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MOBILE PHONE-BASED ARTIFICIAL INTELLIGENCE DEVELOPMENT FOR MAINTENANCE ASSET MANAGEMENT

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16. Abstract

Transportation asset management needs timely information collection to inform relevant maintenance practices (e.g., resource planning). Traditional data collection methods in transportation asset management require either manual operation or support of unique equipment (e.g., Light Detection and Ranging (LiDAR)), which could be labor-intensive or costly to implement. With the advancement of computing techniques, artificial intelligence (AI) has been developed to be capable of automatically detecting objects in images and videos. In this project, we developed accurate and efficient AI algorithms to automatically collect and analyze transportation asset status, including identification of pavement marking issues, traffic signs, litter & trash, and steel guardrails & concrete barriers. The AI algorithms were developed based on the You Only Look Once (YOLO) framework built on Convolution Neural Network as the deep learning algorithms. Specifically, a smartphone was mounted on the vehicle's front windshield to collect videos of transportation assets on both highways and local roads. These videos were then converted and processed into labeled images to be training and test datasets for AI algorithm training. Then, AI models were developed for automatic object detection of the listed transportation assets above. The results demonstrate that the developed AI models achieve good performance in identifying targeted objects with over 85% accuracy. The developed AI package is expected to enable timely and efficient information collection of transportation assets, hence, improving road safety.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

AI	Artificial Intelligence
ASTM	American Society for Testing and Materials
CNN	Convolution Neural Networks
CRP	Close-Range Photogrammetry
CSP	Cross-Stage Partial Network
DOT	Department of Transportation
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
FN	False Negative
FP	False Positive
GPR	Ground-Penetrating Radar
HSI	Hyperspectral imagery
IR	Infrared
IRT	Infrared Thermography
LCMS	Laser Crack Measurement System
LiDAR	Light Detection and Ranging
MLS	Mobile Laser Scanner
PANet	Path Aggregation Network
RCNN	Regional Convolution Neural Networks
RGB	Red, Green, and Blue
SPP	Spatial Pyramid Polling
TAC	Technical Advisory Committee
TLS	Terrestrial Laser Scanner
TP	True Positive
UAV	Unmanned Aerial Vehicle
UDOT	Utah Department of Transportation
YOLO	You Only Look Once

EXECUTIVE SUMMARY

Timely information collection and assessment of transportation assets are beneficial to daily maintenance practices of state departments of transportation (DOTs). However, traditional transportation asset assessment methods either rely on the labor-intensive manual data collection process or employ costly devices (e.g., light detection and ranging (LiDAR)) that are prohibitive in frequent data collection due to high operational costs. With the advancement of computing techniques, artificial intelligence (AI) (e.g., computer vision and deep learning) has demonstrated its capabilities in automatic and accurate object detection, comparable to human eyes. Therefore, to fully explore the applicability of AI in transportation-relevant applications, this project aims to develop reliable and accurate AI algorithms with capabilities of automatic object identification, including pavement marking issues, traffic signs, trash and litter on the roads, and steel guardrails and concrete barriers, aiming to improve the current practice of transportation asset management.

First, this project reviewed the pros and cons of existing technologies in transportation asset data collection. The commonly used techniques include but are not limited to ground-penetrating radar, LiDAR, infrared thermography, and close-range photogrammetry, among which the close-range optical image is considered a reliable way of timely information collection without introducing excessive cost. In addition, we have reviewed the applied AI algorithms in transportation asset monitoring and inspection, including regional convolution neural networks (RCNN), faster RCNN, and You Only Look Once (YOLO). Generally, YOLO, as one of the deep learning-based AI algorithms, excels in object detection with high accuracy and computational efficiency. In the past, these AI algorithms have been widely utilized in pavement issue identification. Limited research has been conducted to apply AI in detecting pavement marking issues and identifying traffic signs, trash & litter on the roads, and steel guardrails and concrete barriers.

Next, a smartphone was mounted on the front windshield of a vehicle to collect videos of targeted transportation assets and issues on state highways and local roads. In total, approximately 31 hours of videos were collected, including all types of objects of interest, i.e., pavement markings, traffic signs, steel guardrails and concrete barriers, and litter and trash on the roads. These videos were processed into labeled images to train robust AI algorithms.

Finally, utilizing labeled images as training and test data, three AI models were developed for the automatic detection of pavement marking issues, traffic signs, and litter and trash. Specifically, the AI model for the identification of pavement marking issues is capable of detecting faded white and yellow pavement markings. The traffic sign model has the ability to identify regulatory signs, speed-related signs, warning signs, and guide signs. The litter and trash model can be used to detect white litter, black litter, dirt, and leaves on the roadside. Additionally, this project developed a prototype AI algorithm to identify steel guardrails and concrete barriers. Iterative training and tuning were implemented to ensure the robust performance of the developed algorithms. The results show that the developed AI models achieve good performance with the accuracy of over 85% in transportation asset identification.

The developed mobile phone-based AI package in this project delivers an accurate, efficient, and automated approach to collect and analyze transportation asset data, hence, enabling the inspection of transportation assets on a more frequent basis and further improving road safety.

1.0 INTRODUCTION

1.1 Problem Statement

Timely assessment of transportation asset conditions facilitates the practice of effective asset management with optimized resource allocation. The damage or deterioration of certain types of assets (e.g., debris on roads, faded pavement markings) also introduces traffic safety risks. Collecting this information on a frequent basis and prioritizing the maintenance of these assets are of significance to further improve asset management practices and road safety. However, traditional asset assessment methods heavily rely on the manual process, which could be labor-intensive and time-consuming (Schnebele et al., 2015). Also, manually collected data are usually incomplete, thus, insufficient for comprehensive assessments of transportation asset conditions (De Blasiis et al., 2020). Despite advances in sensing techniques such as Light Detection and Ranging (LiDAR) and infrared thermography in transportation asset information collection (Lin et al., 2022; Solla et al., 2014), these are expensive to operate. Limited scanning is allowed periodically for information collection. Hence, there is an urgent need to develop a lightweight information collection and assessment technique capable of acquiring transportation asset information in a timely and accurate manner.

In addition to timely information collection, automatic identification and evaluation of transportation assets are beneficial to save labor in asset management practice. Computing-based image analysis and object detection are similar to visual inspection by human inspectors (Spencer et al., 2019). Therefore, one promising solution is to leverage artificial intelligence (AI), more specifically, computer vision and deep learning to facilitate the process. The advancement of computer vision and deep learning has enabled object detection and image classification in various fields, including the automated detection of transportation assets (Du et al., 2020; Ghosh & Smadi, 2021). A well-developed AI model is expected to deliver a low-cost, objective, and efficient approach with timely detection and high accuracy in transportation asset assessment (H. Nguyen et al., 2018; Pang et al., 2021). The key steps to develop AI models include sufficient collection, labeling, and utilization of data (e.g., videos and images) in the algorithm process. In this regard, the basis for AI model development is the image, which can come from different sources, for example, photos taken from drones (Alzraiee et al., 2021), LiDAR images (Lin et al., 2022), Google Street views (Campbell et al., 2019), and images taken by cameras or even phones (Wu & Ranganathan, 2012). Among different sources of images, cameras or phones are cheaper and more available than most other devices (Hanson et al., 2014). Therefore, combining AI models with images taken by phones has great potential in automatic data collection and identification of transportation assets.

Therefore, this project aims to develop accurate and easily deployed AI algorithms to facilitate transportation asset management in an automatic manner. The proposed technology leveraged a smartphone mounted on the front windshield of a vehicle to collect videos. Then, based on these collected videos, we developed AI algorithms that can automatically assess the conditions of pavement markings and identify traffic signs and litter on the roadside. A prototype algorithm for detecting concrete barriers and steel guardrails was also developed. The proposed technology offers an affordable solution to enable maintenance asset data collection on a more frequent basis.

1.2 Research Objectives

There are two research objectives in this project.

The primary objective of this project is to develop usable AI algorithms capable of automatically detecting certain types of transportation assets, including pavement markings, traffic signs, and steel guardrails and concrete barriers, as well as the litter and trash on roads.

With the developed algorithms, the other objective of this research is to evaluate the performance of leveraging a mobile phone as a lightweight and easily implementable data collection method to facilitate the auto-detection of transportation assets.

1.3 Research Scope

The project consists of five main research tasks (listed below), i.e., developing usable AI algorithms to detect pavement marking issues, traffic signs, trash/litter, and a prototype algorithm to identify concrete barriers and steel guardrails. The identification of pavement issues was originally in the scope but removed based on the comments of the TAC. Also, the AI development currently focuses on state roads (highways), although data collection/processing in the AI algorithm development incorporates both state and local roads. The five specific tasks are described below:

Task 1: Literature review: Review existing technologies and current practices in transportation asset information collection.

Task 2: Preliminary study: Record videos of roadways using mobile phones and pre-evaluate the capability of AI in transportation asset identification (basic assumption: an object/phenomenon that human eyes can capture could also possibly be detected by AI).

Task 3: Proof of concept 1: Develop AI algorithms to detect pavement marking issues, traffic signs, and trash and litter on the road.

Task 4: Proof of concept 2: Develop a prototype algorithm for concrete barriers and steel guardrail identification.

