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MOBILE PHONE-BASED ARTIFICIAL INTELLIGENCE DEVELOPMENT FOR MAINTENANCE ASSET MANAGEMENT

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16. Abstract

Transportation asset management requires timely information collection to inform relevant maintenance practices. Traditional data collection methods often necessitate manual operation or the use of specialized equipment, e.g., light detection and ranging (LiDAR), which can be labor-intensive and costly to implement. With advancements in computing techniques, artificial intelligence (AI) has emerged as a powerful tool for automatically detecting objects in images and videos. Therefore, this project aims to develop an implementable AI package that streamlines the inspection of transportation assets through automated processes. Specifically, a smartphone was mounted on the vehicle's front windshield to record videos of transportation assets on both highways and local roads in Utah. These videos were then converted and processed into labeled images, which served as training and test datasets for the AI algorithms. Based on a deep learning framework, i.e., You Only Look Once (YOLO), we developed accurate and efficient AI algorithms to automatically detect and identify transportation assets, which include pavement marking issues, traffic signs, litter and trash, and steel guardrails and concrete barriers. The developed AI models demonstrate good performance in identifying targeted objects, achieving over 85% accuracy. The AI package developed in this project is expected to enable timely and efficient information collection for transportation assets, thereby improving road safety.

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Mobile Phone-Based Artificial Intelligence Development for Maintenance Asset Management

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ABSTRACT

Transportation asset management requires timely information collection to inform relevant maintenance practices. Traditional data collection methods often necessitate manual operation or the use of specialized equipment, e.g., light detection and ranging (LiDAR), which can be labor-intensive and costly to implement. With advancements in computing techniques, artificial intelligence (AI) has emerged as a powerful tool for automatically detecting objects in images and videos. Therefore, this project aims to develop an implementable AI package that streamlines the inspection of transportation assets through automated processes. Specifically, a smartphone was mounted on the vehicle's front windshield to record videos of transportation assets on both highways and local roads in Utah. These videos were then converted and processed into labeled images, which served as training and test datasets for the AI algorithms. Based on a deep learning framework, i.e., You Only Look Once (YOLO), we developed accurate and efficient AI algorithms to automatically detect and identify transportation assets, which include pavement marking issues, traffic signs, litter and trash, and steel guardrails and concrete barriers. The developed AI models demonstrate good performance in identifying targeted objects, achieving over 85% accuracy. The AI package developed in this project is expected to enable timely and efficient information collection for transportation assets, thereby improving road safety.

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EXECUTIVE SUMMARY

Timely information collection and assessment of transportation assets are essential for the daily maintenance practices of state departments of transportation (DOTs). Traditional transportation asset assessment methods often rely on labor-intensive manual data collection or employ costly devices, such as light detection and ranging (LiDAR), which are prohibitive in frequent data collection due to high operational costs. With advancements in computing techniques, artificial intelligence (AI), including computer vision and deep learning, has demonstrated capabilities in automatic and accurate object detection, comparable to human vision. This project aims to explore the applicability of AI in transportation-related applications by developing reliable and accurate AI algorithms for automatic object identification. These AI models will focus on identifying pavement marking issues, traffic signs, trash and litter on the roads, and steel guardrails and concrete barriers. By integrating AI into transportation asset management, we aim to improve current practices, making them more efficient and cost-effective.

This project began by reviewing the pros and cons of existing technologies for transportation asset data collection. Commonly used techniques include ground-penetrating radar, LiDAR, infrared thermography, and close-range photogrammetry. Among these, close-range photogrammetry is considered a reliable method for timely information collection without excessive cost. We also reviewed AI algorithms applied in transportation asset monitoring and inspection, including regional convolutional neural networks (RCNN), Faster RCNN, and You Only Look Once (YOLO). YOLO, a deep learning-based AI algorithm, excels in object detection with high accuracy and computational efficiency. While these AI algorithms have been widely used for pavement issue identification, there has been limited research on applying AI to detect pavement marking issues, trash and litter on roads, and steel guardrails and concrete barriers.

To address this, we mounted a smartphone on a vehicle's front windshield to collect videos of targeted transportation assets and issues on state highways and local roads in Utah. In total, approximately 31 hours of videos were collected, capturing pavement markings, traffic signs, steel guardrails, concrete barriers, and roadside litter and trash. These videos were processed into labeled images to train robust AI algorithms. Using these labeled images as training and test data, we developed three AI models for the automatic detection of pavement marking issues, traffic signs, and litter and trash. Specifically, the AI model for pavement marking issues can detect faded white and yellow pavement markings. The traffic sign model can identify regulatory signs, speed-related signs, warning signs, and guide signs. The litter and trash model can detect white litter, black litter, dirt, and leaves on the roadside. Additionally, we developed a prototype AI model to identify steel guardrails and concrete barriers. Iterative training and tuning ensured the robust performance of these algorithms. The results show that the developed AI models achieve good performance, with over 85% accuracy in transportation asset identification.

The mobile phone-based AI package developed in this project offers an accurate, efficient, and automated approach to collect and analyze transportation asset data. This enables more frequent inspection of transportation assets, ultimately improving road safety.

1. INTRODUCTION

1.1 Background

Transportation assets, such as pavement markings, traffic signs, and guardrails, are the backbone of our transportation systems, contributing to the overall safety and efficiency of our transportation network (Akofio-Sowah et al., 2014; FHWA, 2009). However, over time, these assets are subjected to various environmental factors, heavy usage, and natural wear and tear, which all lead to damage or deterioration (Sassani et al., 2021; S. Xu et al., 2021). For example, pavement markings and traffic signs may become faded or damaged, reducing their effectiveness in conveying important information to road users (Alzraiee et al., 2021; Kuang et al., 2024). Common issues with traffic signs include fading, damage, obstruction, and misplacement, which can lead to reduced visibility and misinterpretation by drivers (Campbell et al., 2019; Gudigar et al., 2016). Guardrails and barriers may experience corrosion or structural weaknesses, compromising their ability to protect vehicles and occupants in the event of a crash (Jin et al., 2024; Li et al., 2018). Also, objects such as plastic bottles, discarded packaging, or vehicle debris on the roadside can cause crashes by obstructing the road or creating hazards that lead to loss of control or tire damage (Chamberlin et al., 2021; Karimi and Faghri, 2021). Therefore, effective transportation asset management and maintenance is necessary to ensure their continued functionality and safety.

Transportation asset management and maintenance needs periodic inspection of transportation asset conditions, such as evaluating the structural integrity, functionality, and visibility (FHWA, 2009; Sinha et al., 2017). Traditional methods of assessing transportation asset conditions have relied heavily on manual efforts or the use of specialized sensing equipment, e.g., light detection and ranging (LiDAR) and retroreflectometers. (Pike et al., 2011; Wei et al., 2021). These approaches are labor-intensive, time-consuming, and costly to implement (Lin et al., 2022; Schnebele et al., 2015; Solla et al., 2014). Hence, there is an urgent need to develop a lightweight technique capable of assessing the conditions of transportation assets in a timely and accurate manner.

With the rapid development of artificial intelligence (AI) techniques, there is now an opportunity to revolutionize the transportation asset assessment process. AI techniques, particularly deep learning and computer vision, have enabled object detection and image classification in various fields, including the automated assessment of transportation assets (Du et al., 2020; Ghosh and Smadi, 2021). AI algorithms are able to extract valuable insights by analyzing large volumes of data, such as images (Gopalakrishnan et al., 2017; Majidifard et al., 2020). Computing-based image analysis and object detection are similar to visual inspection by human inspectors (Spencer et al., 2019). Specific to inspecting transportation asset conditions, based on AI algorithms, developed models can be trained to identify patterns, anomalies, or signs of transportation asset issues that may need duplicate efforts through traditional manual inspections (Kawano et al., 2017; Liu et al., 2017; Park et al., 2023). An example of this application is the identification of pavement distresses, such as cracks and potholes (Abdellatif et al., 2020; Koch et al., 2013).

The advantage of AI-based approaches lies in their ability to automate the assessment process, providing more efficient and accurate results (Gao et al., 2021; Sun et al., 2024; Wei et al., 2021). Also, the use of AI in asset assessment can lead to cost savings by reducing the reliance on manual labor or expensive equipment (Gómez et al., 2022; Kuang et al., 2022). Compared with traditional methods, which are vulnerable to missing emerging issues between inspections, AI models can continuously analyze data and detect anomalies and potential problems as they arise (Karballaeezadeh et al., 2020). This continuous monitoring ensures maintenance activities can be scheduled more responsively, addressing issues before they escalate. Furthermore, these developed lightweight AI models can be integrated into existing asset management systems, allowing for real-time or near-real-time monitoring of asset conditions. This enables state departments of transportation (DOTs) to proactively identify maintenance needs, prioritize repairs, and allocate resources effectively.

Therefore, the objective of this project is to create precise and readily implementable AI models that streamline the inspection of transportation assets through automated processes. The proposed AI packages utilize a smartphone mounted on a vehicle's front windshield to capture videos of the road. Based on these self-collected videos, this project further develops an AI package capable of automatically assessing the conditions of pavement markings, identifying traffic signs, and detecting litter along the roadside. We also created a prototype model for recognizing concrete barriers and steel guardrails. This delivered AI package offers an affordable solution that enables more frequent and efficient data collection for transportation asset maintenance purposes. This approach revolutionizes traditional asset management practices by providing a cost-effective means of acquiring valuable information and assessing the conditions in a timely manner.

