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CONNECTED VEHICLE WINTER SAFETY IMPROVEMENT WITH INFRARED THERMOGRAPHY TECHNOLOGY

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16. Abstract

The primary objective of this research is to utilize dual-spectrum cameras, optical, and infrared thermography (IRT) cameras, to detect slippery road spots and high-crash-risk locations in winter seasons, using field evaluations and machine learning to improve detection algorithms. This capability can be used to detect road surface snow/ice patterns to augment or complement the Spot Weather Impact Warning (SWIW) application that UDOT is in the process of implementing. SWIW uses RWIS and Connected Vehicle (CV) data as inputs, whereas the proposed technology uses wayside IRT camaras and machine learning algorithms for direct measurements, which can be potentially extended for snow/ice detection at non-RWIS locations. The outcome of this research is expected to examine the feasibility of integrating IRT sensor data in future CV control systems.

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LIST OF ACRONYMS

CNN	Convolutional Neural Network
CV	Connected Vehicle
DOT	Department of Transportation
FHWA	Federal Highway Administration
IRT	Infrared Thermography
RWIS	Road Weather Information System
SWIW	Spot Weather Impact Warning
TAC	Technical Advisory Committee
TIM	Traveler Information Message

EXECUTIVE SUMMARY

This project investigates the feasibility of using infrared thermography (IRT) combined with computer vision and machine learning to continuously monitor winter roadway surface conditions and identify hazardous snow and ice coverage that may lead to crashes. While Utah's existing Spot Weather Impact Warning (SWIW) system relies primarily on RWIS and connected vehicle data, the proposed approach provides direct pavement observation, enabling improved spatial coverage and enhanced surface-state awareness, particularly at locations without RWIS installations.

Field-deployable IRT camera systems were installed at two major roadway sites in Utah, Parley's Summit on I-80 and SR-248 near Park City, to capture thermal and optical image datasets over two winters. A dual-modal detection framework was developed:

- Optical images are primarily used for daytime roadway state recognition, when roadway temperature contrast is less obvious.
- Thermal images can support icy roadway detection for nighttime and low-visibility conditions.

A tailored preprocessing workflow (fisheye correction, masking, and perspective transformation) standardizes imagery prior to classification. Transfer learning-based neural network classifiers were then trained to categorize roadway conditions into dry, wet, snowy, and icy. The optical image classifier demonstrated near-perfect performance in distinguishing daytime roadway surface conditions, while the thermal image classifier achieved high accuracy across all four categories and reliably identified cold-region signatures associated with icy roadways, which was not achieved by previous efforts of the research team. Temporal validation showed strong agreement between predicted roadway conditions and field observations during active storm events.

Overall, the results confirm that infrared thermography integrated with machine learning provides a reliable, scalable, and CV-compatible solution for monitoring winter roadway safety. The technology demonstrates strong potential to augment the existing SWIW framework, improve situational awareness, and support proactive winter maintenance and traveler safety strategies.

1 INTRODUCTION

1.1 Problem Statement

Safety is the principal concern of highway transportation. Slippery roads can pose high risks of traffic collisions in snowy regions, which cover about 70 percent of road networks and population in the U.S. USDOT safety data reported 24 percent of weather-related vehicle crashes occurred on icy/snowy roads, and an average of 1,300 deaths and 116,800 injuries per year were caused by winter slippery roads. Meanwhile, more than 35 states of the U.S. experience snowstorms in winter, and some states, such as Utah, can have more than 5 months of winter weather. Icy/snowy roads can significantly reduce tire friction, lengthen vehicle braking distance, and thereby increase the risk of car crashes. Hence, if early warning could be provided to drivers before they enter hazardous locations, potential crash risks could be significantly reduced.

Conventionally, state DOTs use warning signage to alert drivers to hazardous road segments. However, slippery spots are usually hard to predict, and their locations can change over time. Placing static warning signs is limited in addressing such dynamic situations. Recent advancements in connected vehicle (CV) technology offer a new and effective solution to tackle this issue. For example, in collaboration with Panasonic, UDOT has already developed a Spot Weather Impact Warning (SWIW) application, which uses data from Road Weather Information System (RWIS) stations and CV information to determine the existence of potentially slippery road surfaces and then send a message to oncoming CVs.

The current SWIW application relies on ITS roadway equipment, such as RWIS, and partially on information from Connected Vehicles to detect the road surface temperature, moisture, icing, and other metrics to detect road surface conditions where these sensors typically provide single-spot measurements. This project could fill the gap in augmenting or complementing the road-surface condition-detection algorithm. By using IRT technology, this project developed an innovative tool capable of multi-lane roadway temperature mapping and roadway surface condition assessment. The obtained data can be treated as direct evidence and can be used to cross-validate the detection accuracy of the current SWIW system. Moreover, IRT technology can be integrated into the CV-based traffic control loop in the future for better system performance.

This project evaluates and demonstrates a novel method based on infrared thermography (IRT) and deep learning algorithms developed at the University of Utah to identify roadway snow and ice conditions. The method uses high-resolution IRT data but requires minimal computing power and avoids complex tracking algorithms. The results are promising and can potentially support winter safety for CV applications.

1.2 Objectives

The primary objective of this research is to utilize IRT sensors to detect slippery road spots and high-crash-risk locations in winter seasons, using field evaluations and machine learning to improve detection algorithms. This proposed approach is based on the team's experience from a previous Aurora project (Zhu et al., 2024). However, there are two unique contributions of this research: (*i*) a more advanced IRT camera was deployed and tested, which supports superior sensitivity and performance compared with a previous system; and (*ii*) a framework rooted in computer vision and transfer learning was developed for non-contact multi-lane roadway snow and ice detection for both day- and night-time, which is a significant improvement compared with the previous system.

1.3 Scope

The scope of this research is divided into five tasks:

- Task 1 - Literature review: A literature review is conducted to review the existing technologies and current practices in roadway slippery condition assessment.
- Task 2 - IRT deployment and data collection: To meet the objectives of the research, IRT sensors were deployed to cover two sites, I-80 Parley's Summit and SR-248 in Park City, both of which have RWIS installations to facilitate IRT sensor mounting.
- Task 3 - Algorithm performance evaluation: the team used the collected IRT and visual data to map the roadway snow/ice patterns and improve the interpretation of the images. The team further evaluated its performance by comparing with the surface condition detected by RWIS measurements.
- Task 4 - Algorithm improvement: leveraging additional measures, the team further improved the current detection algorithm using machine learning.
- Task 5 - CV integration: The team converted IRT-derived data on road condition into a format compatible with UDOT's existing CV data format.

1.4 Outline of Report

This project report is organized with the following chapters:

- Introduction
- Literature review
- Data collection and methodology
- Results on ice and snow detection
- Conclusions

2 LITERATURE REVIEW

Roadway slipperiness, induced by wet, snowy and icy road surfaces, poses a serious safety risk, contributing to a large share of weather-related crashes. For example, U.S. safety statistics show about 13% of weather-related accidents occur on icy pavement, and 16% on snowy or slushy pavement (Jin et al., 2024). To quantify winter weather severity and evaluate snow removal performance in snowy regions, state DOTs have been employing or investigating winter severity indices. Many DOT agencies indirectly track the severity by calculating to what extent their systems meet the level of service (LOS). On the other hand, many states evaluate the winter-weather severity index by accounting for both the atmospheric and road conditions. Roadway snow detection for road safety has been extensively investigated, aiming to supply local agencies, drivers, or autonomous vehicles with real-time roadway weather information and facilitate their decision-making (Ruiz-Llata et al., 2014; Karsisto and Loven, 2019; Eom et al., 2021). A wide range of sensing technologies have been deployed for real-time data collection, where the road surface temperature and slippery conditions are essential parameters to facilitate hazardous road condition detection and warning. Much effort has been invested on this front, as shown in Table 1. One popular solution is the Roadway Weather Information System or RWIS (Eriksson and Norrman, 2001; Aurora, 2005; Evan et al., 2013; Kwon et al., 2017), which provides temperatures, humidity, and precipitation data (Zang et al., 2019; Jonsson, 2011). Another widely adopted option, remote road surface state sensors, allows measurements of road surface temperature and conditions (Bridge, 2008; Mercelis et al. 2020). However, both options only support single-spot measurements, which do not necessarily represent “true” road surface conditions of interest. Moreover, improvements in measurement accuracy and required calibration frequency become concerns for practical operations. Despite intensive research efforts over the past 20 years, a need for sensing technology for road temperature and surface condition detection persists.

Table 1 Summary of Past Work on Roadway Snow and/or Ice Detection.

Item #	Phenomena/Technique	Investigators/ Relevant Publication
1	RWIS	Aurora, 2005
2	Infrared thermometer	Vaisala DST111 (Bridge, 2008); Ye et al., 2011
3	Passive infrared thermography with radiation polarization	Reed & Barbour, 1997
4	Active infrared radiation backscatter	Vaisala DSC111 (Bridge, 2008); Misener, 1998; Joshi, 2002
5	Video camera	AerotechTelub and Dalarna University, 2002; Saito and Yamagato, 2014
6	Laser light polarization	Schmokel, 2004
7	Microwave reflection	Kubichek &Yoakum-Stover, 1998
8	Pavement temperature sensors	Albrecht, 2005; SRF Consulting Group Inc., 2015

Researchers in this field have focused on the sensor and hardware technologies and expanded the use of computer vision and machine learning algorithms for detecting slippery conditions by classifying road surface images. This section provides a literature review of sensor-based and camera-based detection methods, spanning in-vehicle systems, roadside installations, aerial/satellite remote sensing, and the image processing and machine learning algorithms adopted to analyze roadway surface and weather conditions. As sensing technologies have been implemented in different systems, we categorize them into in-vehicle sensing systems, roadside sensing systems, and aerial- and satellite-based remote sensing approaches. Finally, we discuss the image processing and machine learning algorithms for roadway surface condition assessment.