Task 5: Project report preparation: Prepare the final project report.

1.4 Outline of Report

The remaining report is structured as follows. Section 2 reviews the pros and cons of current common practices in transportation asset data collection and applications of AI algorithms in maintaining various transportation assets. Section 3 introduces the methods used in this project and accuracy metrics to measure the developed algorithms' performance. The results and performance of the developed AI models for the identification of pavement marking issues, traffic signs, and litter/trash, as well as the prototype algorithm for steel guardrail and concrete barrier identification are presented in section 4. Finally, section 5 summarizes the key findings and recommendations for future work.

2.0 LITERATURE REVIEW

2.1 Transportation Assets Data Collection

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

2.1.1 Ground-Penetrating Radar (GPR)

GPR is an electromagnetic-based geophysical method employing radar pulses (200mm-3m) to image the subsurface with either a ground-coupled antenna (60cm-3m) or an air-coupled antenna (200-300mm) (Schnebele et al., 2015). The principle of GPR is shown in Figure 2.1. A GPR transmitter and antenna emit electromagnetic energy into the ground. When the energy encounters a buried object or boundary between materials with different dielectric permittivity, it may be reflected, refracted, or scattered back to the surface. A receiving antenna can then record the variations in the return signal, including the arrival time and the magnitude of the reflected signal (Tong et al., 2020).

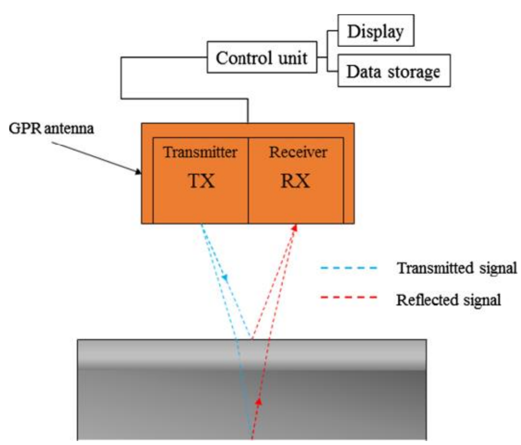

Figure 2.1 The Principle of GPR
(Khamzin et al., 2017)

GPR has been proven to be a useful technology in collecting and assessing pavement conditions. Specifically, within a pavement segment, the dielectric permittivity varies in different pavement conditions. The dielectric permittivity of poor-quality pavement is different from that of high-quality pavement (Khamzin et al., 2017). GPR can also operate on moving survey vehicles (see Figure 2.2), which promotes its application in obtaining and assessing structures and materials of pavements, such as pavement layer thickness measurement, void discovery, and pavement distress detection (Khamzin et al., 2017; Vilbig, 2013).

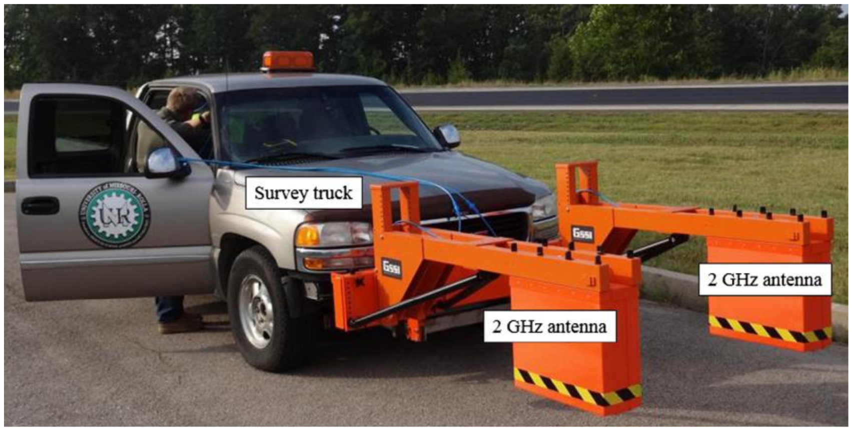

Figure 2.2 GPR Mounted on a Survey Vehicle
(Khamzin et al., 2017)

However, GPR has limitations in application. First, this technology requires the operators to have knowledge of both electromagnetic waves and pavement distress to interpret the results (Tong et al., 2020). Second, GPR can measure the depth and thickness of subsurface irregularities but cannot provide accurate horizontal information (Schnebele et al., 2015). Additionally, GPR is a subsurface detector to map underground anomalies but cannot be applied to collect the aboveground transportation assets (e.g., traffic signs and barriers) (Dai & Yan, 2014).

2.1.2 Light Detection and Ranging (LiDAR)

LiDAR is another common technology applied in transportation. The principle of LiDAR is shown in Figure 2.3. It measures ranges through targeting an object with a laser and then measuring the travel time of the reflected light back to the receiver. There are various types of LiDAR based on laser-mounted platforms, including the Terrestrial Laser Scanner (TLS) and Mobile Laser Scanner (MLS) (Schnebele et al., 2015; Topo, 2020). TLS uses ground-based remote sensing systems, usually mounted on static tripods, to scan objects in all directions. Once the scan in one area is complete, the tripod will be moved to another location to scan from another angle or capture data in a new area. Furthermore, MLS allows the acquisition of 3D data employing one or more laser scanners mounted on moving vehicles, unmanned aerial vehicles (UAVs), or helicopters. Figure 2.4 shows a mounted MLS on a moving vehicle.

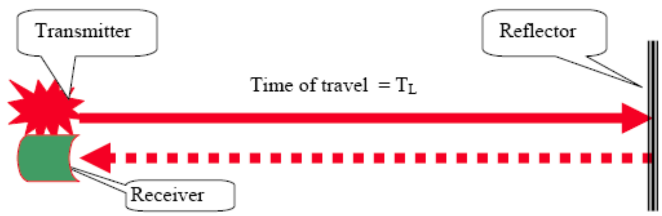

Figure 2.3 The Principle of LiDAR

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

LiDAR is widely applied to retrieve transportation asset information. Laser scanners are able to capture millions of 3D coordinates (also known as points), which form point clouds (Topo, 2020). These point clouds provide accurate and high-resolution 3D data and create digital models of the scanned environment (De Blasiis et al., 2021). For example, the 3D model created for pavement will facilitate the identification and evaluation of different types and severity levels of road roughness and distress (De Blasius et al., 2020; 2021). In addition to the pavement condition assessment, LiDAR is also applicable to collect and assess the information of lane markings (e.g., dashed lines, continuous lines, and direction arrows) and traffic signs (Gargoum et al., 2017; Zeybek, 2021).

LiDAR has several advantages in information collection and assessment of transportation assets. First, it has high accuracy and resolution in transportation asset data collection. Secondly, this technique is not sensitive to the ambient environment of data collection, e.g., humidity or temperature (De Blasiis et al., 2021). However, the cost of LiDAR is much higher than that of 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. Then, the measured amount of thermal infrared radiation can 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 shows examples of pavement IR images.

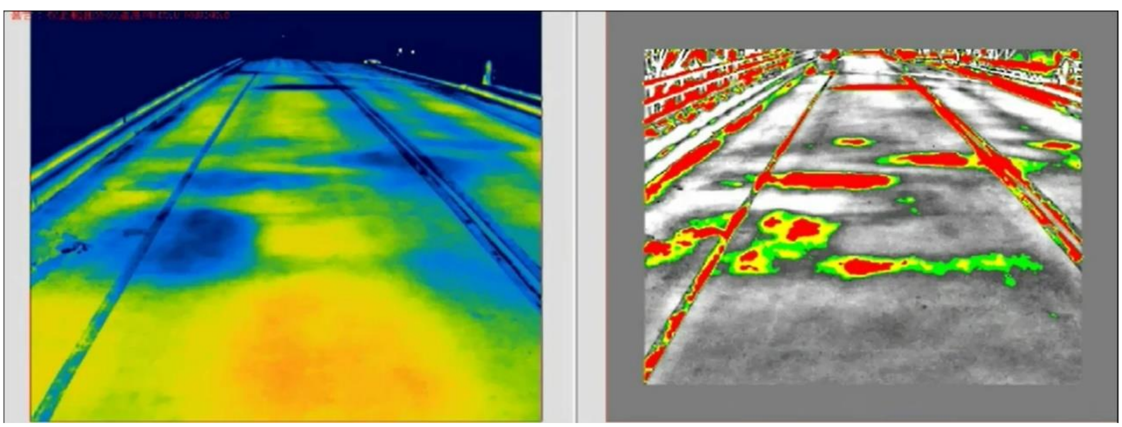

Figure 2.5 IR Image of Pavement [1]

IRT also provides remote measurements of objects of interest in wide areas (Sakagami, 2015). It is usually used to detect issues (e.g., pores, cracks, and delamination) related to asphalt,

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

metal, and concrete (Garrido et al., 2018; Lu et al., 2017). However, the spatial resolution of thermal images for most infrastructure is typically low, hence, affecting the inspection results. Moreover, in contrast to GPR, IRT is usable for horizontal data collection and measurement but not vertical measurements, such as thickness and depth of the subsurface (Schnebele et al., 2015). IR image collection, in many cases, requires costly professional IR cameras for accurate measurement as well (Garrido et al., 2018).

