Automated Pavement Marking Defects Detection

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Abstract –

In 2018, the United States Department of Transportation Federal Highway Administration reported that Americans traverse over 1,000 miles a month on average. Maintenance of pavement marking conditions is crucial to creating a safe driving environment. Traditionally, pavement markings are assessed periodically through manual road inspectors. This method is time consuming and ineffective in capturing the deterioration of the pavement markings throughout their service life. The incorporation of Unmanned Aerial Vehicles (UAVs) and machine learning techniques provide promising ground to detect pavement marking defects. The study proposes a system based on Deep Convolutional Neural Network (DCNN) that can collect, store, and process data to predict pavement marking conditions throughout their service life. The developed pavement marking detection tool has four stages. The Data Collection stage consists of obtaining images using different methods. In the Classification stage, a method for assessing the defects from images is created based on current methods by Departments of Transportation (DOTs) and the Manual on Uniform Traffic Control Devices (MUTCD). The third phase—the Model Development and Data Processing— and the Model Testing phase are to train and test the model using a multi-level classification program and complex algorithms to process the data collected and output a result. The system was implemented, and the preliminary results show that the model can identify and classify the pavement marking defects. The developed system will help transportation authorities identify and forecast future deteriorating rates and intervention timing.

Keywords –

Automation; Construction; Data Acquisition; Transportation

1 Introduction

Road pavement markings are a characteristic of road design that influence drivers' perception of roadway alignment and the ability to maintain safe vehicle positioning [8, 17]. Features such as edge lines, centerline, lane lines, and other pavement markings guide users and provide physical and intuitive barriers that ensure road safety and reduction in traffic congestion [17]. When strategically placed, pavement markings ensure adherence to speed limits [3, 21]. Environmental factors and wear from vehicle contact, as well as misplaced markings, call for the inspection and maintenance of these road markings [21].

The current practices of pavement marking inspection are mainly done manually. Manual inspection techniques such as Visual Nighttime Inspection, Measured Retroreflectivity, Expected Service Life, and Blank Replacement methods are a few of the vision-based techniques employed by DOTs to assess and evaluate pavement marking conditions [9]. Handheld devices, measurements, and Senior Citizen vision characterize these methods. These manual methods allow for high subjectivity and rely on trained inspectors that must go through training to follow the appropriate protocols. These visual assessment techniques require investing time, money, and resources. These processes often require workers to drive in nighttime conditions, evaluate, and record pavement conditions that pose public and individual safety risks.

Experimental studies have found short-term and long-term reductions in speed along hazardous curves by installing and maintaining pavement markings [21, 3]. Drops in speed from 41.3 to 33.9 miles per hour were attributed to pavement markings "designed to make the roadways appear narrower at the beginning of the curves." Other sites saw up to a 50% increase in adherence to advisory speed after the pavement marking installations [3]. Additional pavement markings in 42 sites in advance of roundabouts and termination of high-speed roads saw a 52% reduction in crashes after 2 years. Verbal and symbolic pavement markings consisting of the word "SLOW" and a left curve arrow installed before entering sharp horizontal curves also saw significant reductions in average vehicle speeds [3]. Earlier studies showed crash reductions after the installation of edge lines ranging from 19% to 46% [7, 19]. Despite differences in modern days traffic, vehicle design, and design speeds, more studies continue to report crash reductions as a result of pavement markings. Particularly, a study across 10 states found crash reductions of 36% after installing edge lines and an average of 21% attributed to pavement markings overall [4, 22].

There are two ways of assigning pavement marking defects: manual and automated. A manual evaluation of pavement markings from photogrammetry data would be highly subjective and time-consuming, thus an automated identification method presents an efficient and reliable alternate [2, 13]. This paper aims to propose an innovative UAV-based Pavement Marking Identifier Tool using a deep learning technique that automatically identifies the pavement marking defects. The tool uses data collected from Google Maps to train and test the model. This stage of the research looks at the applicability and efficiency of the technique.