2.1 In-Vehicle Slipperiness Sensing Systems

Modern vehicles are increasingly equipped with sensors and on-board systems that can detect low-friction conditions in real time. Conventional vehicle dynamics sensors, such as wheel speed sensors (ABS), yaw/gyro sensors (ESC), and accelerometers, can be leveraged to infer road friction. For instance, when a vehicle's wheels begin to slip on ice, the mismatch between wheel rotation speed and actual vehicle speed can reveal a loss of traction. Automotive manufacturers have long used such signals internally for anti-lock braking and stability control, but recent work has aimed to expose this information for broader road condition detection. Panahandeh et al. (2017) demonstrated that supervised machine learning can estimate road friction from standard vehicle sensor data, enabling connected vehicles to share real-time friction estimates across a fleet. In the same vein, Mercelis et al. (2020) explored using data from large fleets of regular passenger cars as moving sensors to detect road weather conditions. These approaches treat each vehicle as a sensor node – often called the "probe vehicle" concept – and aggregate signals like ABS activations or traction control events across many vehicles to map slippery spots on the road network.

Beyond using stock vehicle sensors, researchers have developed add-on sensor systems in vehicles to directly measure road surface state. A notable class of such devices are mobile road condition sensors that use optical or electromagnetic principles to assess the pavement in front of or beneath a vehicle. Two prominent examples are the RCM411 and the MARWIS sensors (Brustad et al., 2020). These are typically mounted on a vehicle (e.g., on a bumper or maintenance truck) and emit signals toward the pavement to detect water, ice, or snow. The RCM411, developed in Finland, and the MARWIS, developed in Germany, are multi-sensor road-condition monitoring units that can infer surface grip (friction coefficient), water film thickness, surface temperature, and whether the road is dry, wet, snowy, or icy. They operate using combinations of infrared spectroscopy, laser/light backscatter, and sometimes conductivity or microwave sensing. Laboratory evaluations have shown these sensors can reliably distinguish surface conditions and measure parameters like water thickness with reasonable accuracy. For example, *Fay et al.,* 2018 reported on controlled tests of MARWIS and Teconer sensors, finding strong correlation between their field readings and known laboratory values for surface salt and moisture. Many transportation agencies now equip maintenance vehicles with these sensors to get real-time friction or surface condition readings as the vehicle drives along roads.

Another avenue of in-vehicle sensing is the use of infrared thermography or IRT and radar from the vehicle. Jonsson and Riehm, 2012 demonstrated that a vehicle-mounted infrared thermometer can continuously measure road surface temperature, which is critical for identifying freezing conditions. Modern IR sensors, installed in maintenance trucks or even integrated into some high-end passenger cars, can detect pavement temperature differences and even infer the presence of black ice (since an icy surface often has a distinct temperature profile). Similarly, automotive radar technology has been repurposed for road condition sensing. Häkli et al., 2013 showed that a standard 24 GHz automotive radar could be used to recognize road surface conditions (dry, wet, icy) by analyzing the returned signal characteristics. This radar method relies on the fact that water or ice on asphalt alters the reflective properties of the surface. By 2015, some high-end vehicles began to include slippery-road detection features that use forward-looking radar and camera data to warn drivers of ice. However, this is still an emerging technology and an active research area.

A significant development is leveraging consumer smartphones and OBD-II devices in vehicles to detect slippery roads. This falls under the concept of crowdsourced road condition monitoring. The VehSense system (Hou et al., 2017) exemplifies this approach. It combines a smartphone's inertial sensors with a plugin OBD-II reader to detect vehicle skidding in real time. The smartphone's accelerometer and gyroscope are used to estimate the true movement of the vehicle ("ground speed" and orientation), while the OBD-II adapter provides the wheel speed from the vehicle's ECU when the wheel speed is significantly higher than the vehicle's actual motion. For instance, the system infers a loss-of-traction event, when the wheels spinning on ice and the car does not accelerate. Hou et al. tested this on snow-covered roads in Buffalo, NY, and demonstrated that such a setup can detect vehicle skidding effectively in real driving conditions. Importantly, this approach does not require any proprietary vehicle data or special hardware beyond a $20 OBD adapter and a phone, making it widely deployable. Crowdsourcing data from multiple vehicles is a key advantage – as one study noted, aggregating reports from many connected cars or phones can build a real-time hazard map, which can be communicated to following drivers or traffic management centers.

Finally, researchers are exploring "intelligent tires" as in-vehicle sensors for friction. An intelligent tire is equipped with embedded sensors (such as accelerometers, strain gauges, or piezoelectric transducers) that directly measure tire-road interaction forces. Progress in sensor miniaturization and wireless communication enabled practical trials of this concept. For example, Lee et al., 2021 attached a tri-axial accelerometer inside a tire tread and used the vibration signatures to classify road surface conditions (dry vs. wet asphalt, gravel, etc.) with a deep neural network classifier. They achieved around 95% accuracy in distinguishing dry and wet road surfaces in controlled experiments. While these intelligent tire systems are still experimental, they hold promise for future vehicles to have direct friction sensing at the tire-road interface, arguably the most reliable way to detect slipperiness. In summary, the trend for in-vehicle systems is toward using the vehicle itself as a sensor platform (through built-in electronics, add-on devices, or connected consumer devices) to monitor road conditions and share alerts of ice or low friction.

2.2 Roadside Sensing Systems

Roadside infrastructure has long played a role in detecting adverse road conditions, and recent developments have improved the accuracy and accessibility of these systems. The most widespread installations are Road Weather Information Systems or RWIS – environmental sensor stations placed along highways that measure weather parameters and road surface status. A typical RWIS station is often solar-powered and pole-mounted, which includes atmospheric sensors (air temperature, humidity, wind, precipitation type/intensity, visibility) and pavement sensors (surface temperature and state). Earlier generations of pavement sensors were often embedded in the roadway, such as flush-mounted thermistors or freeze probes, to directly measure temperature and detect ice formation. Many state agencies have upgraded to non-invasive pavement sensors, which can be mounted at the roadside (or on overhead gantries) to remotely sense the road surface. These usually employ infrared and optical techniques. For instance, the Vaisala DST111 is a passive infrared thermometer that measures the road's surface temperature from a distance, and the Vaisala DSC111 is an active optical sensor that emits infrared light and analyzes the backscatter to determine if the surface is dry, wet, icy, or snow-covered. In an evaluation, Ewan et al., 2013 tested such sensors (DST111 and DSC111) and found that while they provide useful data, factors like sensor angle and pavement type can affect reliability. Nonetheless, these non-invasive road sensors have matured significantly – they avoid the maintenance issues of in-pavement sensors and can be easily installed on existing weather station masts or even on vehicles for mobile use.

Beyond these commercial systems, researchers have prototyped new sensor technologies for roadside detection in the last decade. One example is planar capacitive sensors for road wetness detection. Döring et al., 2019 developed a flat capacitive sensor that can be embedded in or on the road surface; it detects the presence of water by measuring changes in capacitance on a planar electrode grid. This approach proved highly sensitive to even thin water films and could distinguish between a dry road and one with hazardous wetness. Another novel approach is acoustic sensing using microphones to "listen" to the sound of tire-road interaction. Pepe et al. 2019 showed that the audio frequency signature of tires on wet pavement is measurably different from that on dry pavement (due to the sound of water spray and slip), and they trained a convolutional neural network to detect road wetness from audio signals. Such a system could be deployed, for example, at a roadside post that listens to passing traffic or even on a vehicle's wheel well. Similarly, Schmiedel et al., 2019 studied the spray pattern of tires as an indicator of road wetness using optical sensors to quantify the amount of water spray kicked up by a vehicle. These emerging sensor types complement the traditional temperature and precipitation measurements by directly targeting the effect (water or ice on the surface) using diverse physical principles.

Fixed cameras and computer vision have also become an important roadside tool for slippery road detection, especially with advances in deep learning. Many highways are already covered by CCTV or traffic cameras; researchers have capitalized on this existing infrastructure by applying image analysis to detect snow, ice, or water on the road. Early efforts used classical image features: For example, Omer and Fu (2010) built an image recognition system that classified winter road conditions (snow, ice, dry) from webcam images using color and texture features. In the 2010s, as convolutional neural networks (CNNs) became dominant, performance greatly improved. Grabowski and Czyżewski, 2020 developed a system in Poland that analyzes live feeds from roadside CCTV cameras and feeds them into a CNN-based classifier. They trained several deep CNN models (ResNet, VGG, DenseNet) on images captured in different lighting and weather, and their best model achieved over 98% accuracy in distinguishing dry, wet, and snow-covered roads. This was integrated into an "intelligent road sign" system that can automatically display warnings or speed limit adjustments when a slippery condition is detected. The advantage of vision-based systems is that they cover a broad area (the entire field of view of the camera) and can directly observe surface conditions without physical contact. However, they depend on sufficient lighting and visibility; thus, infrared cameras are also being employed for night and low-visibility conditions. Thermal infrared cameras can pick up temperature differences and even the distinctive textural appearance of ice. For example, Yamagata (2014) reported a roadside camera system in Japan that could remotely monitor road conditions in winter and aid maintenance decision-making, even under nighttime lighting. More recently, He et al., 2023 showed that using dual-spectrum imaging (fusing regular RGB camera images with thermal infrared images) enhances the detection of snow coverage on road surfaces. Their machine learning models achieved higher accuracy in estimating road snow coverage than single-spectrum approaches. Overall, camera-based roadside monitoring has transitioned from experimental to operational in the past decade, thanks to better algorithms and cheaper cameras – some highway agencies now routinely use video analytics to identify icy patches, sometimes in combination with traditional RWIS data.

In addition to these, various specialized sensors have been trialed at fixed sites. For instance, laser-based sensors that analyze the polarization change of a laser beam reflecting off the pavement can detect thin ice. Low-power microwave radiometers have been tested to sense surface water or ice by its microwave emission signature, though such devices are less common. Some installations also use chemical sensors. An optical sensor by Ruiz-Llata et al., 2014 could remotely measure the residual de-icing salt on a road by analyzing reflected light spectra – indirectly indicating if ice might refreeze due to lack of salt. These fixed-location technologies are often deployed at critical points like bridge decks, steep grades, or known ice-prone spots, where giving an early warning to drivers (via dynamic message signs or connected vehicle alerts) can be lifesaving. The integration of data from multiple roadside sensors is a notable trend. Recent projects blend information from RWIS stations, cameras, and vehicles. For example, the U.S. FHWA Road Weather Management Program encourages combining fixed sensor readings with probe vehicle data to improve coverage and reliability. In summary, roadside detection advanced through more sophisticated sensors (IR/optical, capacitive, acoustic) and smarter analysis of camera feeds, all aimed at real-time identification of slippery conditions to support timely maintenance and traveler warnings.