2.1.4 Hyperspectral Imagery (HSI)

HSI utilizes large numbers of narrow, contiguous spectral bands (sometimes ranging from as much 0.35-2.4μm) to gather detailed spectral information of an observed feature, often related to chemical and mineral properties (Schnebele et al., 2015). Figure 2.6 shows a hyperspectral image cube with two axes describing spatial information and one for spectral information. These are sufficient to differentiate natural and artificial objects (Gomez, 2002). The data collection and analysis by HSI are based on varied spectral reflectance across different materials. For example, the material inside road cracks differs from the material of worn surfaces, which can be captured by different spectral signals in hyperspectral images (Abdellatif et al., 2019). Therefore, HSI is applicable to assess the characteristics of pavement (Özdemir et al., 2020), including the identification of the defects and anomalies of pavement.

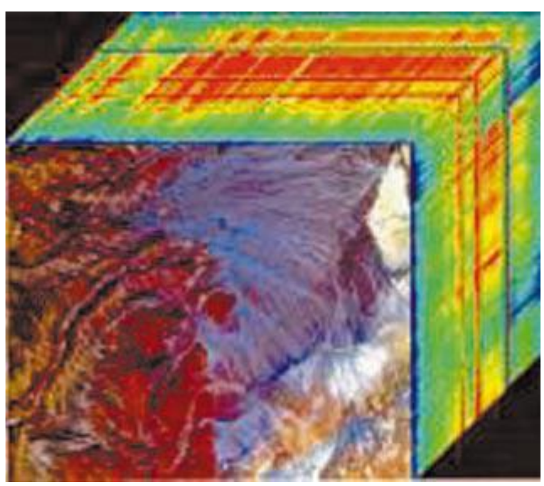

Figure 2.6 Hyperspectral Image Cube
(Gomez, 2002)

HSI is an effective nondestructive technology to determine the physical and chemical parameters (Ayalew et al., 2003). However, due to the operation principles of HSI, its application has certain limitations. First, it is mainly used to assess asphalt pavement conditions (Abdellatif et al., 2020). Moreover, it is difficult to distinguish the degree of weathering of an aged pavement, even when the differences are evident (Schnebele et al., 2015). In addition, the high price limits its application in the field (Ozdemir & Polat, 2020).

2.1.5 Close-Range Photogrammetry (CRP)

CRP is suitable for sensing physical objects at a distance less than 330 ft (100 m) from the camera (Jiang et al., 2008). This technique is usually used to measure and analyze the two-dimensional photographs collected by cameras. The final outputs of CRP can also be three-dimensional models reconstructed from 2D images taken from different angles. The 3D information is usable to assess the condition of objects (Farhadmanesh et al., 2021).

The application areas of CRP are relatively broader than other technologies. For example, cameras mounted on a vehicle (see Figure 2.7) have been utilized to detect transportation asset issues (e.g., pavement, guardrail, and marking) (Farhadmanesh et al., 2021; Liq et al., 2012). Also, these image data can be combined with other techniques, e.g., deep learning and image processing, to extend its application. For example, traffic signs can be detected automatically based on the color of objects, geometrical edge, and corner analysis (Ruta et al., 2010).

Figure 2.7 Mobile Photogrammetry Setup and the View
(Farhadmanesh et al., 2021)

CRP provides a direct way of data collection (through mobile phones or cameras) and analysis, hence, allowing frequent data updates without introducing high costs (Ahmed et al., 2011; Hanson et al., 2014). However, CRP also has limitations. Mainly, its precision and accuracy could be lower compared to other technologies (Ragnoli et al., 2018). Moreover, some factors (e.g., vehicle speed, camera quality, light conditions, etc.) will affect the final resolution of the images collected (Farhadmanesh et al., 2021; Gargoum et al., 2017).

2.1.6 Brief Summary

The comparisons of the five sensing techniques are shown in Table 2.1. Overall, GPR, IRT, and HSI have limited application areas. Although LiDAR, GPR, IRT, and HSI have relatively high accuracy, they need costly professional instruments and expert knowledge to collect and interpret the data. In contrast, CRP is a low-cost method of data collection, which can be easily achieved with mobile phones. Therefore, close-range photogrammetry has demonstrated its great potential as an affordable and reliable approach to assessing the conditions of various types of transportation assets.

Table 2.1 Comparisons 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
HSI	Medium	Complex	Limited	High
CRP	Relatively low	Medium	Wide	Low

2.2 Transportation Asset Maintenance AI Models

AI models (e.g., computer vision and deep learning) perform well in automatic object detection and image classification. Currently, these AI models have been applied in transportation asset monitoring and maintenance practices.

2.2.1 Artificial Intelligence Models

Computer vision is an interdisciplinary research area to understand the underlying physical world by extracting and analyzing valuable information from images or videos (Huang et al., 2021). Image analysis and object detection by computer are similar to visual inspection by human inspectors due to the information captured by images or videos being analogous to that obtained by humans (Spencer et al., 2019). From low-level to high-level processing, computer vision includes image acquisition, segmentation, feature extraction, object recognition, and structure analysis (Koch et al., 2015).

Deep learning has a strong capability to interpret images, sounds, and text by mimicking the mechanisms of the human brain in interpretation. The frameworks of deep learning consist of multiple layers of neuron nodes, and the training dataset is used to solve the weights of the neural network and form the AI model (Lu, 2019). There are large numbers of deep learning frameworks available, such as You Only Look Once (YOLO) (Redmon et al., 2016), Convolutional Neural Networks (CNN), and Region-CNN (RCNN) (Krizhevsky et al., 2017). Compared with other deep learning methods that propose regions of interest first before convolution operation, YOLO performs detection and classification simultaneously (Redmon et al., 2016). This makes YOLO run faster than other algorithms (e.g., Faster RCNN) and achieve higher mean average precision (Redmon et al., 2016). Consequently, YOLO is proven to be an object detection model with high accuracy and speed among deep learning models.

In recent years, due to the high accuracy and fast speed of deep learning, deep learning has fueled significant strides in various computer vision problems, including object detection and image segmentation (Voulodimos et al., 2018). Compared to traditional computer vision algorithms, deep learning has many advantages. Traditional computer vision algorithms use certain programming paradigms to extract features, requiring trial and error to select the appropriate ones (O'Mahony et al., 2020). On the other hand, deep learning directly uses a training framework with a set of inputs and known outputs, which alleviates the tedious process of feature extraction and signal processing (O'Mahony et al., 2020). Second, deep learning can achieve better performance compared to other traditional computer vision methods, especially in big data analysis, e.g., video data processing and analysis (Huang et al., 2021).

2.2.2 Applications of AI Models in Transportation Assets Maintenance

Various AI algorithms have been applied to transportation asset maintenance, among which pavement condition assessment is a major research area. The commonly used deep learning methods include CNN (Gopalakrishnan et al., 2017), Faster RCNN (Majidifard et al., 2020), and YOLO (Mandal et al., 2020). There are also rich public datasets related to pavement distress that were collected by smartphones, cameras, and Google view images (Majidifard et al., 2020; Mandal et al., 2020). Based on these AI models and data sources, multiple types of pavement distresses, for example, transverse cracks, longitudinal cracks, block cracks, potholes, and alligator cracks, can be automatically identified with high accuracy (Du et al., 2020; Ghosh & Smadi, 2021; Majidifard et al., 2020). Besides, there are several studies focusing on the pavement issues related to specific types of pavement, e.g., asphalt pavement (Wang et al., 2017; Wen et al., 2022) and Portland cement concrete (Gopalakrishnan et al., 2017). Some exceptional cases were also studied, such as object detections in nonideal photographic images with low illumination levels or shadows cast by nearby objects (Tepljakov et al., 2019).

Other than pavement, previous studies related to automatic pavement marking condition assessment also exist. Zhang & Ge (2012) adopted traditional image processing methods (e.g., camera calibration, Hough transformation, feature recognition, etc.) to assess conditions of pavement marking automatically. Xu et al. (2021) also applied image pre-processing, feature extraction, and segmentation to detect and assess the damage of pavement line markings. Traditional image processing techniques, however, have insufficient robustness because they rely on accurate feature extractions from images, which could be affected by various types of noise originating from complex real-world situations, e.g., light and shadows (S. Li & Zhao, 2019). In terms of the applications of deep learning, Kawano et al. (2017) applied YOLO to detect faded pavement markings. However, the accuracy of detection was less than 50% due to inaccurate annotations. Kang et al. (2020) developed a framework to evaluate the visibility conditions of pavement markings based on deep learning (YOLOv3). Additional image processing techniques (e.g., edge extraction, mask construction, and gray transformation) for image processing are required in their developed framework. Vokhidov et al., (2016) used the CNN to detect damaged pavement markings with a focus on arrow-based markings. Wei et al., (2021) combined Fater-RCNN with U-Net to evaluate the damage ratio of white pavement markings while neglecting other pavement markings.