1.2 Research Objectives and Scopes

The main research objective of the project is advancing transportation asset management through the application of AI techniques. This study, based on self-collected images, aims to develop a usable AI package that is capable of automatically assessing the condition of pavement marking, identifying traffic signs and steel guardrails/concrete barriers, as well as detecting litter and trash on the roads. Also, the performance of each task is evaluated respectively to verify the capability of leveraging a mobile phone as a lightweight and easily implementable data collection method to facilitate the inspection of transportation assets.

To achieve these research objectives, four specific tasks are involved, illustrated as follows:

Task 1. Literature review: a comprehensive literature review is conducted to explore and examine existing technologies and practices related to transportation asset collection and inspection, including emerging AI technologies.

Task 2. Data collection: A mobile phone, mounted on a vehicle, is used to collect data by recording videos while driving on the highways and street roads of Utah. The capability of AI in transportation asset identification and condition assessment is pre-evaluated.

Task 3. AI package development: Based on self-collected images and utilizing AI algorithms, multiple AI models are developed to inspect and identify transportation assets, including assessing the condition of pavement markings, identifying the various traffic signs, and detecting common litter on the roads. The performance of each model is evaluated.

Task 4. AI package development (proof-of-concept): An AI prototype model is also developed to identify concrete barriers and steel guardrails.

By achieving these research tasks, the project endeavors to contribute to improving transportation asset management practices. The development of a usable AI package for automatic asset detection, combined with the evaluation of mobile phones as data collection tools, is able to facilitate more efficient, accurate, and accessible transportation asset inspection This advancement has the potential to enhance the operation and maintenance of transportation assets and ultimately improve the overall condition and safety of transportation infrastructure.

1.3 Report Outline

The report is structured into several sections. Section 2 reviews the pros and cons of current practices in transportation asset data collection and explores the existing applications of AI algorithms in transportation asset inspection. Section 3 introduces data collection, AI models, and accuracy metrics for evaluating the developed algorithms. Section 4 presents the results and performance of the AI models, covering the identification of pavement marking issues, traffic signs, and litter/trash, as well as a prototype model for steel guardrail and concrete barrier identification. Finally, Section 5 summarizes the key findings and provides recommendations for future work.

2. LITERATURE REVIEW

2.1 Data Collection of Transportation Assets

Various sensing techniques, such as ground penetrating radar (GPR), light detection and ranging (LiDAR), and infrared thermography (IRT), have been developed and utilized for the collection of transportation asset data, including pavement, pavement markings, and traffic signs.

2.1.1 Ground Penetrating Radar (GPR)

GPR, an electromagnetic-based geophysical method, utilizes radar pulses ranging from 200 mm to 3 m to image the subsurface. It employs either a ground-coupled antenna (60 cm to 3 m) or an air-coupled antenna (200–300 mm) (Schnebele et al., 2015). GPR is a non-destructive geophysical method used for subsurface imaging and mapping. It has proven to be an effective tool in various fields, such as civil engineering, geology, archaeology, and environmental studies (Iftimie et al., 2021; Tešić et al., 2021)

GPR works based on the principle of electromagnetic wave propagation and interaction with subsurface materials, as shown in Figure 2.1. It operates by transmitting short pulses of electromagnetic energy into the ground using a transmitter and antenna system (Tešić et al., 2021). The transmitted energy travels through the subsurface and interacts with different materials, such as soil, rocks, and buried objects. When the transmitted energy encounters a boundary between materials with different dielectric permittivity or encounters buried objects, a portion of the energy is reflected back to the surface. The reflected energy, also known as the return signal, carries valuable information about the subsurface features and objects. A receiving antenna is used to capture the variations in the return signal. The antenna records the amplitude (magnitude) and arrival time of the reflected signal (Tong et al., 2020). By analyzing these variations, it is possible to determine the depth, location, and characteristics of subsurface objects, such as buried utilities, voids, geological layers, and archaeological artifacts.

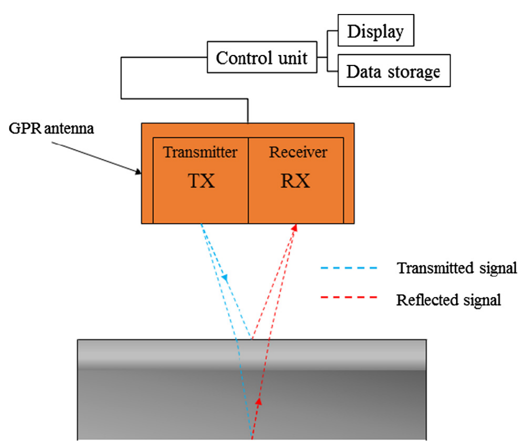

Figure 2.1 The principle of GPR
(Khamzin et al., 2017)

GPR technology has demonstrated its utility in collecting and evaluating pavement conditions, making it an invaluable tool in pavement assessment based on the variation in dielectric permittivity within a pavement segment (Joshaghani and Shokrabadi, 2022; Khamzin et al., 2017). Different pavement conditions exhibit distinct dielectric permittivity values, allowing GPR to differentiate between poor-quality and high-quality pavement (Khamzin et al., 2017; Vilbig, 2013). GPR can operate on moving survey vehicles, as depicted in Figure 2.2. This feature enhances its application in acquiring and evaluating pavement structures and materials. By utilizing GPR on moving vehicles, various pavement characteristics can be measured, including pavement layer thickness, void identification, and detection of pavement distress (Khamzin et al., 2017; Vilbig, 2013).

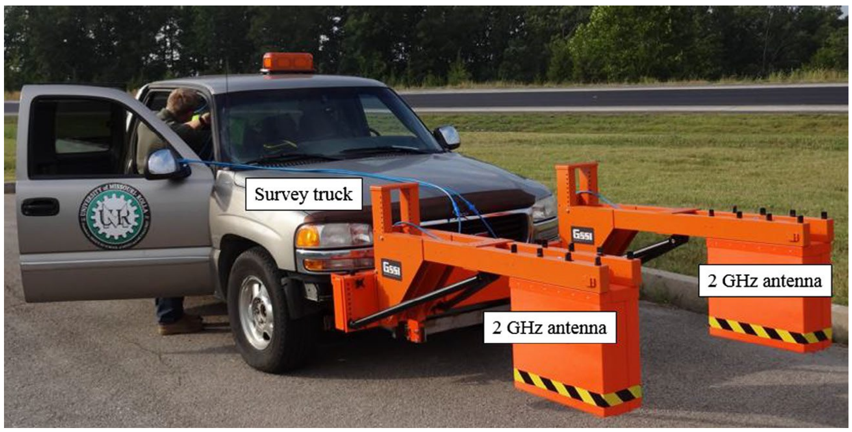

Figure 2.2 GPR Mounted on A Survey Vehicle
(Khamzin et al., 2017)

Although GPR is a valuable technology, it has certain limitations in its application. One limitation is the requirement for operators to possess knowledge of both electromagnetic waves and pavement distress in order to interpret the results obtained from GPR surveys accurately (Tong et al., 2020). The interpretation of GPR data is usually complex and requires expertise to distinguish between various subsurface features and pavement conditions. Another limitation of GPR is its inability to provide precise horizontal information. While GPR can measure the depth and thickness of subsurface irregularities, it is not as accurate in determining the exact horizontal location of features (Schnebele et al., 2015). This means that while GPR can identify subsurface anomalies and variations, it may not provide precise spatial coordinates for mapping purposes. Additionally, GPR is primarily a subsurface detection method and is not suitable for collecting data on aboveground transportation assets such as traffic signs and barriers (Dai and Yan, 2014). Therefore, alternative methods or technologies should be employed to collect information on aboveground transportation assets.

2.1.2 Light Detection and Ranging (LiDAR)

LiDAR is another widely used technology in the field of transportation. Figure 2.3 illustrates the principle of LiDAR, which involves the measurement of ranges by targeting objects with a laser and measuring the time it takes for the reflected light to return to the receiver (Kaartinen et al., 2022).

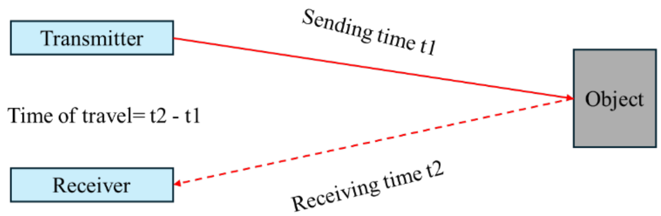

Figure 2.3 The Principle of LiDAR

LiDAR systems can be categorized based on the platforms on which the laser is mounted. Two common types are the terrestrial laser scanner (TLS) and mobile laser scanner (MLS) (Schnebele et al., 2015; Topo, 2020). The TLS is a ground-based remote sensing system typically mounted on static tripods. It scans objects in all directions by emitting laser pulses and capturing the reflected signals. Once a scan in one location is complete, the tripod can be moved to another position to capture data from different angles or cover new areas. TLS is often used for detailed scanning and data collection of specific objects or areas of interest. On the other hand, MLS enables the acquisition of 3D data using one or more laser scanners mounted on moving vehicles, unmanned aerial vehicles (UAVs), or helicopters (Kaartinen et al., 2022). Figure 2.4 depicts an MLS mounted on a moving vehicle. MLS systems capture laser data while the platform is in motion, allowing for the efficient and rapid collection of data over larger areas. MLS is commonly utilized for applications such as topographic mapping, road inventory, and infrastructure monitoring.