2.3 Aerial and Satellite-Based Remote Sensing Approaches

Covering large areas and remote segments of roadway often requires remote sensing from above. Traditionally, weather satellites have provided broad weather and snow cover information, but spatial resolution was too coarse to directly detect ice on specific roadways. In the past decade, the increasing availability of high-resolution Earth observation satellites and unmanned aerial vehicles (UAVs) has opened new possibilities for detecting slippery roads from the sky.

Recent research has evaluated whether satellite imagery can identify hazardous road surface conditions. Optical satellites (e.g., Landsat 8, Sentinel-2, or commercial high-res platforms) can clearly show snow cover on roads after a snowfall, and thermal infrared sensors on satellites (like NASA's MODIS or VIIRS) can estimate land-surface temperatures which might flag freezing spots. However, satellites are limited by overpass timing and weather (cloud cover). A 2013 review by Ewan et al. concluded that as of that time, satellite and aerial remote sensing was not yet reliable enough for real-time road-surface condition monitoring. More recent effort demonstrates the technology advancement. One promising approach is using synthetic aperture radar (SAR) satellites. SAR can penetrate clouds and is sensitive to surface moisture. Some studies have suggested that a frozen road might be distinguishable in polarimetric SAR imagery due to changes in reflectivity. These ideas are largely at the experimental stage. In practice, satellites are currently used more for forecasting support rather than direct driver alerts. For instance, a recent climate study mentioned that understanding large-scale patterns (like mountain snow or urban heat islands) via satellite data can help predict where black ice will form, when combined with ground RWIS data (Jin and McBroom, 2024). Thus, satellites play a complementary role, and their utility will grow as image resolutions improve (today's commercial satellites can see objects ~30 cm, which may eventually allow detecting snow/ice on a highway lane if algorithms are up to task).

Unmanned aerial vehicles or drones have arguably seen the most exciting developments for road condition sensing after 2010. Drones offer on-demand, high-resolution observation at the scale of individual roadway sections. A review by Li et al., 2024 highlights that drones can be equipped with multispectral cameras, thermal infrared imagers, and even LiDAR to capture specific features of ice and snow. Multispectral and hyperspectral cameras, for example, can detect subtle differences in surface reflectance that indicate a thin ice layer (sometimes called "black ice" when invisible to the eye). Infrared cameras on drones can map the temperature of a road surface; a sudden drop in road surface temperature over a short span might signal an icy patch. LiDAR sensors, which provide 3D point clouds, can potentially detect differences in surface texture or the presence of snow cover and even measure snow depth on roadways. Recent experimental studies have started to validate these concepts. In one case, researchers used a drone with a downward-looking IR camera at night and were able to identify icy versus wet sections on a test track by their thermal signature. Another innovative project involved a drone carrying a ground-penetrating radar to measure ice thickness on a temporary ice road (used in northern climates) – demonstrating that drones can reach hazardous or hard-to-access locations to perform measurements that previously required putting sensors or people on the ground (Jin and McBroom, 2024).

One practical use of drones is emerging in winter maintenance operations. Departments of transportation have begun deploying UAVs after storms to survey highway segments and pinpoint where snow drifts or refreezing are occurring. This can guide snowplow routing and salt application more efficiently than relying on patrol drives alone. Drones can also inspect high-risk areas like bridge decks, which cool faster and ice up sooner than normal roads. A notable recent effort is the IcyRoad project (Fowler et al., 2022) in Montana, which, as part of validating a road ice prediction model, experimented with drone-based spectral imaging to detect road ice in real time. The final report of that project suggests that UAV-mounted sensors were able to successfully identify ice patches under certain conditions and could be used to provide ground truth for refining ice formation forecasts. The authors reported that drone technology serves as a promising "mobile RWIS," especially in areas without fixed sensors. Key operational challenges remain, such as flight in severe weather, battery life in cold conditions, and the need for automated image processing to quickly translate drone data into warnings. Nevertheless, UAVs equipped with the right sensors can fill a critical gap by surveying lengths of roadway on-demand and at high detail – something neither fixed sensors nor satellites can do as effectively.

In summary, aerial platforms add a valuable top-down perspective to road condition detection. Satellites provide broad coverage and help with macro-scale risk analysis (e.g., identifying regions with likely ice based on weather patterns and land features), whereas drones offer tactical, high-resolution sensing that can directly observe ice/snow on specific road segments and even carry de-icing material for rapid response in the future. As these technologies mature, they are expected to integrate with ground-based systems. One can envision a winter road management system where satellites flag a general area of concern, ground weather stations confirm marginal conditions, and then a drone is dispatched to scan the route and pinpoint the exact icy spots, all in communication with maintenance crews and connected vehicles.

2.4 Computer Vision and Machine Learning

With recent advancements in machine learning, supervised learning frameworks lend themselves to handling object recognition and image segmentation. Zhao et al., 2017 classified road surfaces into five different types, i.e., dry, wet, snow, ice, and water. They established a road-surface state database by involving 9D color eigenvectors as well as 4 texture eigenvectors and used a support vector machine (SVM) for roadway condition classification. Qian et al., 2016 characterized a prior distribution of road pixel locations from training data and fused the normalized luminance and texture features with probability to classify road surface conditions. To support snowy weather detection, Khan et al., 2019 classified road weather into three categories (‘clear’, light snow,’ and ‘heavy snow’) and developed a real-time in-vehicle snow detection system that supports trajectory-level weather detection. They evaluated the performance of SVM, k-nearest neighbor (K-NN), and random forest (RF) using the dataset from SHRP2 Naturalistic Driving Study Video data. Roser and Moosmann, 2008 used the SVM to classify the inclement weather conditions (clear, light rain, and heavy rain) considering five image features, i.e., local contrast, minimum brightness, sharpness, hue, and saturation. Another study developed convolutional neural networks to identify adverse weather conditions from a road camera, which could be implemented at the in-vehicle level (Dahmane et al., 2018). Lei et al., 2020 introduced their snowy driving dataset to train and test models for pixel-wise semantic labeling.

When illumination or weather conditions are insufficient to support reliable optical image segmentation, infrared thermography provides an alternative measure for object detection, where the infrared image’s pixel intensity represents temperature. Vachmanus et al., 2021 proposed a multi-modal fused RGB-T semantic segmentation using optical and infrared images as the inputs for their networks to study the semantic segmentation of roads in snowy weather, especially focusing on human subjects’ detection in snowy environments. Li et al., 2018 developed an algorithm to identify pedestrians through infrared image segmentation with the help of background likelihood and object-biased saliency. Infrared image segmentation is also widely used for military purposes. Bai et al., 2016 successfully developed a feature-based fuzzy inference system to segment low-contrast infrared images with ships.

Landry and Akhloufi, 2022 contributed to this field by estimating snow coverage using surveillance cameras and proposing a powerful ensemble machine learning model combining CNN and SVM. The results of their study demonstrated superior accuracy compared to existing research. Aparna et al., 2022 approached the challenge of pothole detection with a commendable approach, collecting a diverse dataset of thermal images under various weather conditions. Through data augmentation techniques and leveraging a CNN model, they successfully identified potholes, addressing a critical aspect of roadway safety. To address the limitations of traditional image recognition technology for road recognition in intelligent driving systems, Cheng et al., 2019 proposed an innovative deep learning approach. This approach significantly enhanced the classification of road surface conditions meeting the demand for rapid and accurate roadway condition monitoring.

While the benefits of machine learning in infrastructure inspections are obvious, traditional machine learning algorithms do have disadvantages. They often necessitate massive volumes of labeled data for training, which can be time-consuming and expensive to obtain. To solve these obstacles, researchers and engineers are investigating alternate methodologies. Transfer learning approaches enable the application of knowledge from previously trained models on unrelated tasks to the specific infrastructure inspection task at hand. In recent times, researchers have intensified their focus on transfer learning as a means to augment the accuracy of roadway condition evaluation. This exciting avenue of research holds immense promise, enabling models trained on related tasks to be fine-tuned and applied to road condition analysis, thereby enriching the accuracy and robustness of the assessments. Transfer learning is an advanced machine learning technique that enhances the performance of a model on a new, related task by leveraging knowledge gained from training on different tasks. Rather than starting from scratch, a pre-trained model is utilized as a starting point and then fine-tuned on the new task using a smaller, task-specific dataset. This approach is particularly valuable in scenarios where data is limited, computational resources are constrained, or when aiming to achieve state-of-the-art performance across different domains (Zhuang et al., 2021; Salehi et al., 2023). One notable example of transfer learning's success in roadway condition assessment comes from Brewer et al., 2021. Their innovative approach involved employing a pre-trained CNN model based on data collected in the United States for assessing roadway conditions in Nigeria. By adapting the US model with Nigeria-specific data, they achieved an impressive 94.0% accuracy in predicting the quality of Nigerian roads. This showcased how transfer learning can effectively bridge the gap between different regions and adapt models to local conditions, leading to highly accurate predictions. Additionally, Maarouf and Hachouf, 2022 demonstrated the versatility of transfer learning by training a comprehensive CNN model using roadway condition images taken by smartphones in Japan. They then fine-tuned this model for other countries by mixing the Japanese data with local data. This clever strategy allowed other countries to create their efficient models based on the pre-trained Japanese model. By doing so, they harnessed the power of transfer learning to optimize their model performance, even with limited local data.