Another application area of AI algorithms in transportation asset management is the identification of traffic signs. Hoang et al. (2018) combined different computer vision methods (e.g., image augmentation and region processing) with CNN to establish an AI model for traffic sign recognition. Similarly, Tabernik & Skočaj (2020) used a deep learning model, more specifically mask R-CNN, to build an automatic traffic-sign inventory management system involving 200 categories of traffic signs. Based on open-source images (i.e., Google Street view images), Campbell et al. (2019) built a training dataset and developed a deep learning model to identify the Stop and Give Way signs on the streets. The robustness of automatic traffic sign detection in special scenarios (e.g., snowy days, low illumination) has been studied as well (Chehri et al., 2021; Khan et al., 2018).

Compared to pavement issues, fewer studies were conducted on litter and trash recognition on roads. Liu et al. (2018) applied YOLOv2 to detect garbage on the pavement; however, only one class of garbage was considered. Likewise, the AI model developed by Sayyad et al. (2020) did not classify different types of identified garbage and was only applicable to garbage of large size. P. Zhang et al. (2019) applied Faster R-CNN to identify different categories of litter and count the number automatically. Although this study mentioned eight categories of litter, including inorganic, organic, trash, and tree leaves, the image data used were collected entirely on street roads, which may limit its application to litter detection on highways.

Furthermore, there is far less research to detect steel guardrails and concrete barriers. Hou et al. (2022) proposed an automatic guardrail detection model based on 3D local features extraction; however, the model is based on mobile LiDAR data. Regarding RGB images, Z. Liu et al. (2020) built a standard urban image database containing eight categories of urban images in cities, among which damaged traffic guardrail is one category. Jin et al. (2021) integrated feature extraction with mask RCNN to detect steel guardrails on highways; however, concrete barriers were ignored in this model.

2.2.3 Brief Summary

Overall, deep learning and computer vision have outstanding performance in automatic object detection and image classification. In the past, they have been used in many fields, including transportation assets monitoring and inspection. Pavement condition assessment is one of the most studied areas, followed by traffic signs identification, which proves the great potential of applications of AI models in transportation assets detection. However, relatively less research has been conducted on identifying pavement marking issues, steel guardrails and concrete barriers, and litter/trash on roads.

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[1] is an infrastructure asset management firm that has developed an AI-based system to manage transportation assets, including 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 the asset data. AI algorithms are then developed to process collected data and automatically extract transportation assets (e.g., traffic signs, guardrails, striping, etc.). With imagery and point cloud analysis, the inventory of assets is created with evaluated conditions. Figure 2.8 shows an example of the scanning and automatic extraction of steel guardrails.

Figure 2.8 An Example of Guardrail Scan and Automatic Extraction by Pillar

2.3.2 Esri

Esri[2] has created a deep learning model to predict indicators of road conditions, such as road roughness and level of crack damage, by leveraging road traffic density and road condition

[1] https://www.pillaroma.com/artificial-intelligence-ai-in-transportation-asset-management/
[2] https://www.esri.com/en-us/industries/roads-highways/business-areas/maintenance

data. Esri allows the users to organize road assets comprehensively, understand their location and condition, and integrate systems with the leading asset management solutions for road maintenance. Besides, Esri provides mobile solutions to help with data collection and asset inspection on highways. Florida Department of Transportation (FDOT) has adopted this system, called FDOT's public-facing eMaintenance Web App (see Figure 2.9), which is open to the public to see inspection results for crash cushions and guardrails across Florida[1].

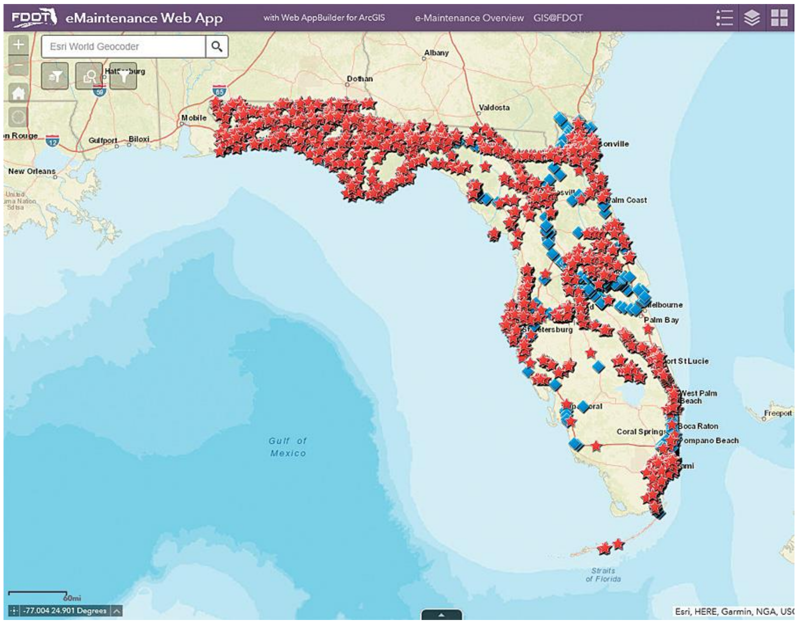

Figure 2.9 The Interface of FDOT eMaintenance Web App

2.3.3 Deep Systems

Deep Systems (Russia)[2] is an automatic road defect detection software developed by one of the leading Russian research groups based on computer vision and deep learning. The algorithm runs in real-time to quickly detect defects (e.g., cracks, holes, and patches) from the recorded video. This system also provides a Web dashboard for monitoring and controlling GPU clusters, including training models, running defects detection, and viewing results. The dashboard page is shown in Figure 2.10. Moreover, it has robust interoperability that supports operators in creating, modifying and populating training samples according to their requirements.

[1] https://www.esri.com/about/newsroom/arcnews/big-data-is-coming-and-fdot-is-prepared/

[2] https://deepsystems.ai/solutions/road-defects-detection

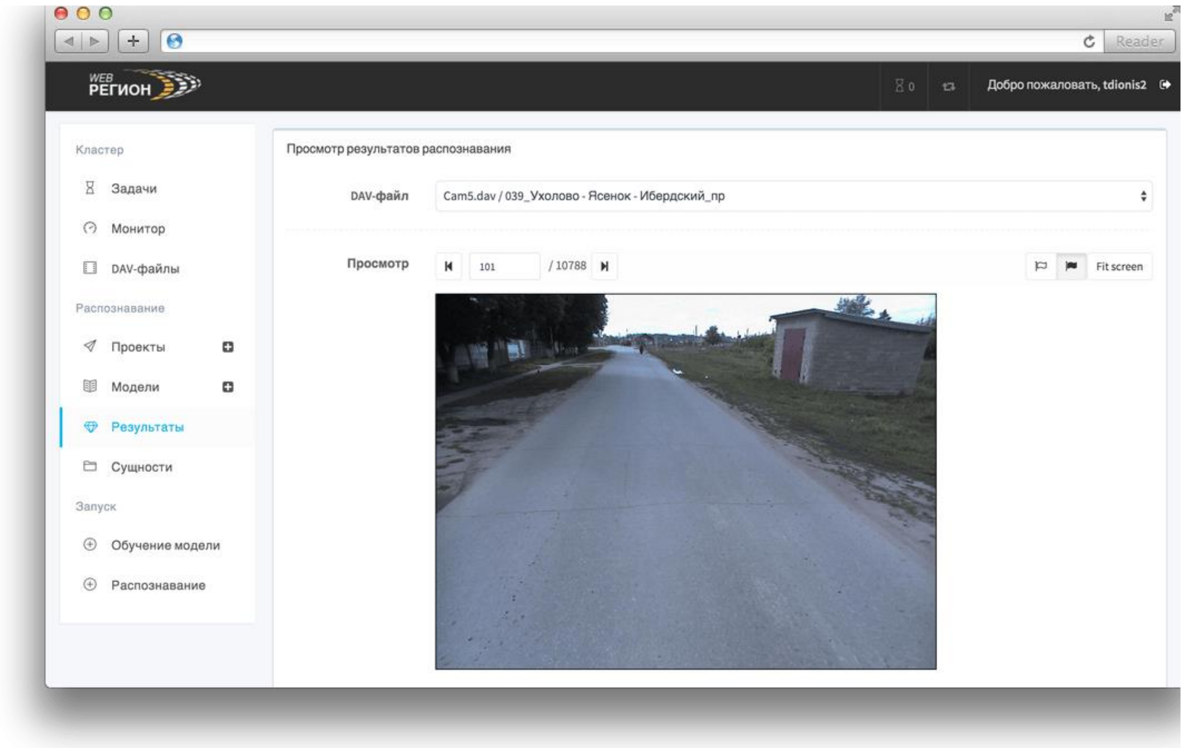

Figure 2.10 Web Dashboard Page of Deep System

2.3.4 TRIK

TRIK[1] is an enterprise software solution that allows the efficient use of drone photography for structural inspection. It automatically turns photos taken by drones into an interactive 3D model, which can be measured and annotated. The 3D model can also serve as a database that supports photo search, structural change detection, and project maintenance directly. Besides, the created model can help detect pavement issues as well.

2.3.5 Pavemetrics

Pavemetrics[2] develops a Laser Crack Measurement System (LCMS-2), which is a 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, including but not limited to cracking, rutting, texture, potholes, bleeding, shoving, raveling and roughness.

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[1] https://gettrik.com/
[2] https://www.pavemetrics.com/applications/road-inspection/lcms2-en/

2.3.6 Brief Summary

TRIK and 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 assist operators in identifying transportation assets and assessing their condition based on deep learning technologies. Increasing combinations of computer vision and deep learning technologies have been applied in transportation asset management.