Figure 2.4 Mobile LiDAR System on a Moving Vehicle
(Olsen et al., 2018)

LiDAR technology offers several advantages in transportation applications. It can generate highly accurate and detailed 3D point cloud data of transportation assets and has several advantages. First, it has high accuracy and resolution in transportation asset data collection. Second, this technique is not sensitive to the ambient environment of data collection, e.g., humidity or temperature (De Blasiis et al., 2021). However, LiDAR has its own limitations, including a much higher cost than other technologies (Ragnoli et al., 2018; Schnebele et al., 2015). Also, the operation and analysis of LiDAR data require expert knowledge, which introduces additional barriers to technology application (Farhadmanesh et al., 2021).

2.1.3 Infrared Thermography (IRT)

IRT operates by measuring the amount of radiation emitted from an object in the infrared range (9–14µm) using infrared (IR) cameras (Schnebele et al., 2015). The measured radiation is affected by the emissivity and temperature of targeted objects, as well as surrounding weather and atmospheric conditions. The measured amount of thermal infrared radiation can then be converted into temperature, which is usable to indicate any anomalies of transportation assets based on the known difference in thermal properties between normal and defective areas (Garrido et al., 2018).

Figure 2.5 provides examples of infrared images of pavement, demonstrating how thermal contrasts can highlight underlying issues. These images showcase the practical application of IRT in maintaining and improving transportation assets.

IRT works by detecting the infrared radiation emitted by objects within the 9–14µm wavelength range using specialized IR cameras (Schnebele et al., 2015). This radiation detection is influenced by several factors, including the emissivity and temperature of the objects, as well as other environmental and atmospheric conditions. By analyzing the captured infrared radiation, thermal cameras can convert these readings into temperature values. These temperature measurements are critical for identifying anomalies in transportation infrastructure. Defective areas often have distinct thermal properties compared with normal areas, allowing IRT to identify issues such as subsurface defects, moisture infiltration, and structural weaknesses. For instance, in roadway pavement assessments, variations in temperature can reveal cracks, voids, and areas of poor adhesion, which are otherwise invisible to the naked eye (Garrido et al., 2018).

Moreover, IRT is a non-contact and non-destructive testing method, making it particularly valuable for ongoing maintenance and monitoring of infrastructure without causing any damage, such as pots, cracks, and delamination in materials like asphalt, metal, and concrete (Garrido et al., 2018; Lu et al., 2017). It is effective under various conditions, although it is crucial to account for weather influences, such as wind, humidity, and ambient temperature, to ensure accurate readings. Figure 2.5 provides examples of infrared images of pavement, demonstrating how thermal contrasts can highlight underlying issues. These images showcase the practical application of IRT in maintaining and improving transportation assets.

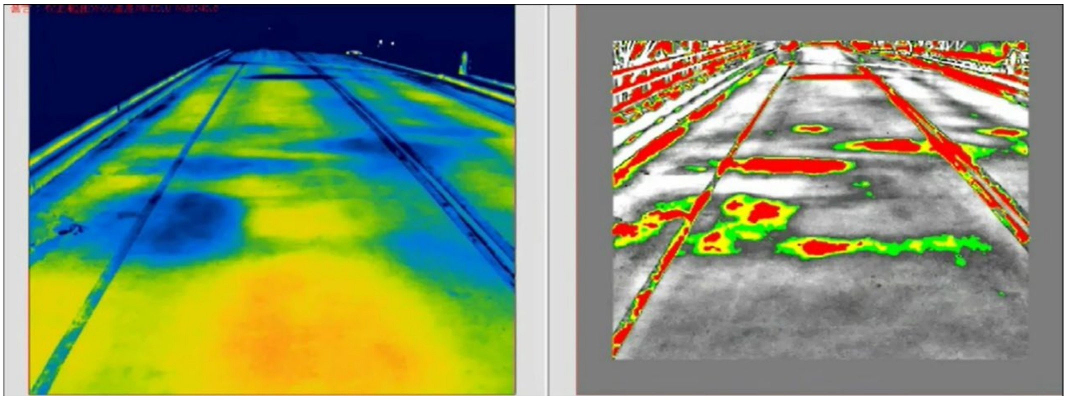

Figure 2.5 IR image of Pavement [1]

[1] https://www.flir.com/discover/rd-science/mobile-infrared-scanning--a-high-tech-accurate-alternative-to-traditional-bridge-inspection-methods/

Despite its advantages, IRT faces challenges with the typically low spatial resolution of thermal images for most infrastructure, which can impact the accuracy of inspection results. Also, unlike GPR, IRT is suitable for horizontal data collection and measurement but cannot measure vertical aspects such as the thickness and depth of subsurface layers (Schnebele et al., 2015). This limitation restricts its ability to provide a complete assessment of certain types of infrastructure. Another consideration is the cost associated with IRT. Accurate measurement often requires high-end professional IR cameras, which can be expensive (Garrido et al., 2018).

2.1.4 Close-Range Photogrammetry (CRP)

CRP is suitable for sensing physical objects within a distance of less than 330 feet (100 meters) from the camera (Jiang et al., 2008). This technique primarily involves measuring and analyzing two-dimensional photographs collected by cameras. CRP can also produce three-dimensional models reconstructed from 2D images taken from various angles. These 3D models are valuable for assessing the condition of objects (Farhadmanesh et al., 2021).

CRP has a wide range of applications, broader than many other sensing technologies. For instance, cameras mounted on vehicles (as illustrated in Figure 2.6) can detect issues with transportation assets such as pavement, guardrails, and road markings (Farhadmanesh et al., 2021; Liq et al., 2012). The image data collected through CRP can be enhanced with other techniques, such as deep learning and image processing, to expand its applications further. For example, traffic signs can be automatically detected using color, geometric edge, and corner analysis (Ruta et al., 2010).

Figure 2.6 Mobile Photogrammetry Setup and the View
(Farhadmanesh et al., 2021)

CRP offers a cost-effective and straightforward method for data collection and analysis, utilizing mobile phones or cameras. This ease of use allows for frequent data updates without incurring significant costs (Ahmed et al., 2011; Hanson et al., 2014). Despite these advantages, CRP has several limitations. Its precision and accuracy may be lower compared with other sensing technologies (Ragnoli et al., 2018). Additionally, various factors such as vehicle speed, camera quality, and lighting conditions can impact the final resolution of the collected images (Farhadmanesh et al., 2021; Gargoum et al., 2017). Nevertheless, the ability to quickly gather and update data makes it a valuable tool in many contexts, particularly when combined with advanced image processing techniques to enhance the quality and utility of the collected data.

2.1.5 Brief Summary

Table 2.1 presents a comparison of these sensing techniques. Overall, GPR and IRT have limited application areas. Secondly, although LiDAR, GPR, and IRT offer relatively high accuracy, they require expensive professional instruments and expert knowledge for data collection and interpretation.

Table 2.1 Comparison of Different Sensing Techniques

Technique	Accuracy	Data analysis knowledge	Application range	Cost
GPR	High	Complex	Limited	High
LiDAR	High	Complex	Wide	High
IRT	Medium	Complex	Limited	High
CRP	Relatively low	Medium	Wide	Low

In contrast, CRP stands out as a low-cost method for data collection that can be easily achieved using mobile phones or basic cameras. This makes CRP a highly accessible and practical option. Despite its lower precision and accuracy compared with some other technologies, CRP's affordability and ease of use allow for frequent data updates, making it a reliable approach for assessing the conditions of various types of transportation assets. Thus, CRP has demonstrated significant potential as an affordable and effective method for infrastructure monitoring.

2.2 Transportation Asset Maintenance AI Models

Artificial intelligence (AI) models, particularly those utilizing computer vision and deep learning, excel in automatic object detection and image classification. Currently, AI models have already been integrated into transportation asset monitoring and maintenance practices, significantly enhancing the efficiency and accuracy of these processes. By automating the detection of issues and analyzing large volumes of image data, AI models contribute to more effective and timely maintenance of transportation infrastructure.

2.2.1 Artificial Intelligence Models

Computer vision is an interdisciplinary field focused on understanding the physical world by extracting and analyzing valuable information from images or videos (Huang et al., 2021). Image analysis and object detection through computer vision resemble human visual inspection because the information captured by images or videos is analogous to that obtained by human observers (Spencer et al., 2019). Computer vision processes range from low-level to high-level tasks, including image acquisition, segmentation, feature extraction, object recognition, and structural analysis (Koch et al., 2015).

Deep learning, a subset of AI, has a remarkable capability to interpret images, sounds, and text by mimicking the human brain's interpretation mechanisms. Deep learning frameworks consist of multiple layers of neuron nodes, where a training dataset is used to determine the weights of the neural network, ultimately forming the AI model (Lu, 2019). Numerous deep learning frameworks are available, such as You Only Look Once (YOLO) (Redmon et al., 2016), convolutional neural networks (CNN), and region-based CNN (RCNN) (Krizhevsky et al., 2017). Unlike other deep learning methods that first propose regions of interest before the convolution operation, YOLO performs detection and classification simultaneously (Redmon et al., 2016). This approach enables YOLO to run faster than other algorithms (e.g., faster RCNN) while achieving higher mean average precision (Redmon et al., 2016). Consequently, YOLO is recognized for its high accuracy and speed in object detection among deep learning models.