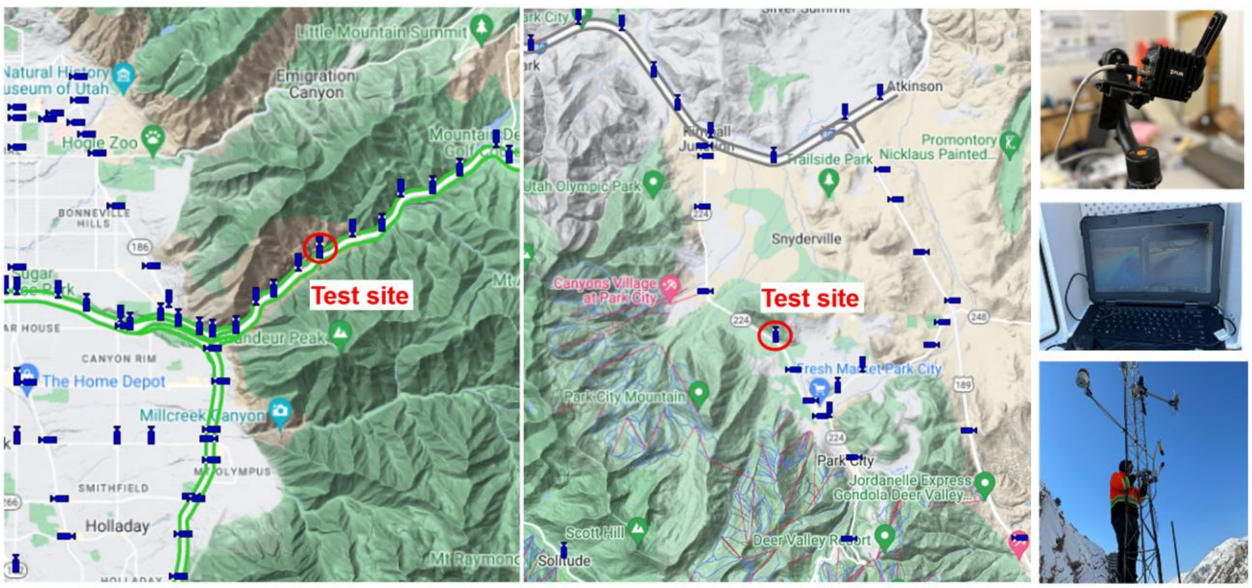
3 DATA COLLECTION AND METHODOLOGY

3.1 Field Data Collection

Field data were collected at two major highway corridors in Utah: Parley's Summit on I-80, as shown in Figure 1(a), and the Park City corridor (RWIS SR-224 at Meadows Drive), as shown in Figure 1(b), both of which experience frequent winter storms, rapid temperature fluctuations, and complex freeze–thaw cycles. These locations were strategically selected to capture a broad range of winter pavement conditions under real-world operating environments. The on-site equipment installation, including the infrared camera and field monitoring laptop, is shown in Figure 1(c). The overall multi-season data-collection periods are summarized in Table 2. During data preparation, the team encountered technical difficulties, including asynchronous dual-spectrum images and hard drive errors, which resulted in reduced data available for model training. As the goal is proof-of-concept for the IRT-based technology, we focused on several monitoring periods covering multiple storm events and transitional road-surface conditions, as shown in Table 3. It is notable that the results from the Park City site do not conform to expectations. While snow detection is viable via computer vision algorithms, the particular infrared sensor does not indicate ice detection due to its coarse resolution and sensitivity. Therefore, the research focused on in this report analyzes the data collected from the Parley's summit site with the FLIR infrared camera.

Representative optical and thermal imagery obtained via the dual-spectrum camera during data collection is presented in Figure 2, demonstrating the wide variability in lighting, snowfall intensity, traffic activity, and pavement surface states. Collectively, these multi-season, multi-modal datasets form a comprehensive foundation for the development, training, and evaluation of the proposed road-condition classification system.

The collected dataset captures a wide range of winter road-surface conditions, enabling the development of a robust multi-class classification system. Four target categories, dry, wet, snowy, and icy, are visually represented in Figure 3(a), (b), (c), and (d), respectively. Dry pavement (Figure 3 (a)) appears uniform with consistent brightness and minimal texture variations. Wet pavement (Figure 3 (b)) displays darker regions and reflective streaks caused by surface moisture. Snow-covered pavement (Figure 3 (c)) shows bright, granular patterns with varying thickness due to snowfall intensity, plowing, or drifting. In contrast, icy pavement (Figure 3 (d)) exhibits smooth, low-texture areas that may resemble wet pavement but present subtle tonal and reflectance differences, especially under colder temperatures. These four categories form the basis of the labeling strategy used throughout this study and serve as the ground truth for training and evaluating both optical and thermal classification models.



(a) (b) (c)

Figure 1 Field deployment locations and hardware setup: (a) RWIS test site at Parley's Summit along I-80; (b) RWIS test site near Park City; (c) on-site installation of the dual-spectrum FLIR camera system integrated with existing RWIS

Table 2 Summary of Multi-Season Data-Collection Periods at Two Field Sites.

Location	Winter Season 1	Winter Season 2
I-80 Parley's	Feb 2- April 14, 2023	Nov. 21, 2023 to Apr. 11, 2024
Park City	-	Nov. 21, 2023 to Apr. 11, 2024

Table 3 Focused Monitoring Periods Used for Capturing Snowstorms and Transitional Winter Road-Surface Conditions for Both Field Sites.

Location	Period 1	Period 2
I-80 Parley's	March 30-April 7, 2023	Jan 3-9, 2024
Park City	Jan 3-9, 2024	April 4-8, 2024

(a) (b) (c) (d)

Figure 2 Representative thermal and optical images from the field site showing winter roadway conditions during (a and b) daytime and (c and d) nighttime

(a) (b) (c) (d)

Figure 3 Examples of road-surface conditions captured in the dataset: (a) dry, (b) wet, (c) snowy, and (d) icy

3.2 Data Processing Workflow

The preprocessing workflow, illustrated in Figure 4, standardizes the incoming optical images prior to feature extraction and classification. The process begins with fisheye distortion correction on optical images (Figure 4(a)) to remove lens curvature and restore true roadway geometry. Next, a trapezoidal masking step (Figure 4(b)) isolates the pavement region by removing sky, roadside features, and other irrelevant background elements while also excluding frames in which vehicles obstruct the view. Following region isolation, a perspective transformation (Figure 4(c)) converts the oblique roadside camera angle into a consistent, top-down representation of the pavement surface, ensuring geometric uniformity across different days, weather conditions, and installation angles. Additional normalization steps reduce brightness variations caused by snowfall intensity, illumination changes, or environmental conditions. The final output of this preprocessing pipeline is a set of geometrically corrected, background-filtered, and visually standardized images that preserve critical road-surface features while eliminating noise and irrelevant content. This ensures that subsequent feature-extraction and classification stages operate on clean, consistent, and reliable inputs. For the collected infrared images, the last two steps of trapezoidal masking and perspective transformation were conducted for preprocessing purposes.

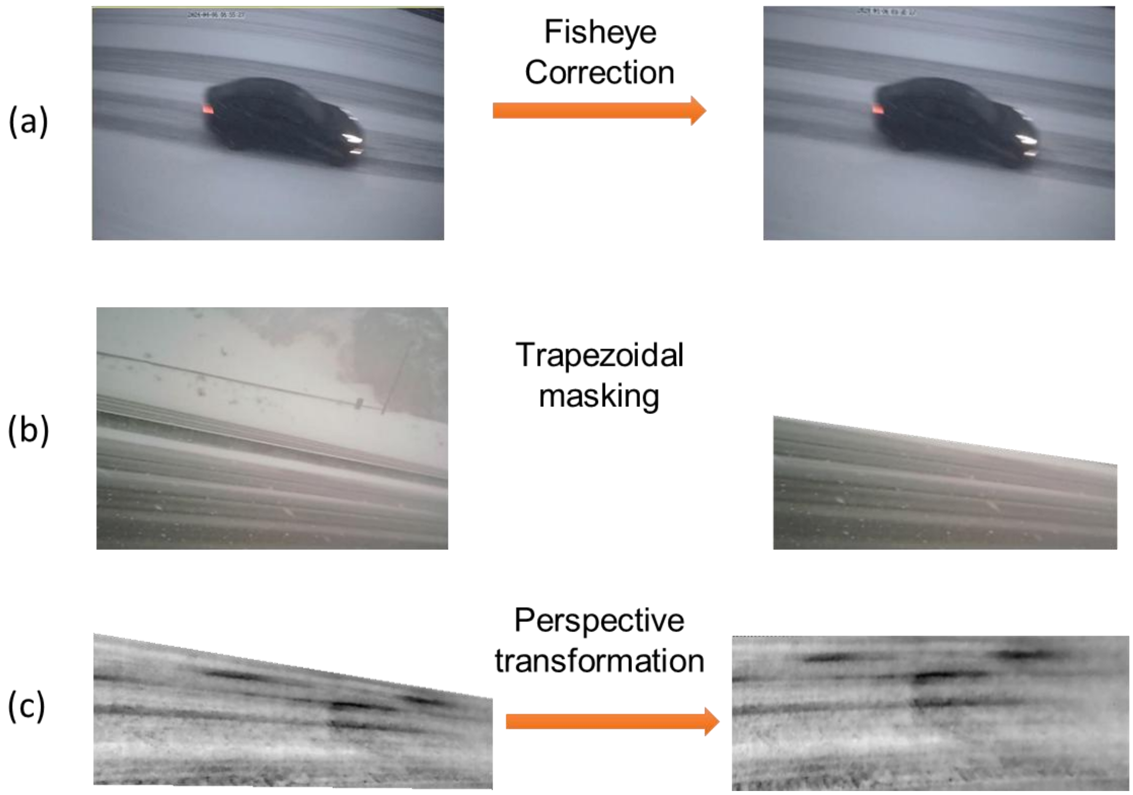


Figure 4 Preprocessing pipeline for optical images: (a) fisheye distortion correction; (b) trapezoidal masking to isolate the roadway region; and (c) perspective transformation to generate a top-down road surface

The overall decision-making framework of the proposed road-condition classification system is illustrated in Figure 5, which outlines the full sequence of operations from raw data acquisition to final surface-condition output. The pipeline begins with the simultaneous collection of optical and thermal images from roadside camera units. A car-passing detection module first evaluates whether a vehicle is present in the frame; frames containing vehicles are excluded to ensure that only unobstructed pavement areas are analyzed. For remaining frames, the system determines whether conditions correspond to daytime or nighttime, enabling an adaptive selection of the most informative sensing modality. During daytime, optical images are routed to Feature Extraction 1, where brightness, dark-channel, and texture-based descriptors are computed before being processed by Classifier 1, which predicts dry, wet, or snowy conditions. During nighttime, or when low visibility compromises optical imagery, the system transitions to thermal-based analysis. Thermal images pass through Feature Extraction 2, where grayscale contrast, thresholding, and Sobel-edge features are generated, and are subsequently classified by

Classifier 2 into dry, wet, snow, or ice. The outputs from each classifier flow into the final decision layer, which provides the corresponding pavement-condition label. This modular flowchart structure in Figure 5 ensures consistent performance across varying lighting, weather, and traffic conditions.

