0.11
MAX TEMP, SUBSURFACE TEMP, VISIBILITY	30.0, 29.0, 0.89	0.0, 0.0, 0.40

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