3.0 METHODOLOGY

3.1 Research Process Overview

The overall workflow of AI model development is shown in Figure 3.1. In general, AI algorithm development follows an iterative process. First, a mobile phone was mounted on the front windshield of vehicles for video collection. These collected videos were then converted into images and labeled for AI model training and test. Specifically, these labeled images were fed into the YOLO framework to train the AI models. Model tests were then performed using the test videos to identify remaining issues in object detection (manual verification). Then, based on identified issues, new images related to these remaining detection errors were further added into the training dataset to start a new round of iterative training. The full cycle was repeated for iterative model improvement.

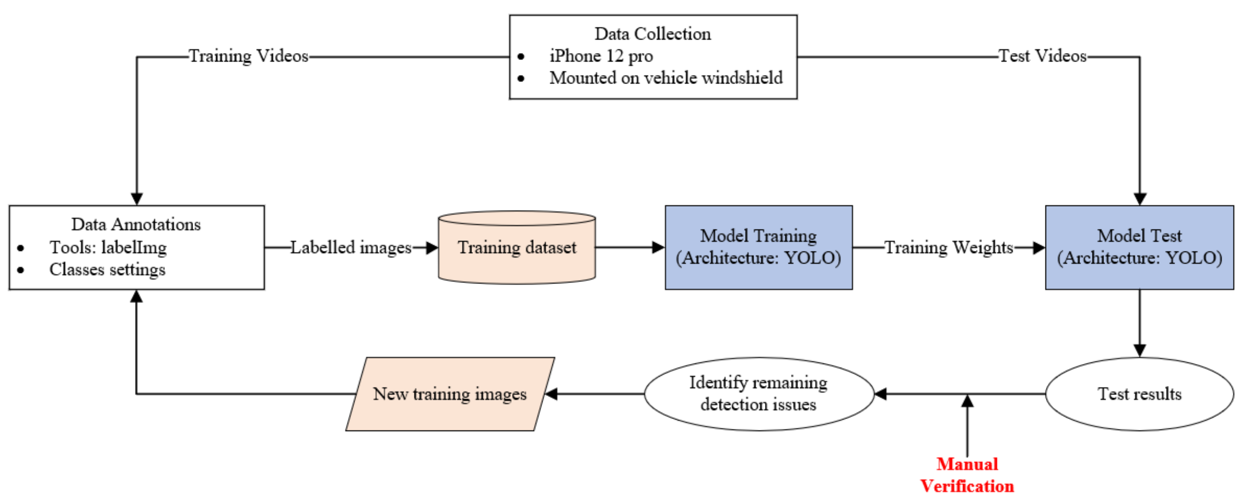

Figure 3.1 Flowchart of Model Development and Improvement

3.2 Data Collection and Processing

To collect transportation asset data for AI model training and test, a mobile phone (iPhone 12 pro with a 12-megapixel triple-lens camera at the back) was mounted on the front windshield of a vehicle on the passenger side, hence, viewing transportation assets from a front view. The setup of video collection on a vehicle is shown in Figure 3.2.

Figure 3.2 Setup of Video Collection

The collected videos have 30 frames per second (fps). In total, approximately 31 hours of videos (estimated to contain ~3.3 million images) have been collected on highways and local streets. These videos cover all types of transportation assets targeted in the project, including pavement markings, traffic signs, steel guardrails and concrete barriers, and litter & trash. Certain special scenarios, such as strong glare and low illuminance days, are included in data collection as well. To avoid missing objects, each image frame in the recorded videos was extracted in sequence. Only extracted images of high quality (e.g., with clear objects) were included in the training and test dataset. Additionally, to reduce duplicate images for one object, a maximum of 3 images for a single object were selected as training images.

In addition to the self-collected images, this project has utilized other data sources, e.g., images processed from the UDOT Roadview Explorer dataset and Google Street view, to train AI models. Our tests found that the self-collected data achieved the best performance in algorithm training due to the straight and clear view of transportation assets from the front windshield. Therefore, in this stage, only images processed from self-collected videos were used to build AI models.

3.3 Data Annotations

This project adopted LabelImg[1] to label objects with bounding boxes in the development of training and the test dataset. LabelImg is a free and open-source tool to label images graphically. We labeled our training dataset separately for the identification of different transportation assets in different tasks.

3.3.1 Pavement Markings Annotations

In this project, we differentiated the pavement markings into white and yellow markings and assessed the conditions of these markings correspondingly. Based on ASTM (2020) and Zhang & Ge (2012), markings with over 50% of faded or missing areas were labeled as faded. Hence, faded markings were classified into two classes, i.e., “y_faded” (yellow faded markings) and “w_faded” (white faded markings) in this study. The “y_faded” includes faded double and single curb or lane markings in yellow. “w_faded” includes faded longitudinal lane markings, horizontal markings (e.g., crosswalk, stop line), arrow markings, and delineators in white.

3.3.2 Litter & Trash Annotations

This project classified trash and litter on the pavement into four types, namely “leaves”: vegetation and leaves on the roadside; “dirt”: dirt on the roadside; “w_litter”: litter in white or light colors (e.g., plastic, foam); “b_litter”: litter in black or dark colors (e.g., used tire, rubber, branch).

3.3.3 Traffic Signs Annotations

Based on the Manual on Uniform Traffic Control Devices (FHWA, 2009), traffic signs have been classified into four types, that is, (1) “regulatory”: stop signs, yield signs, Do not enter (most in red or white); (2) “speed”: speed limit, school zone (most in white); (3) “warning”: warning signs, object markers (most in yellow); and (4) “guide”: destination guide signs, traffic movement (most in green).

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

3.3.4 Guardrails and Barriers Annotations

There were two classes presented, namely “concrete”, including cast-in-place concrete barriers and New Jersey shape barriers, and “w_beam steel”, such as w-beam with steel blocks and w-beam guardrails.

3.4 You Only Look Once (YOLO)

YOLO is an object detection model that was pretrained using the COCO dataset. YOLO proposes regions of interest and makes detection simultaneously; therefore, YOLO is faster than most state-of-the-art algorithms (Redmon et al., 2016). YOLO predicts bounding boxes of target objects and probabilities of the associated class directly after one scan of images. Only prediction with more than 30% confidence will be considered an effective identification and labeled with bounding boxes. YOLO is able to crop the labeled objects for further processing after detection.

In this project, we use YOLOv5[1] as the base AI framework and continue the development. The architecture of YOLOv5 is shown in Figure 3.3 (S. Xu et al., 2021). The backbone, neck, and output are the three main parts of the YOLO framework. First, in the backbone network, a cross-stage partial network (CSP) and spatial pyramid polling (SPP) are used to extract feature maps from the input image in different scales across multiple convolutions and pooling layers (Z. Li et al., 2022). In this way, the inference speed and accuracy can be improved. Then, a path aggregation network (PANet) is employed in the neck network to make useful information in each feature level propagate directly to the following subnetwork. It improves the propagation of low-level features through the enhanced bottom-up path and leverages adaptive feature pooling to increase the utilization of accurate location signals in lower layers (S. Xu et al., 2021). Finally, the head is the output of YOLO. It generates three different sizes of feature maps (18x18, 36x36, and 72x72) to detect objects in multiple scales (Redmon et al., 2016; S. Xu et al., 2021). With the developed framework, YOLOv5 has a high detection speed and accuracy.

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[1] https://github.com/ultralytics/yolov5/

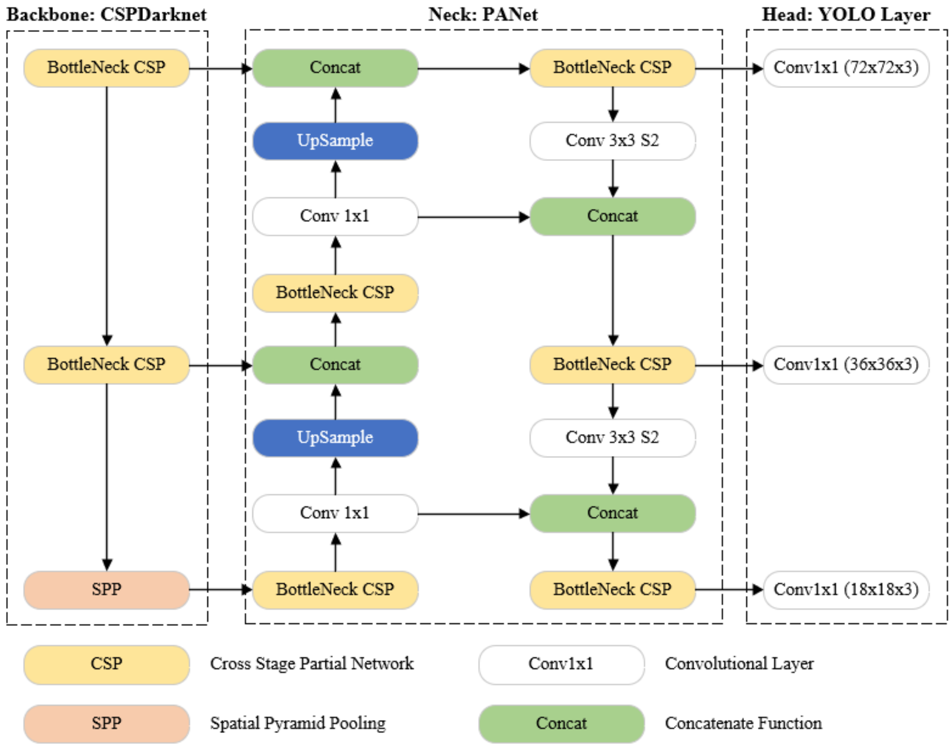


Figure 3.3 The Architecture of YOLOv5

(R. Xu et al., 2021)