In recent years, the high accuracy and speed of deep learning have driven significant advancements in various computer vision problems, including object detection and image segmentation (Voulodimos et al., 2018). Compared with traditional computer vision algorithms, deep learning offers several advantages. Traditional algorithms rely on specific programming paradigms to extract features, which often involves extensive trial and error to select the appropriate features (O'Mahony et al., 2020). In contrast, deep learning employs a training framework with a set of inputs and known outputs, reducing the tedious process of feature extraction and signal processing (O'Mahony et al., 2020). Moreover, deep learning often outperforms traditional computer vision methods, especially in big data analysis, such as video data processing and analysis (Huang et al., 2021).

2.2.2 Applications of AI Models in Transportation Assets Maintenance

AI algorithms have been increasingly applied to transportation asset maintenance, with pavement condition assessment being a prominent area of research. The primary deep learning models used in this field include CNN (Gopalakrishnan et al., 2017), faster RCNN (Majidifard et al., 2020), and YOLO (Mandal et al., 2020). Publicly available datasets related to pavement distress, collected from smartphones, cameras, and Google Street View images, have supported these advancements (Majidifard et al., 2020; Mandal et al., 2020). These AI models, combined with diverse data sources, enable accurate automatic identification of various types of pavement distresses, such as transverse cracks, longitudinal cracks, block cracks, potholes, and alligator cracks (Du et al., 2020; Ghosh and Smadi, 2021; Majidifard et al., 2020). Additionally, some studies have focused on specific pavement types, including asphalt pavement (Wang et al., 2017; Wen et al., 2022) and Portland cement concrete (Gopalakrishnan et al., 2017). Exceptional cases have also been explored, such as object detection in challenging photographic conditions like low illumination or shadows (Tepljakov et al., 2019).

Beyond pavement distress, there is significant research on automatic pavement marking condition assessment. Zhang & Ge (2012) employed traditional image processing techniques, such as camera calibration, Hough transformation, and feature recognition, to assess pavement markings. Xu et al. (2021) used image pre-processing, feature extraction, and segmentation to detect and evaluate pavement line markings. However, traditional image processing methods often struggle with robustness due to their reliance on precise feature extraction, which can be hindered by noise from complex real-world scenarios such as varying light conditions and shadows (Li & Zhao, 2019).

In the fields of deep learning applications for pavement markings, Kawano et al. (2017) used YOLO to detect faded pavement markings, although the accuracy was limited to less than 50% due to issues with annotation precision. Kang et al. (2020) developed a framework using YOLOv3 to assess pavement marking visibility, which also incorporated additional image processing techniques such as edge extraction, mask construction, and gray transformation. Vokhidov et al. (2016) applied CNN to detect damaged pavement markings, focusing specifically on arrow-based markings. Wei et al. (2021) combined Faster-RCNN with U-Net to evaluate the damage ratio of white pavement markings, though their method did not account for other types of pavement markings.

Another significant application of AI algorithms in transportation asset management is traffic sign identification. For example, Hoang et al. (2018) combined various computer vision techniques, such as image augmentation and region processing, with CNN to create an AI model for traffic sign recognition. Similarly, Tabernik & Skočaj (2020) developed an automatic traffic sign inventory management system using Mask R-CNN, which handled 200 categories of traffic signs. Campbell et al. (2019) used open-source images, like those from Google Street View, to build a training dataset and develop a deep learning model specifically for identifying "stop and give way" signs. Additionally, research has addressed the robustness of traffic sign detection in challenging conditions, such as snowy weather or low illumination (Chehri et al., 2021; Khan et al., 2018).

In contrast to the extensive research on pavement issues, fewer studies have focused on recognizing litter and trash on roads. Liu et al. (2018) utilized YOLOv2 to detect garbage on pavements, but their study considered only one type of garbage. Similarly, the AI model developed by Sayyad et al. (2020) was limited to large-sized garbage and did not classify different types of trash. Zhang et al. (2019) applied Faster R-CNN to identify and count different categories of litter, including inorganic, organic, trash, and tree leaves. However, their dataset was exclusively collected from street roads, which may restrict its effectiveness for litter detection on highways.

Research on detecting steel guardrails and concrete barriers is even more sparse. Hou et al. (2022) proposed an automatic guardrail detection model that uses 3D local feature extraction based on mobile LiDAR data. In terms of RGB images, Liu et al. (2020) developed a standard urban image database that includes eight categories of urban images, one of which is damaged traffic guardrails. Jin et al. (2021) combined feature extraction with Mask R-CNN to detect steel guardrails on highways but did not include concrete barriers in their model.

2.2.3 Brief Summary

Deep learning and computer vision have demonstrated exceptional performance in automatic object detection and image classification. These technologies have been widely applied across various fields, with transportation asset monitoring and inspection being prominent examples. Pavement condition assessment has been extensively researched, showcasing the robust capabilities of AI models in this area. Traffic sign identification is another well-studied application, highlighting the potential of AI for detecting and managing transportation infrastructure.

However, there is comparatively less research focused on other aspects of transportation asset management, such as identifying pavement marking issues, detecting steel guardrails and concrete barriers, and recognizing litter and trash on roads. Expanding research into these areas could further enhance the utility of AI in comprehensive transportation asset detection and maintenance.

2.3 Commercial Practices of Transportation Assets Data Collection and Management

Leveraging these data collection techniques and AI models, companies and organizations have developed commercial platforms to facilitate transportation asset management practices.

2.3.1 Pillar

Pillar[2] is an infrastructure asset management firm that has developed an AI-based system to manage transportation assets. This system includes data collection to form an inventory database, assessment of asset conditions, development of maintenance plans, and execution assistance. In this system, mobile LiDAR and imagery scanning are used to collect transportation asset data. AI algorithms are then developed to process the collected data and automatically extract transportation assets (e.g., traffic signs, guardrails, and striping). With imagery and point cloud analysis, an asset inventory is created, including evaluated conditions. Figure 2.7 shows an example of the scanning and automatic extraction of steel guardrails. By employing these advanced techniques, Pillar enables comprehensive and efficient management of transportation infrastructure, ensuring timely maintenance and accurate condition assessments.

[2] https://www.pillaroma.com/artificial-intelligence-ai-in-transportation-asset-management/

Figure 2.7 An Example of Guardrail Scan And Automatic Extraction by Pillar

2.3.2 Esri

Esri[3] has developed a deep learning model to evaluate indicators of road conditions, such as road roughness and the level of crack damage, by leveraging road traffic density and road condition data. Esri's platform allows users to organize road assets comprehensively, understand their location and condition, and integrate with leading asset management solutions for road maintenance. Additionally, Esri provides mobile solutions to assist with data collection and asset inspection on highways.

The Florida Department of Transportation (FDOT) has adopted this system, known as FDOT's public-facing eMaintenance Web App (see Figure 2.8). This application is open to the public and provides inspection results for crash cushions and guardrails across Florida. By utilizing Esri's system, FDOT enhances its ability to monitor and maintain transportation infrastructure effectively.

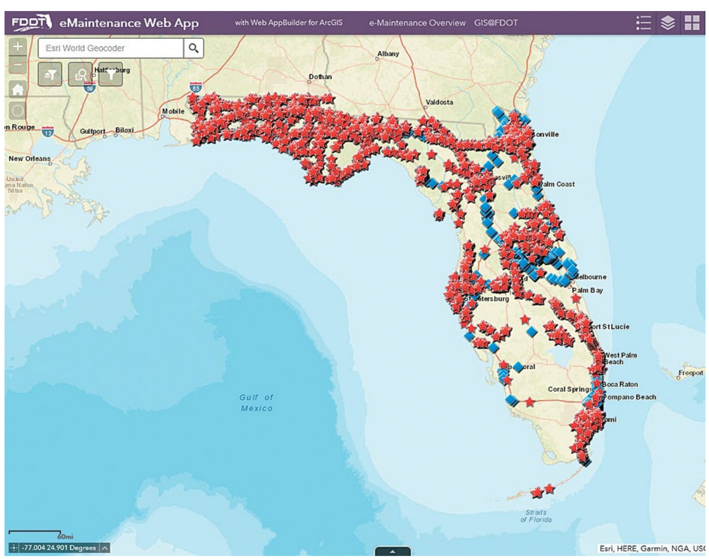

Figure 2.8 Interface of FDOT eMaintenance Web App

3 https://www.esri.com/en-us/industries/roads-highways/business-areas/maintenance

2.3.3 Deep Systems (Russia)

Deep Systems[4] is an automatic road defect detection software developed by one of the leading Russian research groups, utilizing computer vision and deep learning. The algorithm operates in real-time to quickly detect defects such as cracks, holes, and patches from recorded video. This system also offers a web dashboard for monitoring and controlling GPU clusters, including training models, running defect detection, and viewing results. The dashboard interface is shown in Figure 2.9. Additionally, Deep Systems provides robust interoperability, allowing operators to create, modify, and populate training samples according to their specific requirements. By leveraging this advanced technology, Deep Systems enhances the efficiency and accuracy of road defect detection, providing a comprehensive tool for infrastructure maintenance and monitoring.