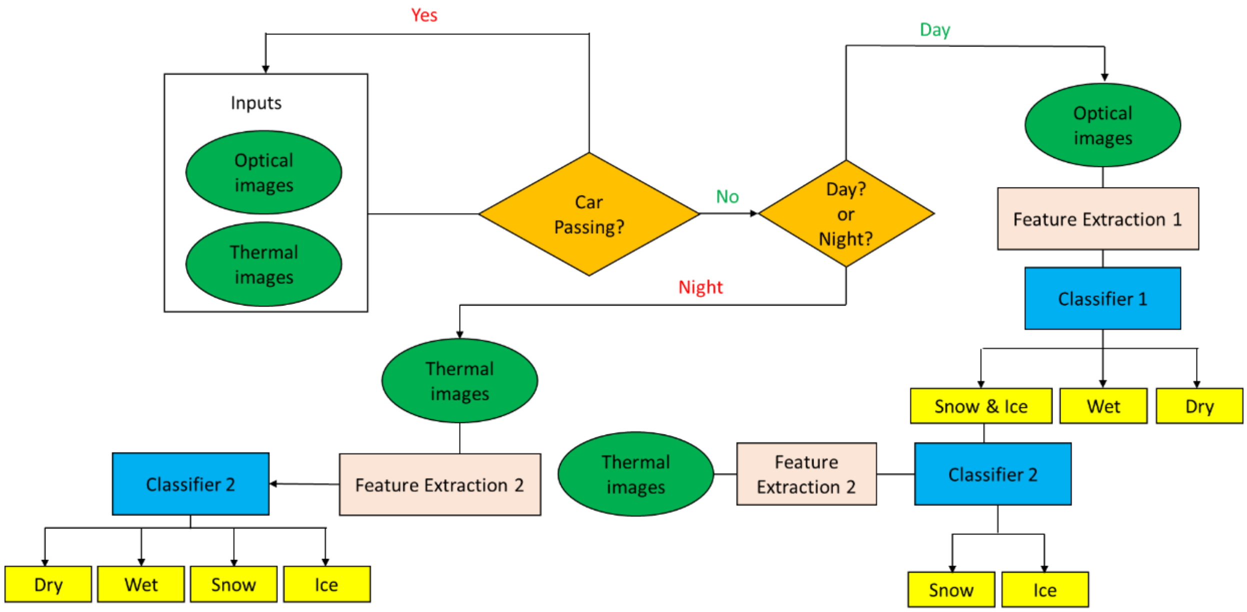


Figure 5 System flowchart outlining the complete roadway surface condition classification framework, including data acquisition, preprocessing, feature extraction, and multi-stage classification

The workflow for the daytime optical classifier is illustrated in Figure 6, which outlines the training pipeline for Classifier 1. The process begins with the curated optical-image dataset, which is first divided into training and validation subsets to ensure unbiased performance evaluation. Standard image transformations and augmentation techniques are then applied to enhance robustness against varying lighting, snow intensity, and subtle visual differences in pavement appearance. A pretrained ResNet-18 model is loaded as the feature extractor, and its convolutional backbone is frozen to preserve the generalized low-level features learned from large public image datasets. The original classification head is replaced with a newly designed fully connected network consisting of a Linear (512→128) layer followed by ReLU activation, dropout regularization, and a final Linear (128→4) output layer corresponding to the target categories (dry, wet, snowy, and snow/ice merged where necessary). During training, only the new classification head is optimized using the cross-entropy loss function and the Adam optimizer, allowing the model to adapt efficiently to domain-specific visual cues. After each epoch, validation metrics, including accuracy, precision, and recall, are computed, and an early-stopping mechanism halts training when performance plateaus. This pipeline enables Classifier 1 to reliably interpret daytime optical images and distinguish among visually separable winter road conditions.

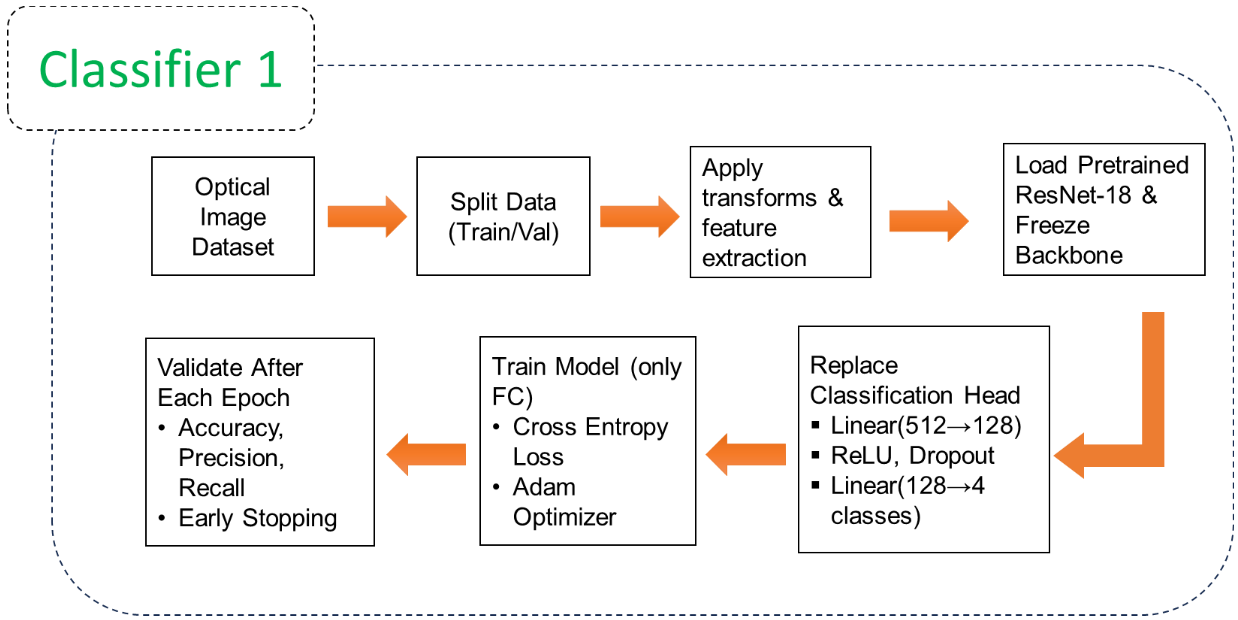


Figure 6 Classifier 1 architecture for daytime roadway surface condition assessment, including brightness analysis and dark-channel extraction

The thermal-image classification pipeline is shown in Figure 7, detailing the workflow for Classifier 2, which is designed to operate during nighttime or low-visibility conditions when optical images become unreliable. The process begins with assembling a thermal-image dataset, followed by splitting the data into training and validation sets. A suite of physically informed feature-extraction steps is then applied to each thermal frame: (1) the raw thermal image is first converted to grayscale, (2) a threshold map is generated to highlight cold regions indicative of ice, (3) vertical Sobel edge detection is applied to capture sharp thermal gradients formed at the boundaries of icy patches, and (4) the three resulting channels—grayscale, threshold map, and Sobel edges—are stacked to form a unified 3-channel input representation. After applying the required transformations, this processed image is fed into a pretrained ResNet-18 model with a frozen backbone, mirroring the transfer-learning strategy used in Classifier 1. The classifier head is replaced with the same fully connected architecture (Linear(512→128) → ReLU → Dropout

→ Linear(128→4)), which is then trained using cross-entropy loss and the Adam optimizer. Validation metrics are computed after each epoch, and an early-stopping criterion ensures optimal generalization. This design enables Classifier 2 to effectively leverage thermal-gradient patterns and cold-region features to accurately detect not only dry, wet, and snow conditions, but also ice, which is often visually ambiguous in optical imagery.