3.5 Accuracy Metrics

This project applies YOLO to train the AI modes for transportation asset detection. The metrics are defined as follows:

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

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

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

TP describes the true positive, i.e., a positive object is captured by a prediction box, while a false positive (FP) dictates that a prediction box is made but captures a wrong object. Likewise, false negative (FN) means that a positive object is not detected with any prediction box. The precision reflects the reliability in classifying objects as positive, while the recall measures the models' ability to detect positive objects (i.e., TP). To avoid outperforming in one of the two metrics (i.e., precision and recall) but underperforming in the other, the F1-score is introduced to balance recall and precision by weighting them equally (Arya et al., 2020). In the reported metrics, since our objective is to identify the objects of interest, these objects will be marked as true positive as long as they are captured by the developed AI algorithms in the video detection process.

4.0 AI MODEL DEVELOPMENT FOR TRANSPORTATION ASSETS

4.1 Model Training Environment and Parameter Setting

The training and test in AI model development were performed using a Windows 10 desktop. The hardware information, configurations of the AI development environment, and training parameters are shown 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

1479 images were incorporated into our training dataset for pavement marking model development, in which 1088 images were used for training while 391 were used as validation images.

4.2.1 Model Training and Test Performance

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

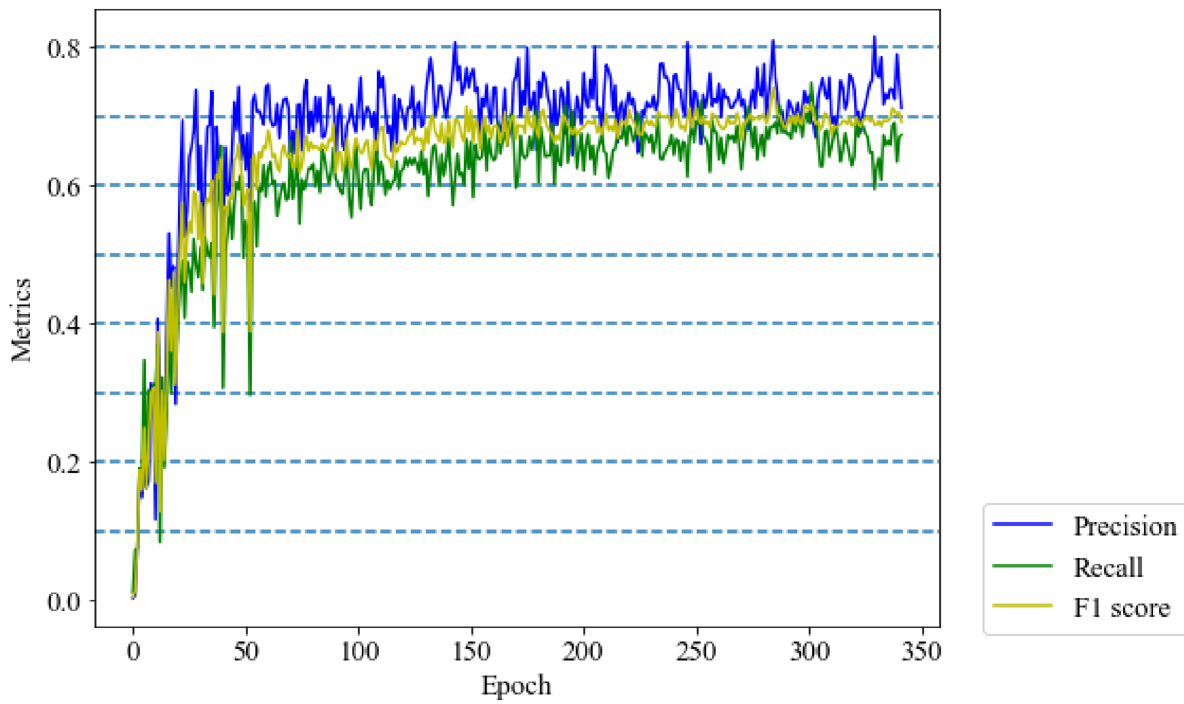


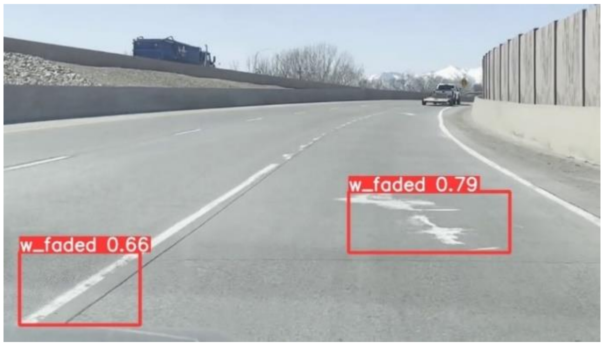
Figure 4.1 Accuracy Metrics of Pavement Marking Issues During Training

Table 4.3 Training Results of Pavement Marking Issues

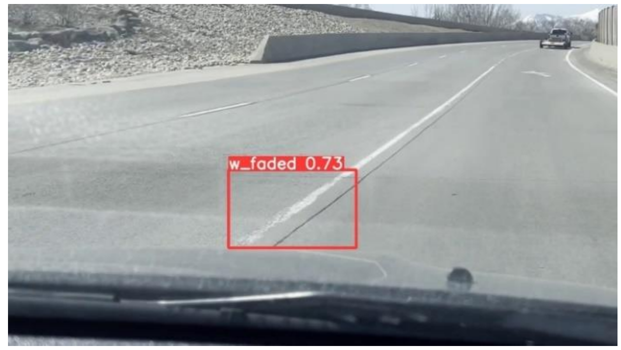
Class	Precision	Recall	F1 score
all	0.87	0.9	0.89
w_faded	0.88	0.91	0.89
y_faded	0.86	0.89	0.87

4.2.2 Examples of Pavement Marking Issues Detection

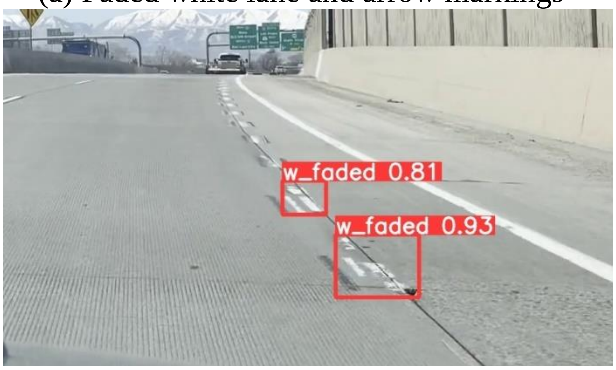
In the iterative improvement process, we have performed visual inspections on approximately seven hours of videos to validate the performance. More training images were incorporated to correct wrong identifications. The addressed detection issues include false detection of normal markings as faded markings, wrong classification of pavement issues as faded markings, and wrong detection 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