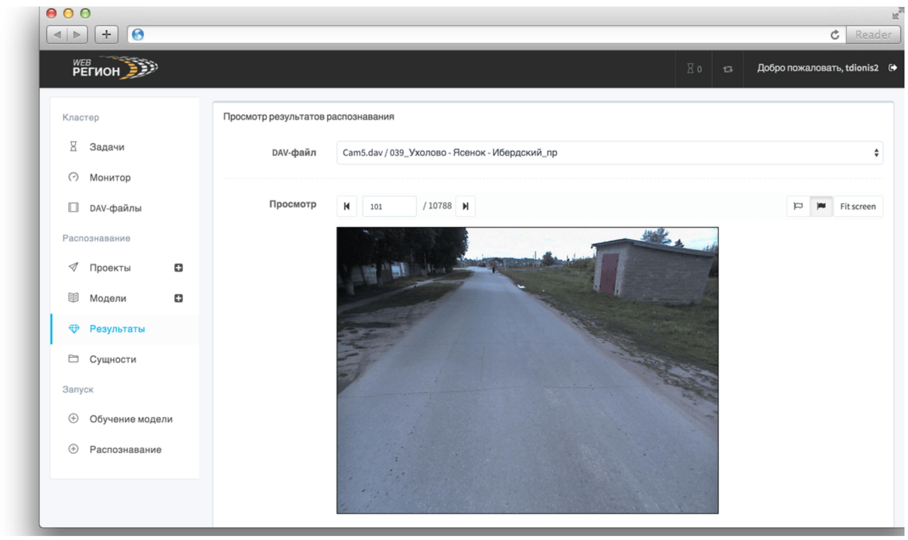

Figure 2.9 Web Dashboard Page of Deep Systems

2.3.4 TRIK

TRIK[5] is an innovative enterprise software solution designed to optimize the use of drone photography for structural inspections. It seamlessly transforms photos taken by drones into interactive 3D models, which can be easily measured and annotated. These 3D models not only facilitate detailed structural analysis but also serve as comprehensive databases, supporting photo searches, detecting structural changes, and maintaining project records. Additionally, TRIK's capabilities extend to identifying pavement issues, making it a versatile tool for a wide range of inspection and maintenance needs.

2.3.5 Pavemetrics

Pavemetrics[6] has developed the Laser Crack Measurement System (LCMS-2), a cutting-edge single-pass 3D sensor for pavement inspection. The LCMS-2 can automatically geotag, measure, detect, and quantify critical functional parameters of pavement in a single pass. These parameters include cracking, rutting, texture, potholes, bleeding, shoving, raveling, and roughness, among others.

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[4] https://deepsystems.ai/solutions/road-defects-detection
[5] https://gettrik.com/
[6] https://www.pavemetrics.com/applications/road-inspection/lcms2-en/

2.3.6 Brief Summary

TRIK and 2.3.5 Pavemetrics are commercially available platforms to collect and manage data, which can be further processed for pavement condition assessment. Pillar, Esri, and Deep Systems are AI-based platforms to help operators identify transportation assets and assess their condition based on deep learning technologies. Increasing combinations of computer vision and deep learning technologies have been applied in transportation asset management.

3. METHODOLOGY

The comprehensive workflow of AI model development is depicted in Figure 3.1. In general, AI algorithm development follows an iterative process in this project. Initially, a mobile phone was mounted on vehicle's windshield to capture video data. These videos were then converted into images and annotated for AI model training and testing. The labeled images were input into the YOLO framework for model training. Subsequent model tests used separate video samples to identify any remaining object detection issues through manual verification. Based on these findings, new images related to detection errors were added to the training dataset to initiate a new round of iterative training. This cycle was repeated to drive iterative model improvement.

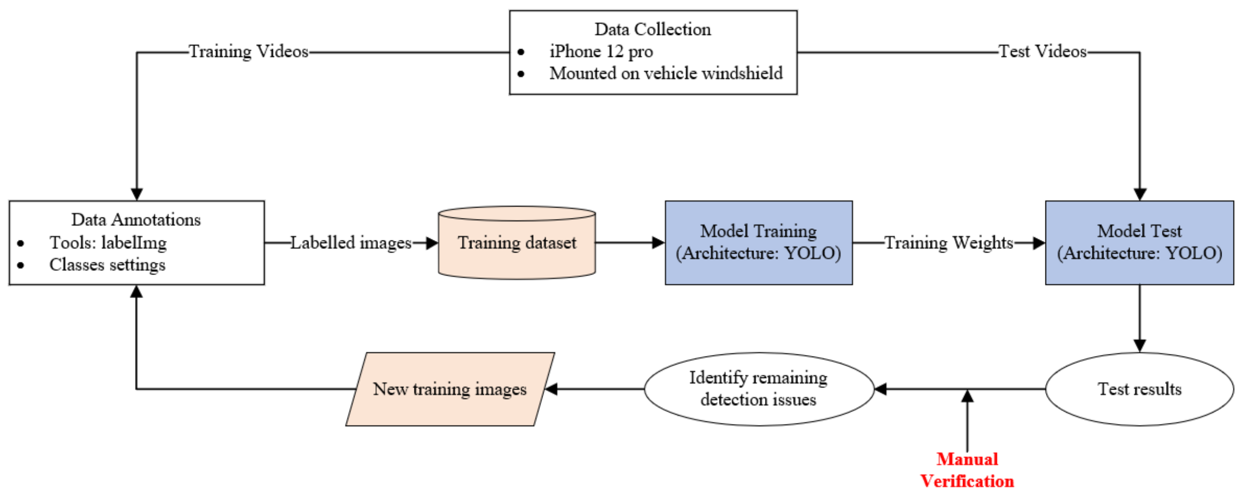


Figure 3.1 Flowchart of Model Development and Improvement

3.1 Data Collection and Processing

To collect transportation asset data for training AI models, a mobile phone (iPhone 12 Pro with a 12-megapixel triple-lens camera at the back) was mounted on the passenger side of a vehicle's front windshield. This placement allows the phone to capture transportation assets from a front-facing perspective. The setup of the video collection on the vehicle is depicted in Figure 3.2.

The collected videos were recorded at 30 frames per second (fps). Approximately 31 hours of videos (estimated to contain around 3.3 million images) have been collected on highways and local streets in Utah. These videos encompass all types of transportation assets targeted in the project: pavement markings, traffic signs, steel guardrails, concrete barriers, and litter and trash. Certain special scenarios, such as strong-glare and low-illumination days, are also included in the data collection.

In data processing, each image frame in the recorded videos was extracted sequentially. Only images clearly capturing targeted objects were extracted and incorporated into our training and test dataset. Moreover, to streamline the dataset and mitigate redundancy, a maximum of three images per object were chosen for training purposes, thereby optimizing the efficiency of the dataset while maintaining the requisite diversity needed for robust model training.

Figure 3.2 Setup of Video Collection

Besides using self-collected images, this project has explored other open-source datasets, e.g., UDOT Roadview Explorer dataset and Google Street View, to train AI models. Through rigorous analysis, it was discerned that the self-collected data yielded the most optimal performance due to the direct and unobstructed views of transportation assets captured from the front windshield. Therefore, in this project, only images processed from self-collected videos were used to develop AI models.

3.2 Data Annotations

We used LabelImg to label objects with bounding boxes for the development of our training and test datasets. LabelImg[7], a free and open-source graphical annotation tool, allows us to label images accurately. We labeled our dataset separately for different tasks, corresponding to different targeted transportation assets, to identify or assess their conditions.

3.2.1 Pavement Marking Annotations

In this project, we differentiated pavement markings into white and yellow classes and assessed their conditions accordingly. Following ASTM (2020) and Kuang et al. (2022), markings with over 50% of their areas faded or missing were labeled as faded (excluding fully faded). Consequently, faded markings were differentiated into two categories: "y_faded" (yellow faded markings) and "w_faded" (white faded markings). The "y_faded" includes faded double and single curb or lane markings in yellow, while "w_faded" includes faded longitudinal lane markings, horizontal markings (e.g., crosswalks, stop lines), arrow markings, and delineators in white.

3.2.2 Litter & Trash Annotations

This project classified trash and litter on the pavement into four types: "leaves" (vegetation and leaves on the roadside), "dirt" (dirt on the roadside), "w_litter" (litter in white or light colors, such as plastic and foam), and "b_litter" (litter in black or dark colors, such as used tires, rubber, and branches).

[7] https://github.com/heartexlabs/labelImg

3.2.3 Traffic Sign Annotations

According to the Manual on Uniform Traffic Control Devices (FHWA, 2009), traffic signs are classified into four types: (1) “regulatory,” which includes stop signs, yield signs, and “Do not enter” signs (mostly in red or white); (2) “speed,” encompassing speed limit and school zone signs (mostly in white); (3) “warning,” covering warning signs and object markers (mostly in yellow); and (4) “guide,” consisting of destination guide signs and traffic movement signs (mostly in green).

3.2.4 Guardrail and Barrier Annotations

This project also considers guardrails and barriers. There are two classes presented: “concrete,” which includes cast-in-place concrete barriers and New Jersey shape barriers, and “steel beam,” encompassing w-beams with steel blocks and w-beam guardrails.

3.3 You Only Look Once (YOLO)

YOLO is a pre-trained object detection model based on the COCO dataset. It simultaneously proposes regions of interest and makes detections, making it faster than most state-of-the-art algorithms (Redmon et al., 2016). YOLO predicts the bounding boxes of target objects and the probabilities of their associated classes in a single scan of images. Only predictions with more than the threshold of confidence (30% in this study) are considered effective and are labeled with bounding boxes. Additionally, YOLO can crop the labeled objects for further processing after detection.

In this project, we utilize YOLOv5 as the base AI framework to develop AI models for each research task. The architecture of YOLOv5, illustrated in Figure 3.3 (S. Xu et al., 2021), consists of three main parts: the backbone, neck, and output.