2 Literature Review

2.1 Overview

An assessment of the effects of pavement markings on road safety reveals the importance of identifying and addressing current defects and missing pavement markings. Efforts are underway to mitigate the risks of missing important pavement markings and those in poor condition. For example, the Michigan Department of Transportation (MDOT) plans to require wrong-way arrows at all target exit ramps [18]. At paired exit/entrance ramps, the left turn into the exit has resulted in several fatal crashes. By installing pavement marking extension lines, vehicles could be guided into the correct ramp. They are considered a low-cost treatment with a benefit-cost ratio of 45.9 and the potential to reduce traffic-related deaths and increase road safety [3, 18]. A study was also conducted to assess whether pavement markings before wrong way entries in two sites were in good condition, or at all present [14]. The study found that both sites lacked pavement markings, such as Wrong-Way Arrows and stopping lines, which are linked to a reduction in fatal crashes. Also, in 2004, the Missouri Department of Transportation began implementing lane departure countermeasures consisting of pavement markings such as edge lines, centerlines, and skip lines, as well as other road features focused on lane departure countermeasures [8]. As a result, from 2005 to 2007, there was a 25 percent reduction in lane departure fatalities. Pavement markings wear out due to constant vehicle contact and weathering and therefore require inspection and maintenance. Given the role they play in road safety and the limited resources some cities struggle to keep pavement markings up to the standards due to limited resources. In addition, prioritizing pavement repair and maintenance in a very efficient way is critical for decision-makers to plan future budget allocation and prioritizing road maintenance.

2.2 Data Acquisition

New technologies of real-time data collection such as drones are an increasingly popular technology in construction and transportation [5, 19]. A recent study developed a framework for using UAVs in transportation, which defined the drone block as (1) flight planning, (2) flight implementation, and (3) data acquisition [15]. This framework was implemented by a later study to capture images of pavement defects [14]. This study outlined the importance of taking weather conditions and flight restrictions into account in the flight planning process. This ensured optimized visuals and adherence to regulations. For flight implementation, flights can be conducted manually or autonomously. For automated surveys, an advanced image processing algorithm is required such as Support Vector Machines (SVM) or Structure from Motion (SfM) [12, 13, 2]. These machine learning algorithms allow UAVs to quickly identify the presence of defects and cracks on the road, although they have yet to be implemented to detect defects in pavement markings. The SfM is an innovative photogrammetry method used to transform photo data sets into 3D models; however, research on its applications for road pavement is limited [13]. The data acquisition consists of captured images by the drones. These images are deemed adequate for analyzing and monitoring the condition of unpaved roads [23] and road pavement distresses [13], but there is very limited research in its applications to pavement markings. Data collection via UAVs also mitigates the risks associated with workers in high traffic zones [14].

2.3 Data Processing and Inferencing

Data processing and analysis is critical in developing an automated defects detection system. Efficient data extraction, noise removal, and storage are necessary components to have a functioning system [15]. Manual evaluations of the drone-captured images based on visual observations are associated with high levels of subjectivity, and low production rates [13]. For example, in a study analyzing the condition of road pavement, different crack types were assigned different ratings to assess and prioritize remedial actions according to the severity and average traffic volume [2]. Due to limited resources and a large area to cover, metric accuracy must be consistent [13]. Therefore, automated identification methods and severity numerical index assignments are considered a fundamental goal in transportation efforts to maintain the assets. Autonomous surveys incorporating machine learning algorithms can process the images automatically to identify the distress type [13]. A study that incorporated a UAV-based system with a machine learning algorithm observed an accuracy in pavement crack identification of 90.16 [12].