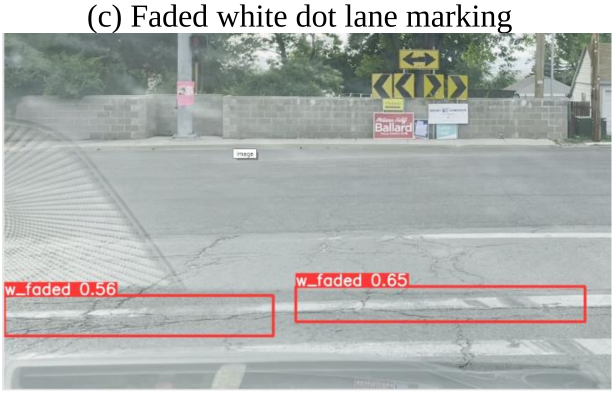


(b) Faded white lane marking

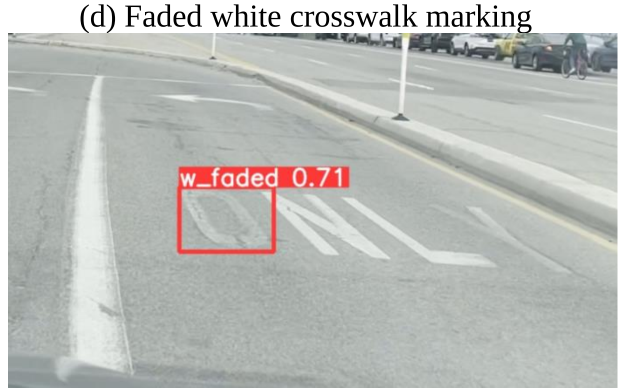


(c) Faded white dot lane marking

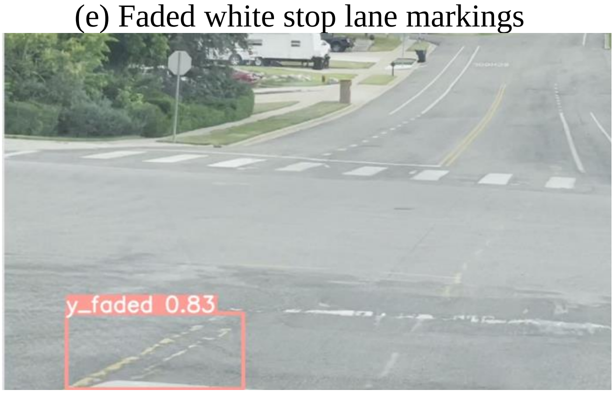
(d) Faded white crosswalk marking



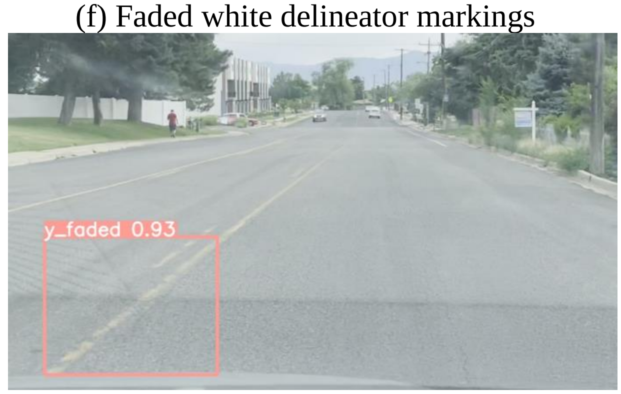
(e) Faded white stop lane markings



(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

1916 images were used to develop the AI model for trash and litter detection with 1371 and 545 for training and validation, respectively.

4.3.1 Model Training and Performance

The AI model for litter & trash identification converges after 457 epochs since there existed no obvious improvement in the last 100 epochs. The optimal training model was achieved at the epoch 357. The training process and accuracy metrics are shown in Figure 4.3 and Table 4.4. The precision and recall rate of the developed AI model are 86% and 92%, respectively. The F1 score is 89%.

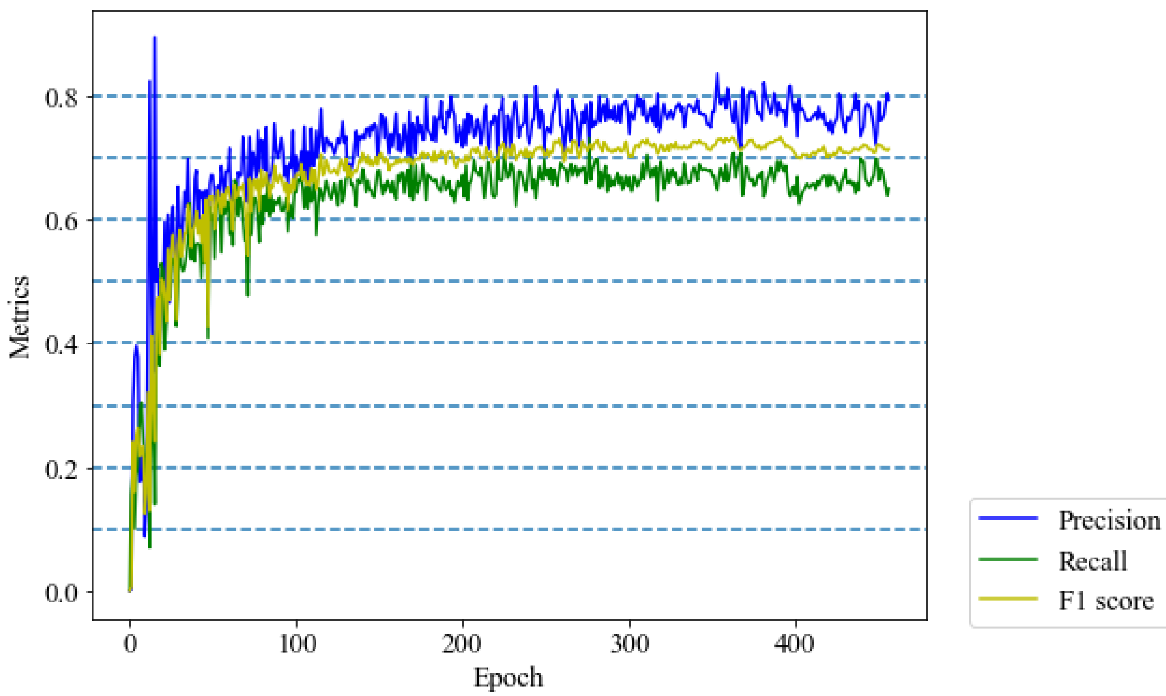


Figure 4.3 Accuracy Metrics of Litter & Trash Identification During Training

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

Around four-hour videos have been tested in the iterative AI model development process. The addressed litter & trash detection issues include misclassification of outfall points on highways as “b_litter”, and wrong 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.

4.4 AI Model Development to Identify Traffic Signs

Overall, 1456 images were used to train the AI model for traffic signs detection, among which 1026 and 430 images were employed for training and validation, respectively.

4.4.1 Model Training and Performance

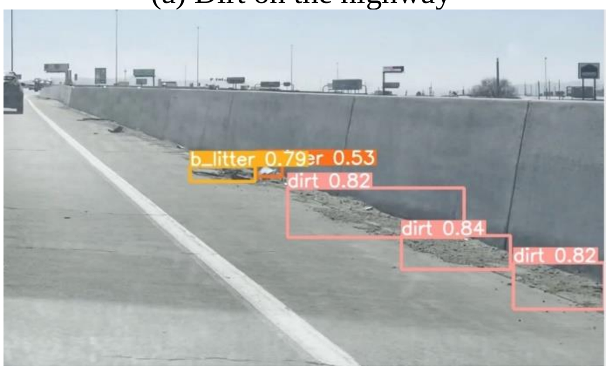
The training process stopped in 315 epochs as no improvement was observed in the last 100 epochs. The best results were observed at epoch 215. Training results are shown in Table 4.5 and Figure 4.5. The AI model for traffic sign identification reaches convergence within the training process. The overall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

(a) Dirt on the highway

(b) Black litter on the highway



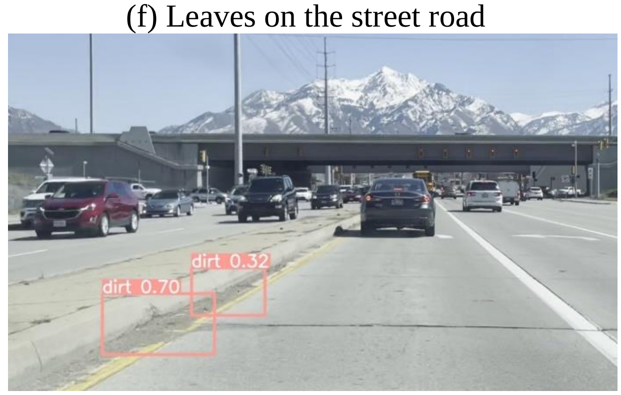
(c) Dirt and litter on the highway

(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

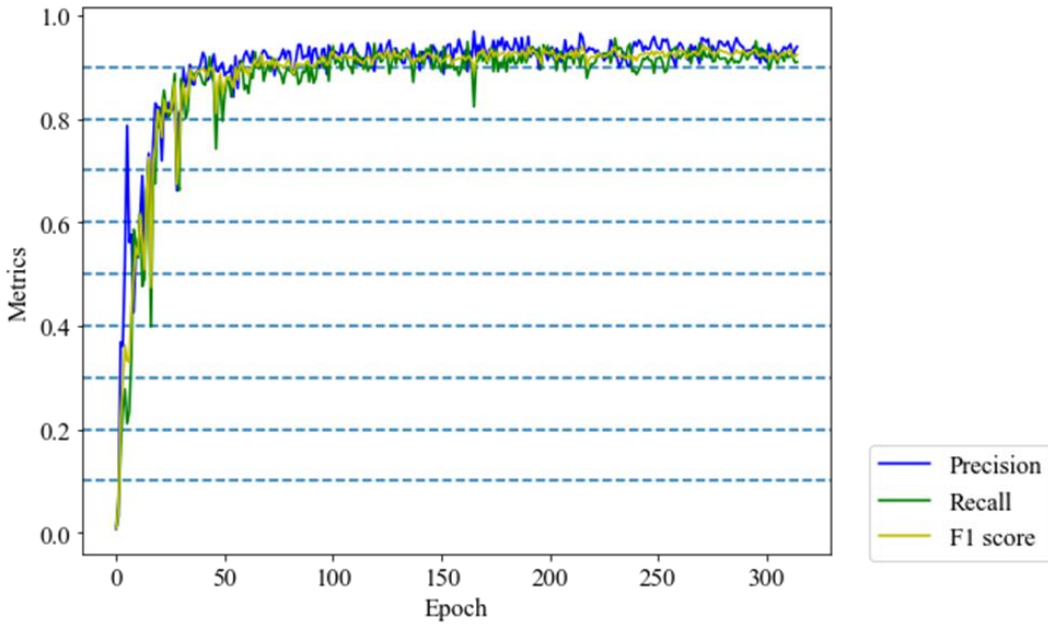


Figure 4.5 Accuracy Metrics of Traffic Signs During Training

4.4.2 Examples of Traffic Signs Detection

The model developed for traffic signs was tested on 2-hour videos in the improvement process. The addressed detection issues in the iterative improvement process include the misclassification of advertisement boards on highways as traffic signs and the failure of sign detection when it is obscured by trees. Examples of using AI to identify traffic signs are shown in Figure 4.6.