- **Backbone:** The backbone network employs a cross-stage partial (CSP) network and spatial pyramid pooling (SPP) to extract feature maps from the input image at different scales through multiple convolution and pooling layers (Li et al., 2022). This method enhances both inference speed and accuracy by efficiently processing and consolidating features at various resolutions.
- **Neck:** The neck network uses a path aggregation network (PANet) to ensure that useful information at each feature level propagates directly to subsequent subnetworks. PANet improves the propagation of low-level features through an enhanced bottom-up path and uses adaptive feature pooling to maximize the utilization of accurate location signals in lower layers (S. Xu et al., 2021). This results in better feature fusion and helps the model maintain high performance, even with complex input data.
- **Head:** The head is the output of YOLO, generating three different sizes of feature maps (18 x 18, 36 x 36, and 72 x 72) to detect objects at multiple scales (Redmon et al., 2016; S. Xu et al., 2021). This multi-scale detection capability allows YOLOv5 to accurately identify objects of varying sizes within the same image, enhancing its versatility and robustness.

With this developed framework, YOLOv5 achieves high detection speed and accuracy. Its efficient architecture and advanced feature extraction techniques make it well-suited for real-time object detection tasks, ensuring reliable performance in a wide range of applications. By building on YOLOv5, our project benefits from these advancements, enabling precise and rapid detection of target objects, e.g., traffic signs, litter, and pavement marking issues.

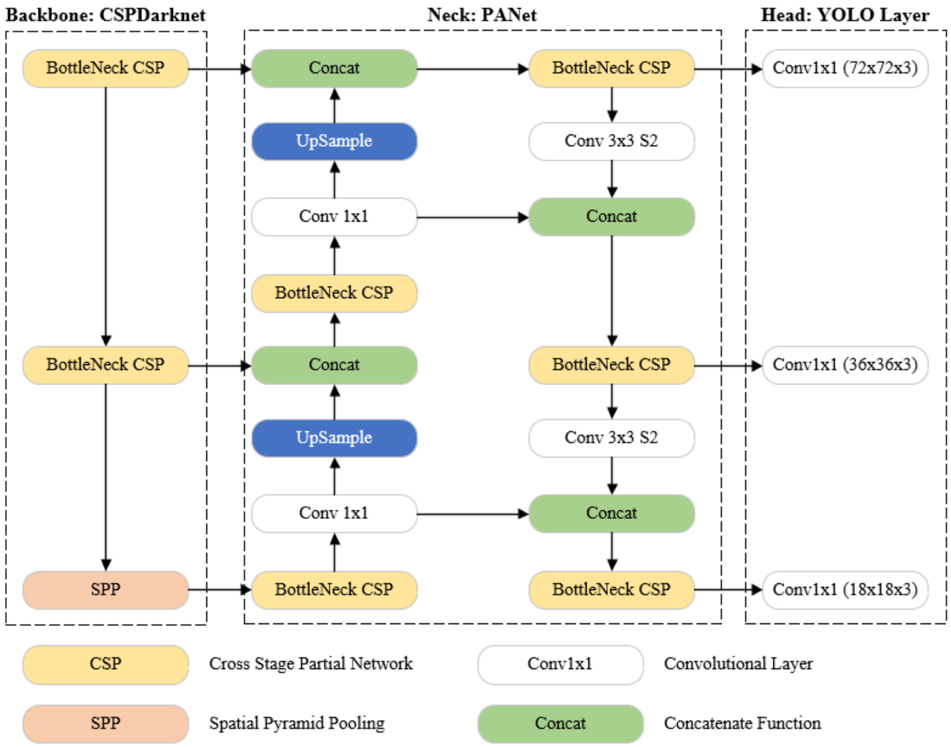


Figure 3.3 The Architecture of YOLOv5

(R. Xu et al., 2021)

3.4 Accuracy Metrics

This project applies YOLO to train AI models for transportation asset detection. The metrics used to evaluate performance are defined as follows:

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 * precision * recall}{precision + recall}$$

Here, TP (true positive) describes a scenario where a prediction box correctly captures a positive object. A FP (false positive) occurs when a prediction box captures an incorrect object, while a FN (false negative) means that a positive object is not detected by any prediction box. Therefore, precision and recall evaluate the performance of the model from different perspectives:

- **Precision** reflects the reliability of the model in classifying objects as positive.
- **Recall** measures the model's ability to detect positive objects (i.e., true positives).

To ensure a balance between precision and recall, the F1-score is introduced, which weights them equally to avoid outperforming in one metric while underperforming in the other (Arya et al., 2020). In the reported metrics, our objective is to identify objects of interest accurately. These objects are considered as true positives as long as the developed AI algorithms detect them during the video detection process once. This approach ensures that our model reliably captures and identifies the relevant transportation assets, thereby optimizing the detection performance across various metrics.

4. RESULTS

4.1 Model Training Environment and Parameter Setting

The training and testing in AI model development were performed using a Windows 10 desktop. The hardware information, configurations of the AI development environment, and training parameters are detailed in Table 4.1 and Table 4.2.

Table 4.1 Training Environment Configuration

Environment	**Configuration**
CPU	8-Core
GPU	NVIDIA GeForce RTX 3070
Memory	64GB
Operating System	Windows 10
Language	Python 3.10.4
Deep Learning Framework	PyTorch 1.10.2
CUDA	Version 11.3

Table 4.2 Training Parameter Settings

Parameter	**Setting**	**Parameter**	**Setting**
Size of Input Images	640 x 640	Learning Rate	0.01
Initial weight	Yolov5s	Epochs	1000
Optimizer	Adam	Batch size	16

4.2 AI Model Development to Identify Pavement Marking Issues

A total of 1,479 images were incorporated into our training dataset for pavement marking model development. Out of these, 1,088 images were used for training, while 391 images were used for validation.

4.2.1 Model Training and Test Performance

The training process stopped at 315 epochs as no further improvement was observed in the last 100 epochs. The best model training result was achieved at epoch 215. Figure 4.1 illustrates the reported accuracy metrics during the algorithm training process, showing that the AI model finally reached convergence. The model achieved a precision of approximately 87%, a recall rate of 90%, and an F1 score of 89% (Table 4.3).