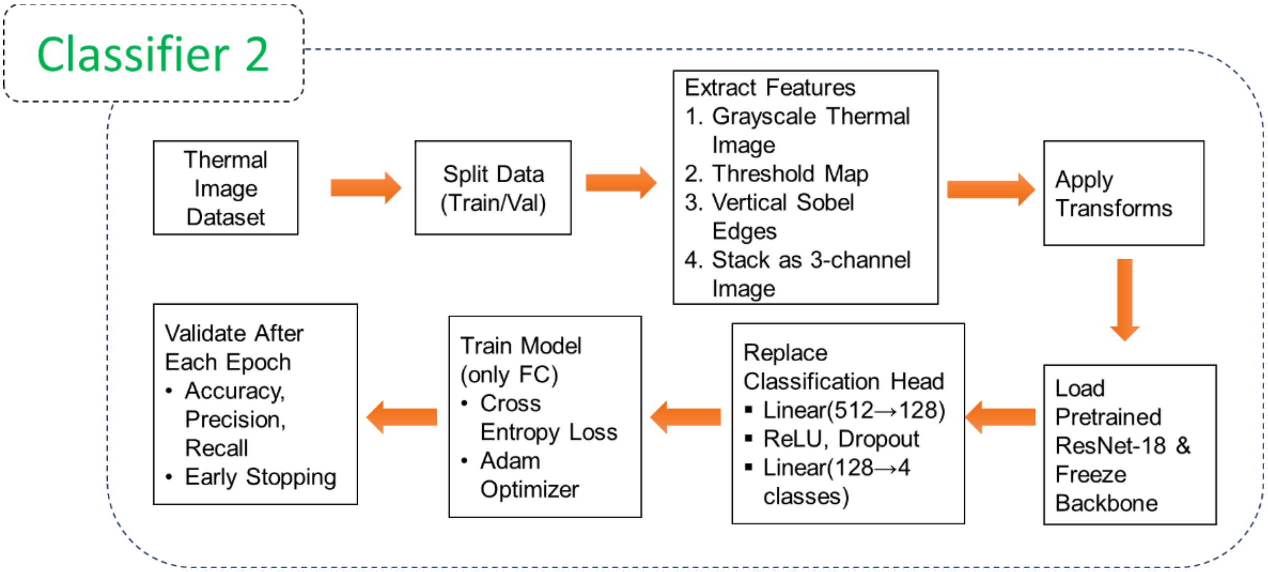
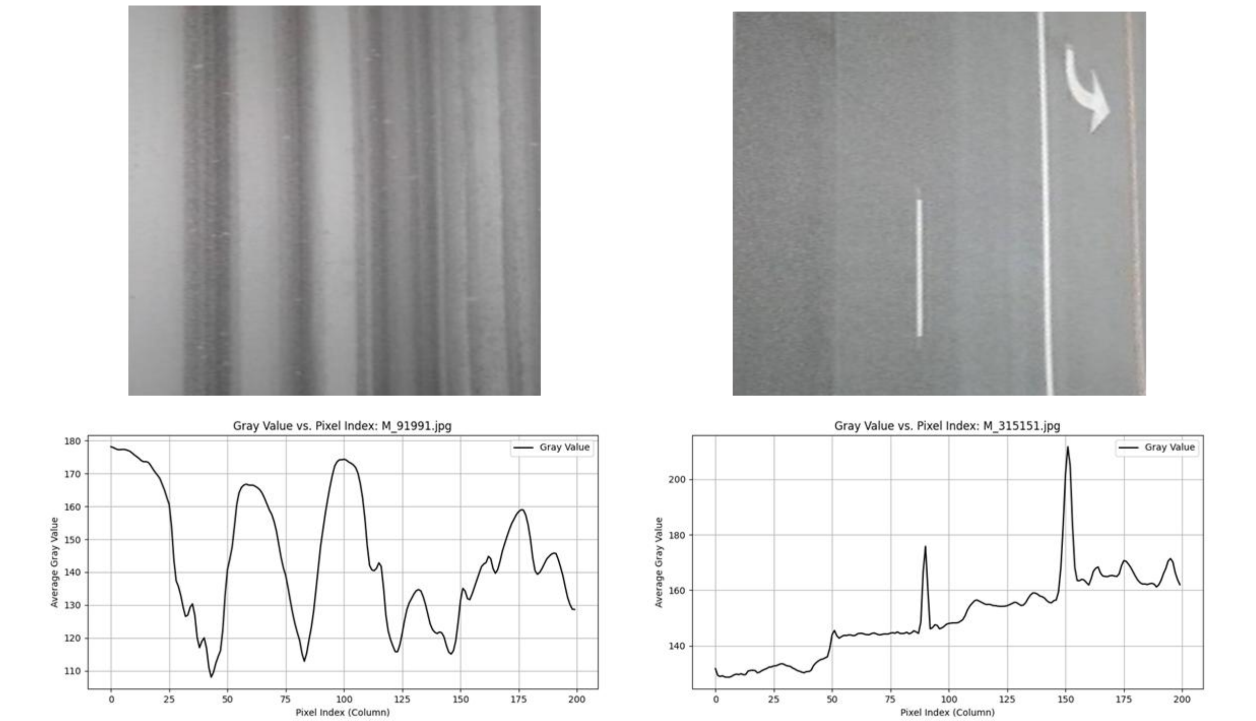


Figure 7 Classifier 2 architecture for nighttime roadway surface condition assessment using thermal imaging, integrating thresholding and Sobel edge detector-based feature extraction

Feature extraction from optical images focuses on capturing texture-, brightness-, and contrast-related cues that distinguish different road surface states under daytime visibility. As illustrated in Figure 8, color optical images are first converted to grayscale, reducing redundancy while preserving essential structural information. Representative examples in Figure 8 show how dry and snowy surfaces produce distinct gray-value distributions, which are further visualized through pixel-intensity profiles. These profiles reveal meaningful fluctuations caused by snow accumulation, water films, or bare pavement, enabling the optical classifier to learn discriminative patterns directly from spatial and intensity-based textures. The resulting grayscale and intensity-profile features form the core of the daytime classification module, allowing the model to reliably differentiate road states when optical imagery is clear and well illuminated.



(a) (b)

Figure 8 Optical image feature extraction process of brightness analysis: (a) snowy roadway and (b) dry roadway

Thermal feature extraction, as shown in Figure 9, focuses on capturing temperature-driven characteristics that reveal hazardous conditions, such as ice or compacted snow, particularly in low-visibility scenarios. Thermal images are first converted to grayscale thermal maps, followed by perspective correction to transform the side-view camera angle into a consistent top-down representation of the pavement. Additional feature maps, including adaptive thresholding outputs that isolate colder (potentially icy) regions and vertical Sobel edge maps that highlight temperature gradients, are computed and stacked to create a multi-channel representation of the thermal scene. These processed features amplify subtle thermal variations that are not apparent in the raw imagery, enabling the thermal classifier to perform robustly during nighttime, storms, and cases where optical imagery provides limited information. Together, the feature extraction steps in Figure 8 and Figure 9 ensure that each modality contributes complementary, high-quality information to the overall classification framework.

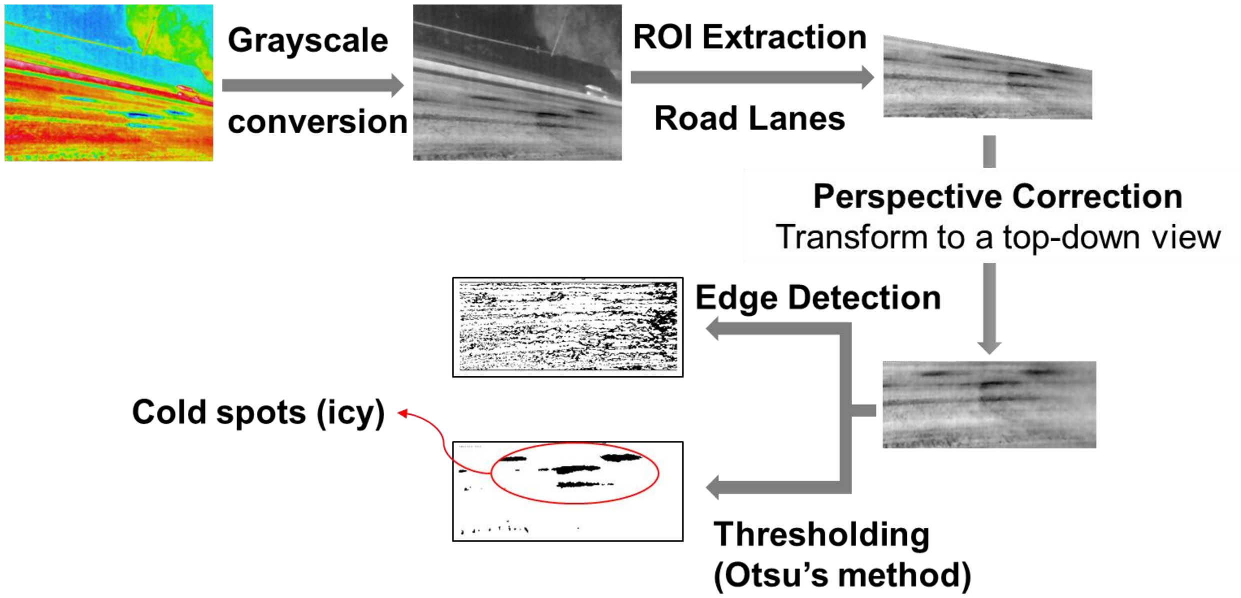


Figure 9 Thermal image feature extraction workflow: threshold-based region segmentation and Sobel edge detection to highlight temperature transitions and delineate icy surface boundaries

Figure 10 presents representative examples of four target road-surface conditions: (a) dry, (b) wet, (c) snowy, and (d) icy—along with their corresponding thermal feature maps. The first column shows the grayscale thermal images, capturing the raw pavement temperature distribution. The middle and right columns display the binary threshold maps and vertical Sobel edge responses, respectively, which highlight thermal and structural cues relevant to classification. Dry roadway (Figure 10(a)) exhibits uniform temperature fields with minimal threshold activation and weak edge responses, consistent with the absence of moisture or surface irregularities. Wet roadway (Figure 10(b)) shows smoother textures but higher localized contrast, resulting in intermittent threshold activation and more pronounced edge responses due to thin water films. Snow-covered roadways (Figure 10(c)) produce bright, elevated thermal regions and strong, widespread activation in both threshold and Sobel maps, reflecting significant surface roughness and accumulated snow. Icy roadway (Figure 10(d)) reveals distinct cold patches with sharp binary segmentation and clear vertical gradient transitions, enabling reliable separation from wet or compacted snow surfaces. Collectively, the examples in Figure 10 demonstrate how thermal imaging and derived feature maps capture the key physical characteristics of winter road states, supporting robust multi-class classification in the proposed framework. The ground truth of the roadway surface condition was obtained via data collected by the nearby RWIS station.