4.5 AI Prototype Development to Identify Guardrails and Barrier

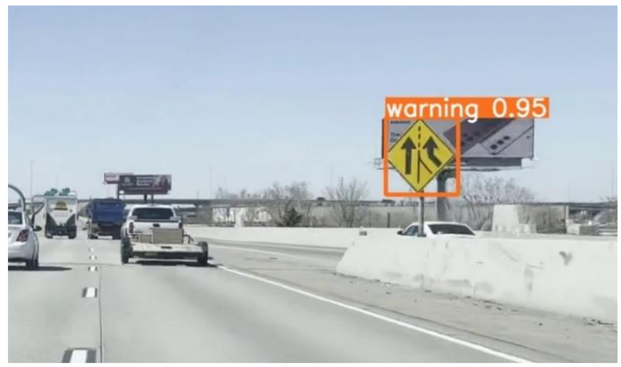
A prototype AI algorithm for steel guardrail and concrete barrier identification was developed using 241 images, among which 153 and 56 images were used for training and validation, respectively. The training process of this prototype AI algorithm development stopped in 265 epochs since no improvement was observed in further training. The best results were observed at epoch 165.

The training process is shown in Figure 4.7. The AI model converges during the training process with ~80% accuracy in concrete barrier and steel guardrail detection. The training results demonstrate great potential to develop a high-performance model to identify steel guardrails and concrete barriers. The detection examples for the two classes are shown in Figure 4.8.

(a) Traffic movement guide and speed warning

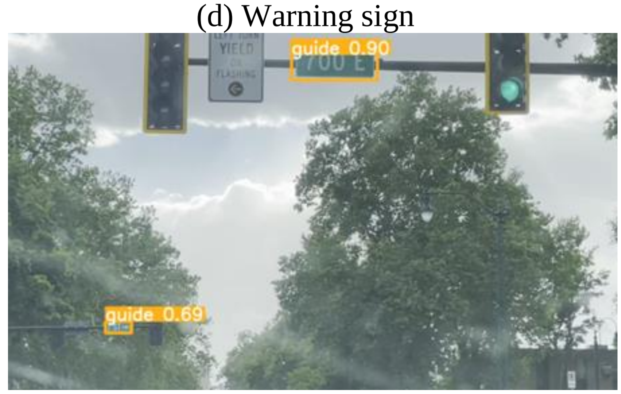
(b) Traffic movement guide

(c) Exit guide and warning marker



(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

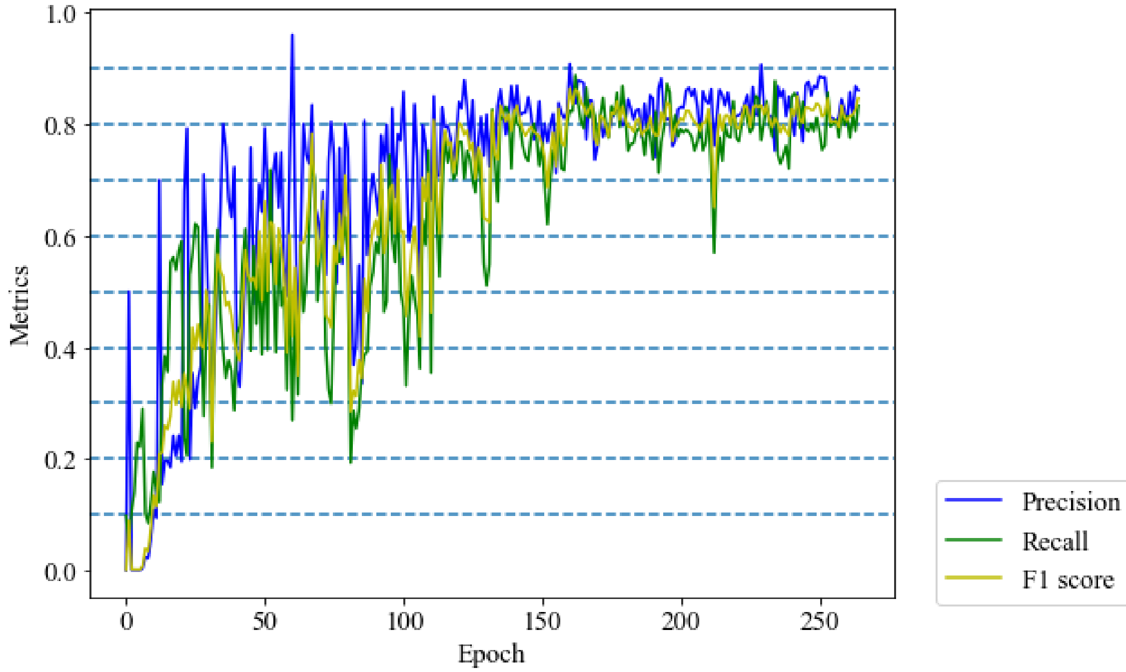
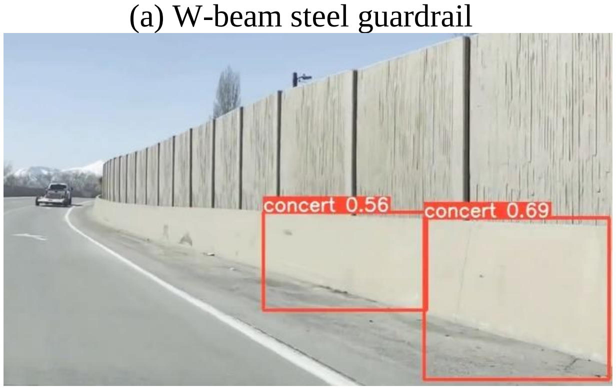


Figure 4.7 Accuracy Metrics of Guardrails and Barriers During Training

(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

<u>5.0 CONCLUSIONS</u>

5.1 Summary

Close-range photogrammetry (including photogrammetric data collection by mobile phones) enables a lightweight solution for timely transportation asset information collection without introducing additional cost. Meanwhile, AI models (e.g., computer vision and deep learning) perform well in automatic object detection and image classification, showing great potential in transportation asset monitoring and maintenance. Therefore, this project develops reliable and affordable AI algorithms, capable of analyzing collected videos by mobile phones, to facilitate automatic information collection and assessment of transportation assets, including pavement markings, traffic signs, trash & litter, and steel guardrails and concrete barriers.

In total, we collected approximately 31 hours of videos, covering both highways and local roads, with a smartphone mounted on the windshield of a vehicle. With videos processed into labeled images for training and validation, the AI package was developed for automatic information collection of all targeted types of transportation assets listed above. The results show that the developed AI models are capable of automatically collecting relevant transportation asset information with high accuracy (over 85%) and efficiency.

5.2 Findings

In this study, three AI models for automatic detection of pavement marking issues, traffic signs, and litter & trash, as well as a prototype model for steel guardrail and concrete barrier identification were developed based on training and test images processed from self-collected videos by a mobile phone mounted on the windshield of a vehicle. Specifically:

(1) 1496 images were used to train the AI model for pavement markings issue detection, where pavement marking issues have been classified into two classes by color, i.e., faded yellow markings (“y_faded”) and faded white markings (“w_faded”). The precision, recall, and F1 score of this AI model are 87%, 90%, and 89%, respectively.

(2) 1916 images were used to develop the AI model for trash and litter identification, including four major classes, i.e., leaves, dirt, white litter (“w_litter”), and black litter (“b_litter”). The model achieves 86% precision, 92% recall, and 89% as the F1 score.

(3) 1456 images were used to train the AI model for traffic sign identification. The traffic signs have been classified into four categories: “regulatory,” “speed,” “warning,” and “guide.” The accuracy metrics of the developed model are 88% for precision, 90% for recall, and 89% for the F1 score.

(4) A prototype AI algorithm for steel guardrail and concrete barrier identification was developed using 241 images. The AI model performs well in identifying both steel guardrails and concrete barriers in tested videos and demonstrates great potential to achieve high-accuracy detection with further development.

5.3 Limitations and Future Work

With decent performance in current AI model development, limitations still exist. Firstly, the training dataset is still limited, leading to false detections in certain scenarios. Secondly, the performances of the developed AI models are not tested in special scenarios (e.g., rainy days, daytime with strong or low illuminance, etc.). These scenarios represent more challenging situations for accurate transportation asset information collection. The performance of the developed algorithms needs to be further evaluated under these scenarios.

Considering these limitations, further improving the detection accuracy and robustness with AI algorithm validation on a large scale is a promising direction to continue in. More training and test images under special circumstances should be incorporated in algorithm performance evaluation for all types of transportation assets.

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