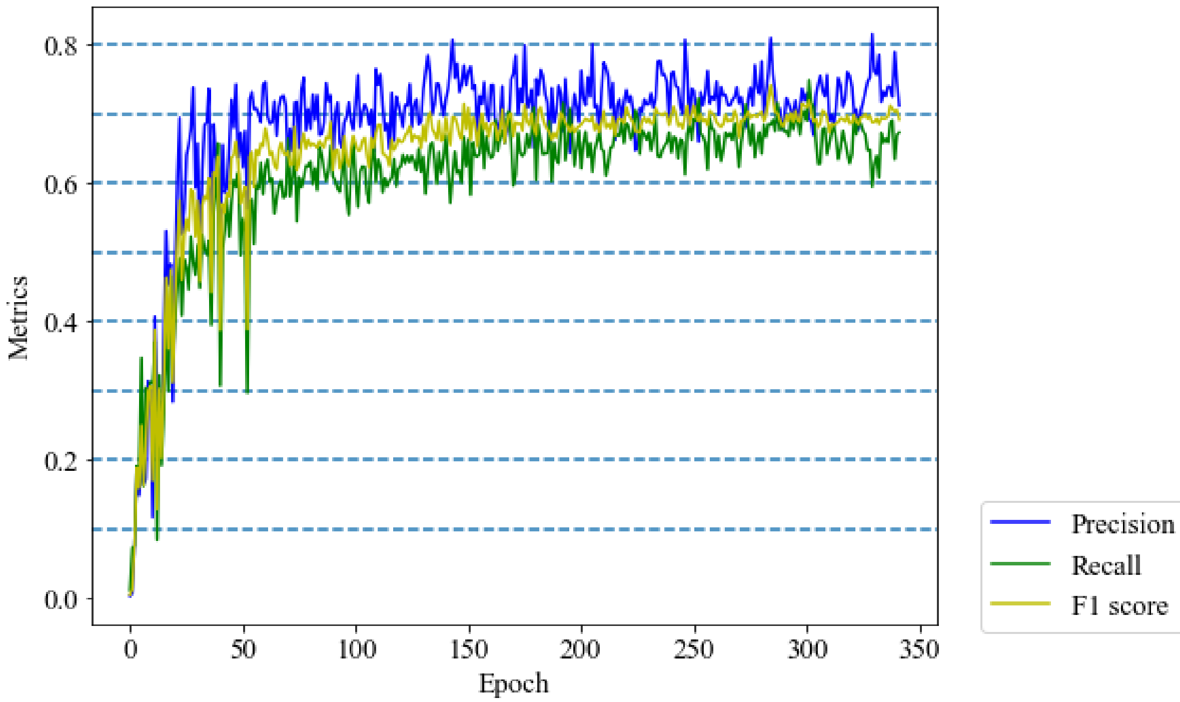


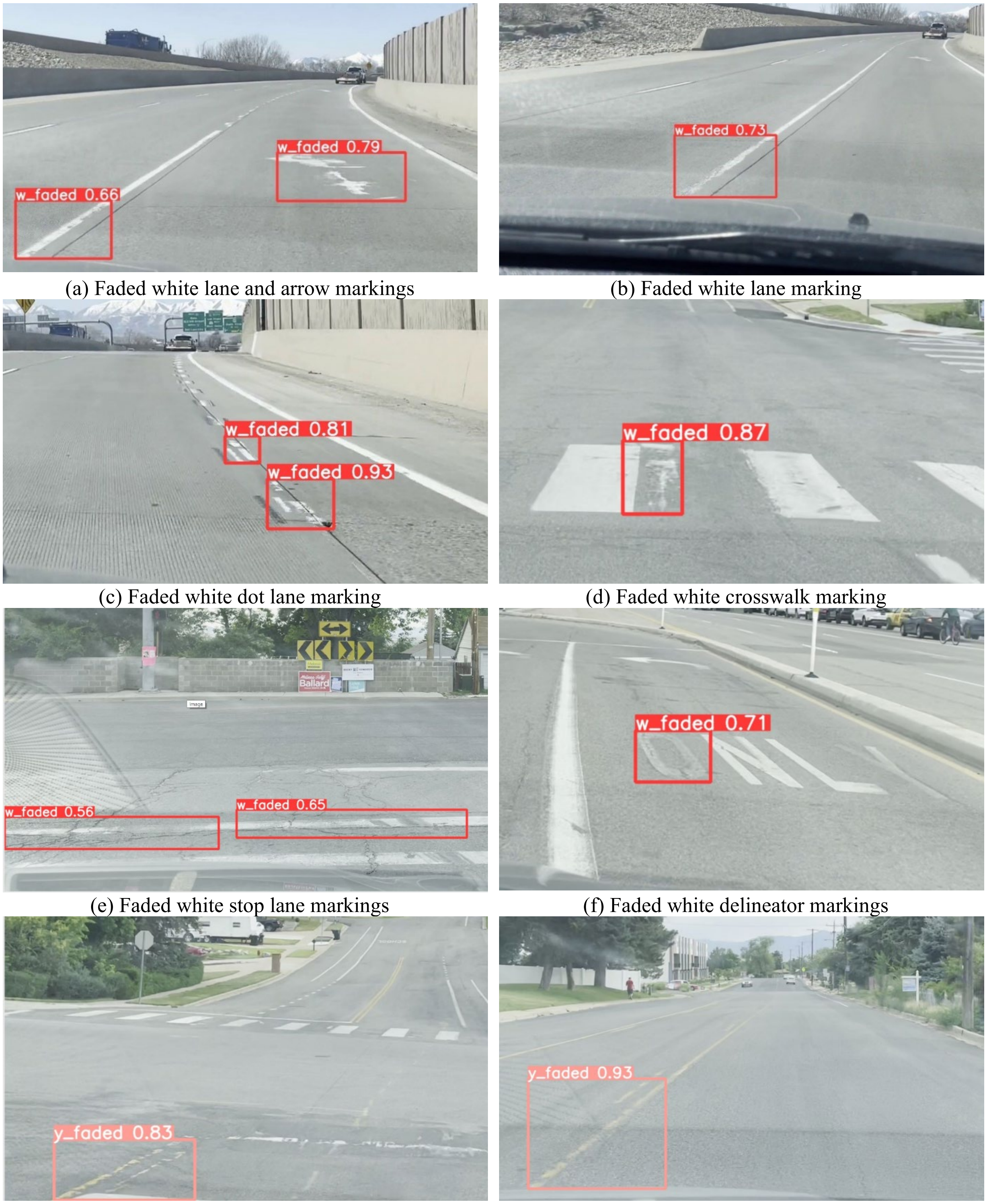
Figure 4.1 Accuracy Metrics of Pavement Marking Issues During Training

Table 4.3 Training Results of Pavement Marking Issues

Class	Precision	Recall	F1 score
all	0.87	0.9	0.89
w_faded	0.88	0.91	0.89
y_faded	0.86	0.89	0.87

4.2.2 Examples of Pavement Marking Issues Detection

In the iterative improvement process, we performed visual inspections on approximately seven hours of videos to validate the model's performance. To correct wrong identifications, we incorporated more training images. The addressed detection issues included false detection of normal markings as faded markings, incorrect classification of pavement issues as faded markings, and misidentification of special markings as faded markings. Examples of pavement marking detection by the developed AI model are shown in Figure 4.2.



(a) Faded white lane and arrow markings
(b) Faded white lane marking
(c) Faded white dot lane marking
(d) Faded white crosswalk marking
(e) Faded white stop lane markings
(f) Faded white delineator markings
(g) Faded double yellow lane marking
(h) Faded single yellow lane marking

Figure 4.2 Examples of Detection Results of Pavement Marking Issues

4.3 AI Model Development to Identify Litter & Trash

A total of 1,916 images were used to develop the AI model for trash and litter detection. Of these, 1,371 images were used for training, and 545 images were used for validation.

4.3.1 Model Training and Performance

The AI model for litter and trash identification converged after 457 epochs as no significant improvement was observed in the last 100 epochs. The optimal training model was achieved at epoch 357. The training process and accuracy metrics are shown in Figure 4.3 and Table 4.4. The developed AI model achieved a precision of 86%, a recall rate of 92%, and an F1 score of 89%.

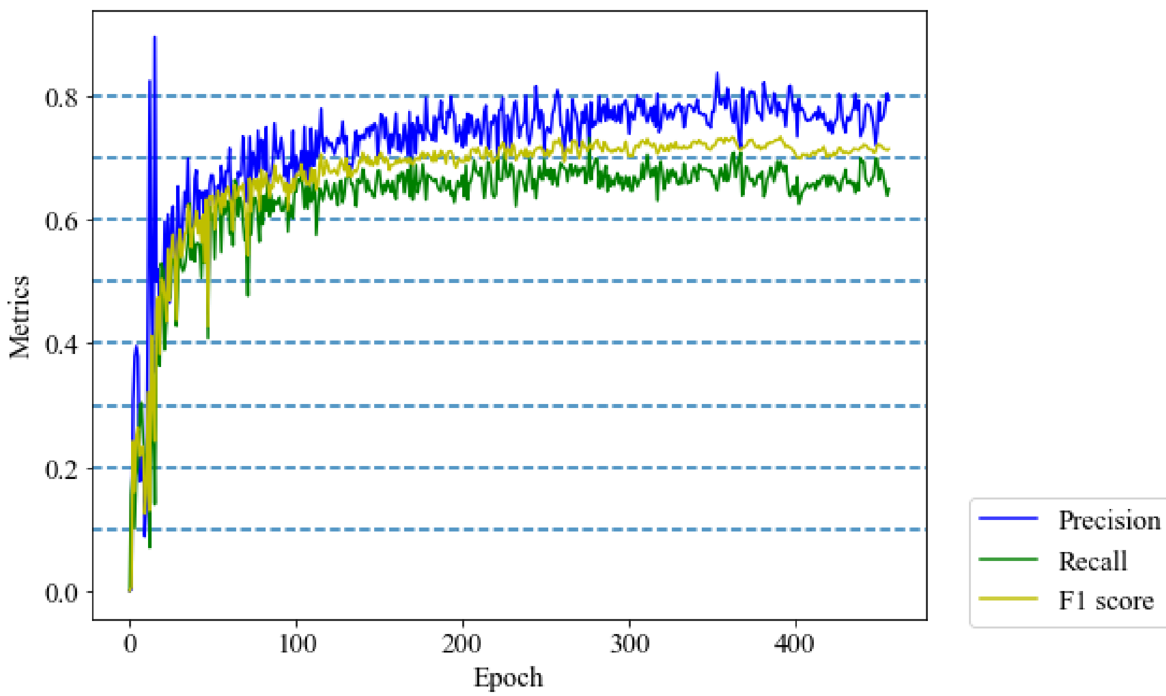


Figure 4.3 Accuracy Metrics of Litter & Trash Identification During Training

Table 4.4 Training Results of Trash & Litter

Class	Precision	Recall	F1 score
all	0.86	0.92	0.89
leaves	0.88	0.93	0.90
dirt	0.91	0.91	0.91
w_litter	0.79	0.93	0.85
b_litter	0.88	0.92	0.90

4.3.2 Examples of Litter & Trash Identification

During the iterative AI model development process, around four hours of videos were tested. The addressed litter and trash detection issues included the misclassification of outfall points on highways as "b_litter" and the incorrect detection of white markings or pavement as "w_litter" or "b_litter." Examples of trash and litter identification by the developed AI algorithm are demonstrated in Figure 4.4.

(a) Dirt on the highway
(b) Black litter on the highway
(c) Dirt and litter on the highway
(d) White litter and dirt on the highway
(e) Leaves on the street road
(f) Leaves on the street road
(g) Black and white litter on the street road
(h) Dirt on the street road

Figure 4.4 Examples of Detection Results of Trash & Litter

4.4 AI Model Development to Identify Traffic Signs

A total of 1,456 images were used to train the AI model for traffic sign detection. Of these, 1,026 images were used for training, and 430 images were used for validation.

4.4.1 Model Training and Performance

The training process for the AI model for traffic sign detection stopped at 315 epochs as no improvement was observed in the last 100 epochs. The best results were observed at epoch 215. Training results are shown in Table 4.5 and Figure 4.5. The AI model reached convergence within the training process, achieving an overall precision of 88%, a recall rate of 90%, and an F1 score of 89%.