To evaluate the performance of both the optical and thermal classifiers, three standard metrics were used: Accuracy, Precision, and Recall, defined in the equations below. Accuracy measures the overall proportion of correctly classified samples, providing a broad indication of model correctness. Precision quantifies the percentage of predicted positives that are truly correct, reflecting the model's ability to minimize false positives. Recall, also known as sensitivity, measures how effectively the model identifies all actual positives, indicating its ability to reduce false negatives. Together, these metrics enable a comprehensive assessment of classifier reliability across the different winter road-surface conditions.

$$Accuracy = \frac{TP}{TP+FP+FN} \tag{3-1}$$

$$Precision = \frac{TP}{TP+FP} \tag{3-2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3-3}$$

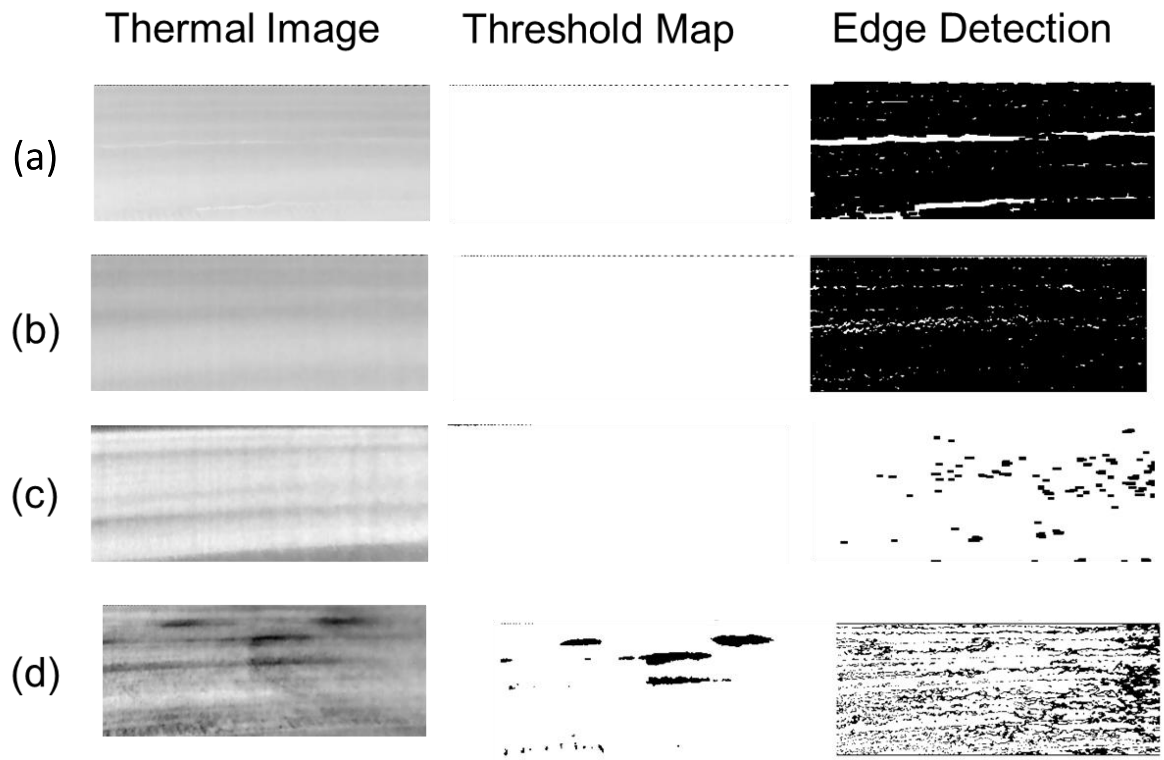


Figure 10 Examples of thermal-image feature representations for four road-surface categories: (a) dry, (b) wet, (c) snowy, and (d) icy with corresponding grayscale images, threshold maps, and Sobel edge responses used for classification

4 RESULTS ON ICE AND SNOW DETECTION

The performance of the optical-image classifier (classifier 1) was evaluated using accuracy, precision, and recall over 20 training epochs. As shown in Figure 11, the model converged rapidly, reaching perfect scores (1.00) for all three metrics by the second epoch and maintaining this performance for the remainder of training. This rapid stabilization indicates that the classifier effectively learned the visual distinctions between dry, wet, and snowy pavement conditions with minimal overfitting or oscillation. The tightly overlapping curves for accuracy, precision, and recall further suggest balanced performance, with no trade-offs between false positives and false negatives during training.

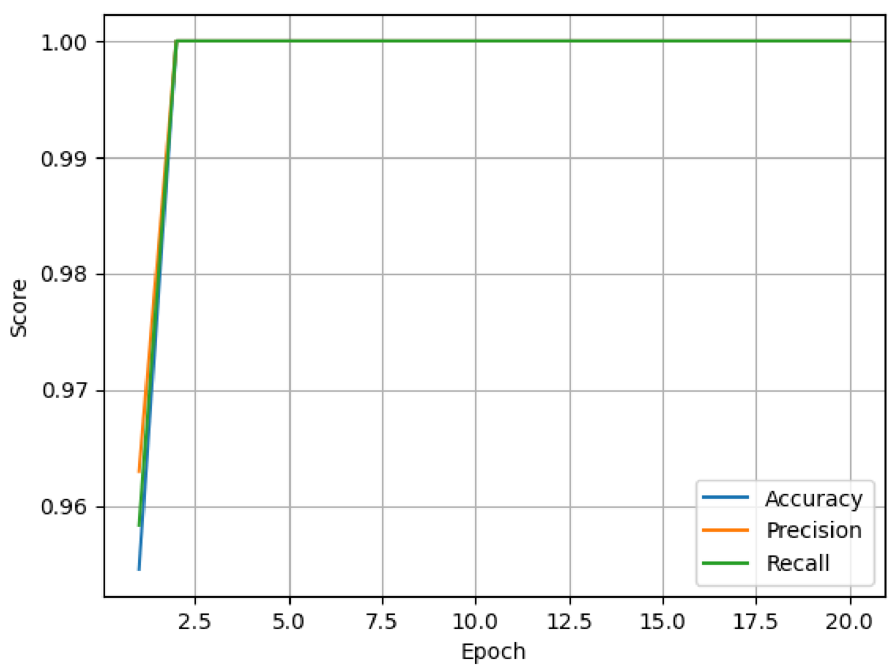


Figure 11 Training performance of the optical classifier showing accuracy, precision and recall over 20 epochs

The generalization performance on the held-out test set is illustrated in the confusion matrix in Figure 12. The classifier achieved 100% accuracy, correctly identifying all 53 dry, 44 wet, and 51 snowy roadway conditions without a single misclassification. As the optical images cannot distinguish between snowy and icy roadway conditions, only three road surface conditions (dry, wet, and snowy) were considered. Every row and column contains non-zero values only on the diagonal, confirming that the model successfully captured the unique visual characteristics of each surface state. The absence of confusion between wet and snowy, often the most visually similar classes under variable lighting and moderate snowfall, highlights the effectiveness of the preprocessing pipeline and the discriminative power of the optical features. Overall, the results demonstrate that the optical classifier provides highly reliable performance under daytime conditions where visual information is most informative.

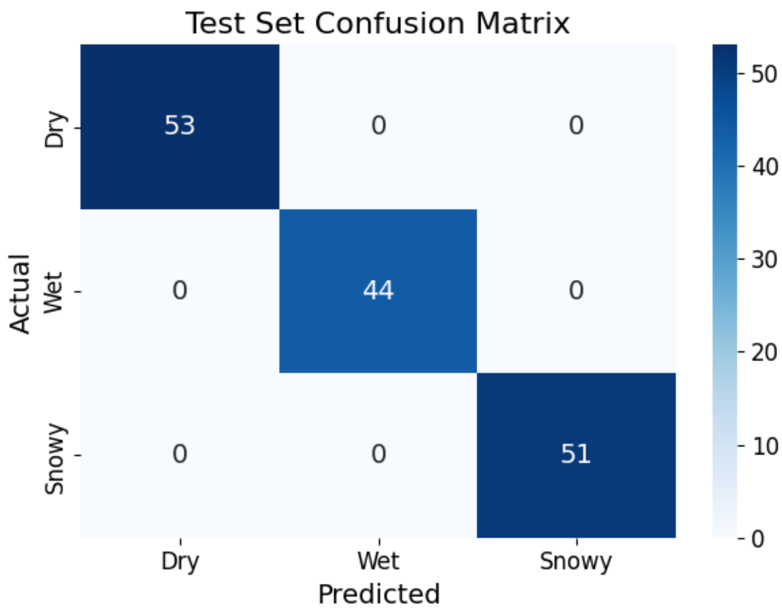


Figure 12 Confusion matrix for the optical classifier evaluated on the test dataset

The thermal classifier (classifier 2) demonstrates strong and stable learning behavior, as shown in Figure 13. Precision and recall increase rapidly during the early epochs and gradually converge to consistent values around 0.85–0.90, indicating that the model effectively extracts meaningful features from thermal imagery despite sensor noise and low contrast. The slight divergence between the two curves is expected given the complexity of thermal road patterns and the limited amount of labeled thermal data. Overall, the smooth convergence of both metrics suggests that the model learns robust thermal features without signs of overfitting.

The performance of the thermal classifier or classifier 2 on the held-out test set is illustrated by the confusion matrix in Figure 14. The model correctly identifies the majority of samples across all four categories (dry, wet, snow, and ice) with most predictions concentrated along the diagonal. Misclassifications occur primarily between visually similar conditions, such as wet versus snow and snow versus ice, reflecting the subtle thermal differences that arise during transitional weather periods. Despite these challenges, the classifier achieves strong overall performance, demonstrating the capability of thermal features, including temperature gradients, cold-spot distributions, and textural cues, to reliably distinguish roadway slippery conditions.

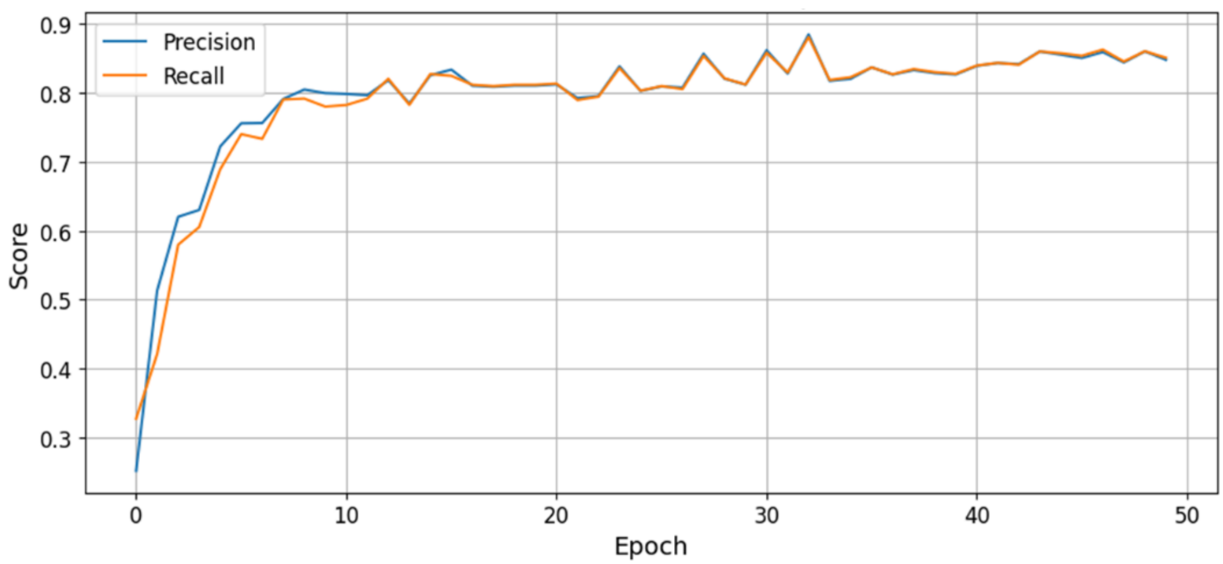


Figure 13 Training performance of the thermal classifier showing precision and recall over 50 epochs

Figure 15 presents the per-class accuracy, further highlighting the classifier's balanced performance. Snow achieves the highest accuracy due to its distinct thermal signature, while wet and icy surfaces show slightly lower accuracy because their thermal patterns often overlap in low-temperature environments. Even so, all classes maintain accuracy above 85%, confirming the effectiveness of the thermal-based methodology. These results underscore the value of thermal imaging as a complementary sensing modality, particularly in nighttime or low-visibility conditions where optical methods degrade. Combining these thermal insights with optical classifier outputs strengthens the robustness of the overall road-condition recognition system.