Table 4.5 Training Results of Traffic Signs

Class	Precision	Recall	F1 score
all	0.88	0.90	0.89
regulatory	0.94	0.81	0.87
speed	0.84	0.93	0.88
warning	0.83	0.93	0.88
guide	0.89	0.94	0.91

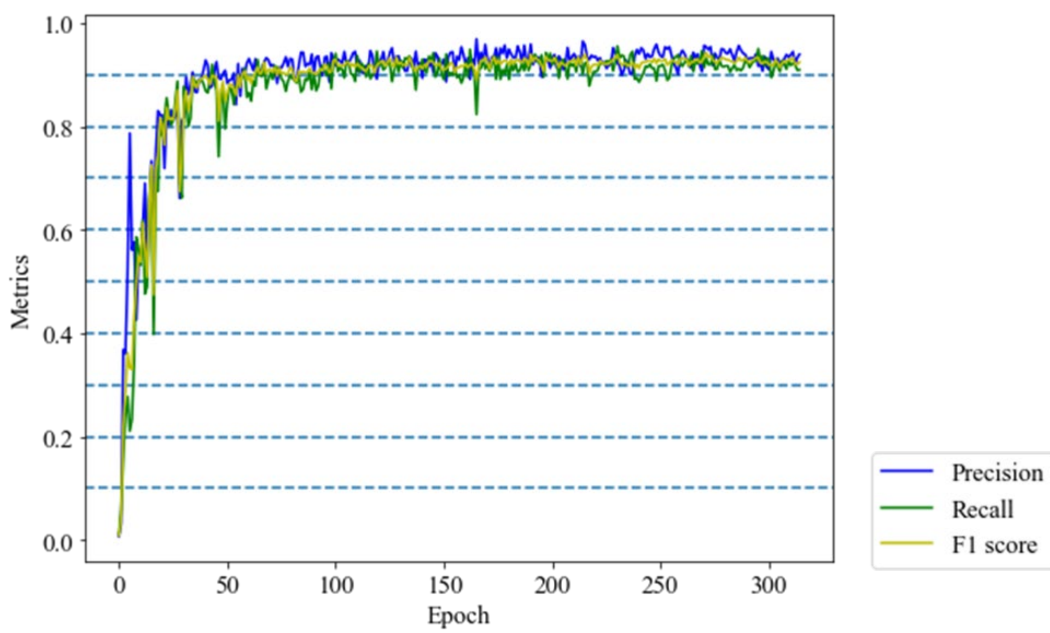


Figure 4.5 Accuracy Metrics of Traffic Signs During Training

4.4.2 Examples of Traffic Signs Detection

The model developed for traffic sign detection was tested on two-hour videos during the improvement process. The addressed detection issues in the iterative improvement process included the misclassification of advertisement boards on highways as traffic signs and the failure to detect signs obscured by trees. Examples of using AI to identify traffic signs are shown in Figure 4.6.

(a) Traffic movement guide and speed warning

(b) Traffic movement guide

(c) Exit guide and warning maker

(d) Warning sign

(e) Speed limit

(f) Street guide

(g) Stop sign and street guide

(h) Do not enter and street guide

Figure 4.6 Examples of Detection Results of Traffic Signs

4.5 AI Prototype Development to Identify Guardrails and Barrier

A prototype AI algorithm for steel guardrail and concrete barrier identification was developed using 241 images, with 153 images used for training and 56 images for validation. The training process for this prototype AI algorithm stopped at 265 epochs as no further improvement was observed. The best results were achieved at epoch 165.

The training process is illustrated in Figure 4.7. The AI model converged during the training process, achieving approximately 80% accuracy in detecting concrete barriers and steel guardrails. The training results indicate significant potential to develop a high-performance model for identifying steel guardrails and concrete barriers.

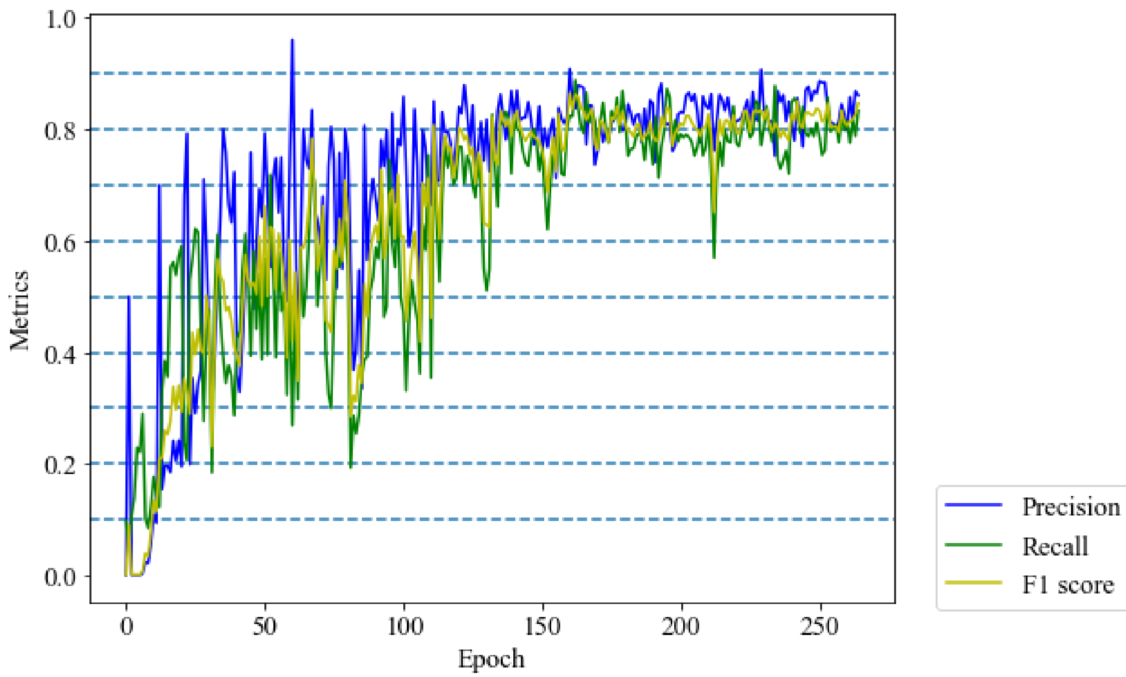


Figure 4.7 Accuracy Metrics of Guardrails and Barriers During Training

Detection examples for these two classes are shown in Figure 4.8. The developed AI prototype demonstrates its ability to identify both steel beam guardrails and concrete barriers. However, additional image data are required to enhance this prototype further.

(a) W-beam steel guardrail (b) Concrete barrier and steel guardrail

(c) Concrete barrier (d) Concrete barrier and steel guardrail

Figure 4.8 Examples of Detection Results of Guardrails

5. CONCLUSIONS

5.1 Summary

Close-range photogrammetry, including data collection via mobile phones, offers a lightweight and cost-effective solution for timely transportation asset information collection. Concurrently, AI models such as computer vision and deep learning excel in automatic object detection and image classification, demonstrating significant potential in transportation asset monitoring and maintenance.

This project, therefore, focuses on developing reliable and affordable AI algorithms capable of analyzing videos collected by mobile phones to facilitate automatic information collection and inspection of transportation assets, including pavement markings, traffic signs, trash and litter, steel guardrails, and concrete barriers.

We collected approximately 31 hours of videos, covering highways and local roads in Utah using a smartphone mounted on a vehicle's windshield. These videos were processed into labeled images for training and validation. The developed AI package is designed for automatic information collection of all the targeted types of transportation assets mentioned above. The results indicate that the AI models are capable of automatically detecting relevant transportation assets with high accuracy (over 85%).

5.2 Findings

In this study, three AI models were developed for the automatic detection of pavement marking issues, traffic signs, and litter and trash, along with a prototype model for identifying steel guardrails and concrete barriers. These models were trained and tested using images extracted from videos recorded on a mobile phone mounted on a vehicle's windshield. Specifically:

(1) For pavement marking issue detection, 1,496 images were used to train the AI model. The pavement marking issues were classified into two categories based on color: faded yellow markings ("y_faded") and faded white markings ("w_faded"). The performance metrics for this model are a precision of 87%, a recall of 90%, and an F1 score of 89%.

(2) To develop the AI model for trash and litter identification, 1,916 images were utilized. This model included four major classes: leaves, dirt, white litter ("w_litter"), and black litter ("b_litter"). The model achieved a precision of 86%, a recall of 92%, and an F1 score of 89%.

(3) The AI model for traffic sign identification was trained with 1,456 images. The traffic signs were classified into four categories: regulatory, speed, warning, and guide signs. The performance metrics for this model are 88% precision, 90% recall, and an F1 score of 89%.

(4) A prototype AI algorithm for steel guardrail and concrete barrier identification was developed using 241 images. This prototype performed well in identifying both steel guardrails and concrete barriers in tested videos and shows great potential for achieving high-accuracy detection with further development.

These AI models were developed to facilitate the automatic information collection and assessment of transportation assets, leveraging videos processed into labeled images for training and validation. The results show that the developed AI models are capable of accurately and efficiently collecting relevant transportation asset information.

5.3 Limitations and Future Work

Despite the decent performance of the current AI models, limitations still exist. First, the training dataset is limited, leading to false detections in certain scenarios. Second, the performance of the developed AI models has not been tested in special scenarios, such as rainy days or daytime, with strong or low illuminance. These conditions present more challenging situations for accurate transportation asset inspection. Therefore, the performance of the developed algorithms needs further evaluation under these scenarios.

Considering these limitations, further improving the detection accuracy and robustness through large-scale AI algorithm validation is a promising direction. Incorporating more training and test images under special circumstances is essential for evaluating algorithm performance across all types of transportation assets.

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