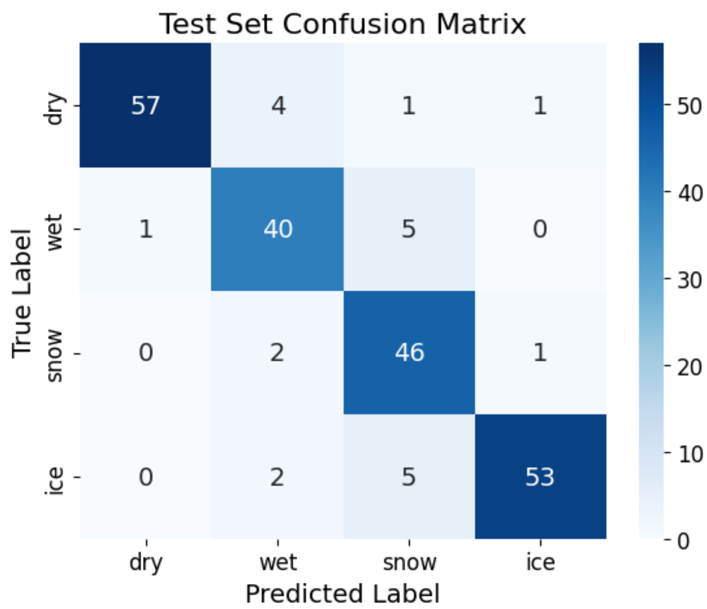


Figure 14 Confusion matrix for the thermal classifier on the test dataset across four categories (dry, wet, snow, and ice)

Figure 16 illustrates the time history of the predicted road-surface conditions compared with the ground-truth labels over a full storm event, providing an end-to-end evaluation of the proposed framework under real operational conditions. The model successfully captures major transitions between Wet, Snowy, Icy, and Dry states, closely matching the temporal patterns observed in the ground truth. Occasional short-term deviations occur during rapidly changing conditions, particularly around Snowy–Icy boundaries, yet the overall temporal agreement remains strong, reflected by a correlation coefficient of 0.81. A few false negatives were observed on the night of March 31 and early morning of April 1, which occurred due to the lack of a vehicle detection mechanism at night. This result demonstrates that the integrated optical-thermal classification framework is capable of reliably monitoring road-surface evolution over time, even in the presence of variable illumination, snowfall intensity, and temperature fluctuations. Collectively, the high per-class accuracy, stable training behavior, and strong temporal correlation confirm that the full system performs robustly and is well suited for continuous winter road-condition assessment in real-world deployments. Once a slippery condition is detected, the information can be converted to the Traveler Information Message

(TIM). Figure 17 shows an example TIM, which displays a warning when an icy roadway condition is detected.

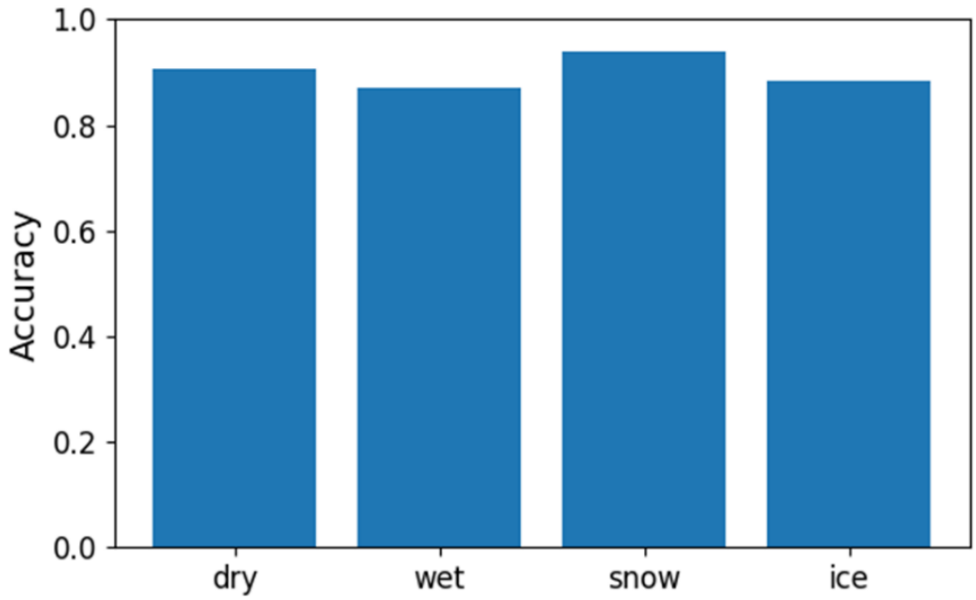


Figure 15 Per-class accuracy of the thermal classifier across all four surface conditions

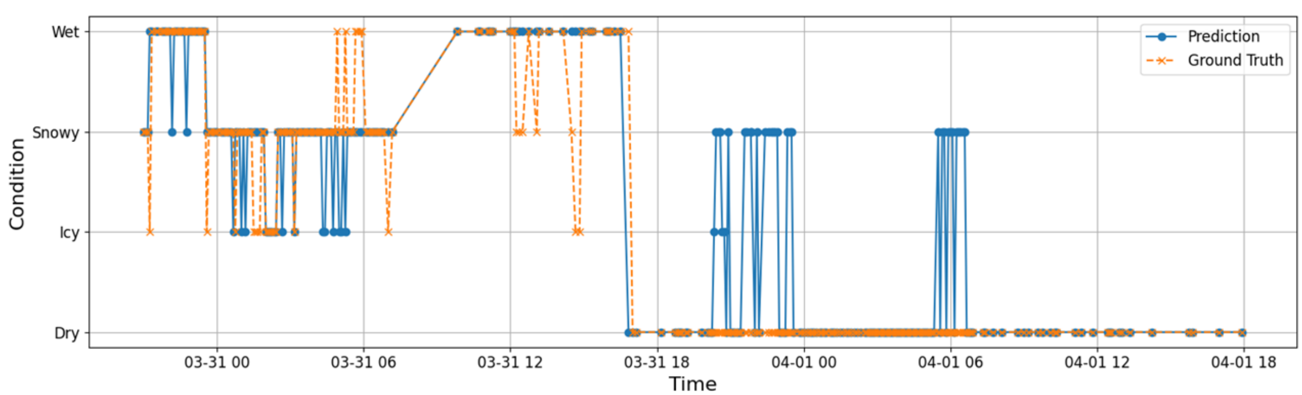


Figure 16 Time history of road-condition classification results compared with ground-truth labels over a full snowstorm on March 31, 2024, at the I-80 Parley's Summit site

```
{
  "msgID": "TIM",
  "packetID": "road_cond_001",
  "startTime": "2025-06-23T08:00:00Z",
  "duration": 3600,
  "priority": 7,
  "msgContent": {
    "location": {
      "lat": 39.0012,
      "long": -76.9356,
      "elevation": 51.3
    },
    "heading": 270,
    "width": 3.5,
    "extent": 100,
    "advisory": {
      "type": "Warning",
      "text": "Slippery road: icy roadway reported",
      "category": "hazard",
      "severity": "high"
    }
  }
}
```


Figure 17 Sample TIM for roadway slippery condition warning

5 CONCLUSIONS

This study introduced a dual-modal framework that uses both optical and thermal cameras to identify winter road conditions with high reliability. By combining these two sensing approaches with a tailored preprocessing pipeline (fisheye correction, masking, and perspective alignment) and a transfer learning framework, the developed technology can clearly distinguish four roadway surface conditions, including dry, wet, snowy, and icy. The field data collected from two major Utah highway corridors provided a strong foundation for training the optical and thermal classifiers, each of which performed well across a wide range of storm events. Notably, the system was able to closely follow real changes in roadway conditions during an active storm, achieving a correlation of 0.81 with RWIS ground-truth data. The optical classifier achieved excellent performance in identifying daytime roadway states, while the thermal classifier demonstrated strong accuracy under nighttime and low-visibility conditions and successfully detected icy pavement signatures. When tested across full storm evolution periods, the system closely tracked temporal transitions in roadway surface conditions, confirming strong potential for real-time operational monitoring. These results show that integrating multiple sensor types can offer a dependable and scalable approach for monitoring winter road conditions in real time.

These findings indicate that integrating IRT sensing with machine-learning analytics can augment or complement UDOT's current SWIW capabilities, potentially at non-RWIS locations, along complex mountainous corridors. The technology provides a pathway toward enhanced roadway situational awareness, improved safety messaging for connected vehicles, and more proactive winter maintenance strategies.

Future work should focus on expanded deployments, larger datasets across broader environments, framework integration with UDOT CV infrastructure, and continued algorithm refinement to further improve nighttime and transitional-condition performance. With continued development, IRT-enabled roadway monitoring can become a key component of Utah's winter safety ecosystem. In conclusion, this research confirms that dual-spectrum camera systems offer a new and powerful way to identify winter road-surface conditions. With further deployment and integration, they can become central tools in proactive intersection safety management.

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