Other studies incorporating the use of multi-level classification and deep machine learning to develop predictive models for addressing pavement defect repairs and maintenance continue to advance [25]. These improvements in machine learning models are pivotal to the development of smart cities and autonomous vehicles. Furthermore, deep convolution neural networks (DCNNs) have been implemented to detect pavement cracks and reduce noise [24]. Using datasets for training and testing models set the basis for a system that can characterize road conditions [25].

Multiple studies have also incorporated a Geographic Information System (GIS) to enable automatic visualization of road conditions and automated pavement management [2, 12, 16, 6, and 20]. This system can be used to position classified images into Google Maps [12] and can cover thousands of miles of roadways as well as smaller volume roads [14]. GIS has spatial analysis capabilities that can integrate the graphical display of pavement condition and the assigned prioritization based on classification to facilitate pavement management operations [6, 20]. Currently, the system cannot predict the rate of deterioration of pavement marking based on its current condition but using a Matlab-GIS-based application, it can rate the condition of road segments [2]. Studies integrating this system for the inspection of pavement markings are very limited.

3 Methodology

The proposed framework for the pavement marking identifier tool is outlined in Fig.1. The framework encompasses four stages: (1) data collection using UAV, (2) data classification, (3) model development and training, and (4) model testing.

3.1 Data Collection

In the proposed framework, the data concerning pavement marking condition is collected using either a UAV or a Light Detection and Ranging (LIDAR) device. In this paper, the authors are using the UAV method given the high number of images that can be collected in a short time. For training and testing the model, two sets of data are required. The authors used Google maps and the Google search engine to collect images that show the defects as highlighted in Table 1.

3.2 Data Classification

The data classification phase consists of developing terminology that informs developed framework users of the pavement marking defects present in a surveying site. These terms, as specified in Table 1, are designed to provide a visual evaluation based on criteria outlined in the MUTCD. Per the standards, all lines must be continuous, and uniform in shape. Class 3, 7, and 8 defects address this standard. Lines must also have clear and sharp square edges, as well as be parallel to each other with discernible space. Class 1, 2, 4, 5 address this. Marking visibility and obstruction are addressed in defect classes 6 and 9.

Based on these standards, the set of defects was developed to inform the user when a pavement marking did not fall within these guidelines, as seen in Table 1. This study categorizes the images by lane feature and the associated defect type. These terms can be modified or expanded to suit the needs of any given road segment or the regulations of a company or department of transportation. The output is the class type.

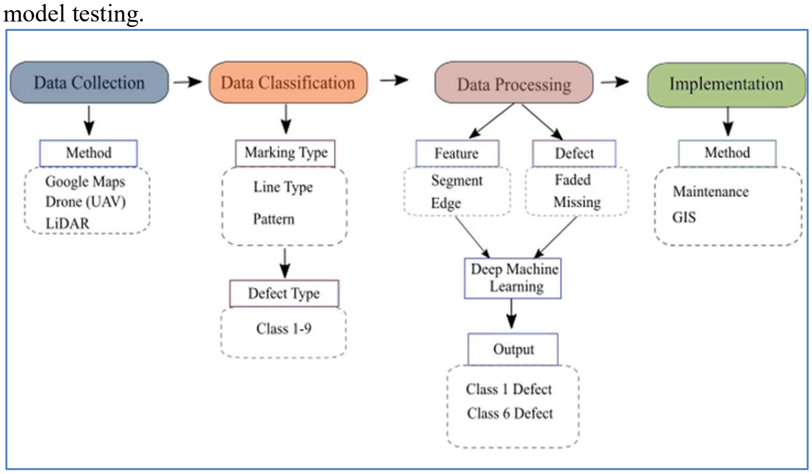


Figure 1. Automated System for Identifying Pavement Marking Defects

Table 1. Classes of Defects

Class Type	Feature
Class 1	Edge Missing
Class 2	Corner Missing
Class 3	Segment Missing
Class 4	Edge Faded
Class 5	Corner Faded
Class 6	Segment Faded
Class 7	Misalignment
Class 8	Cracking
Class 9	Ghost Marking

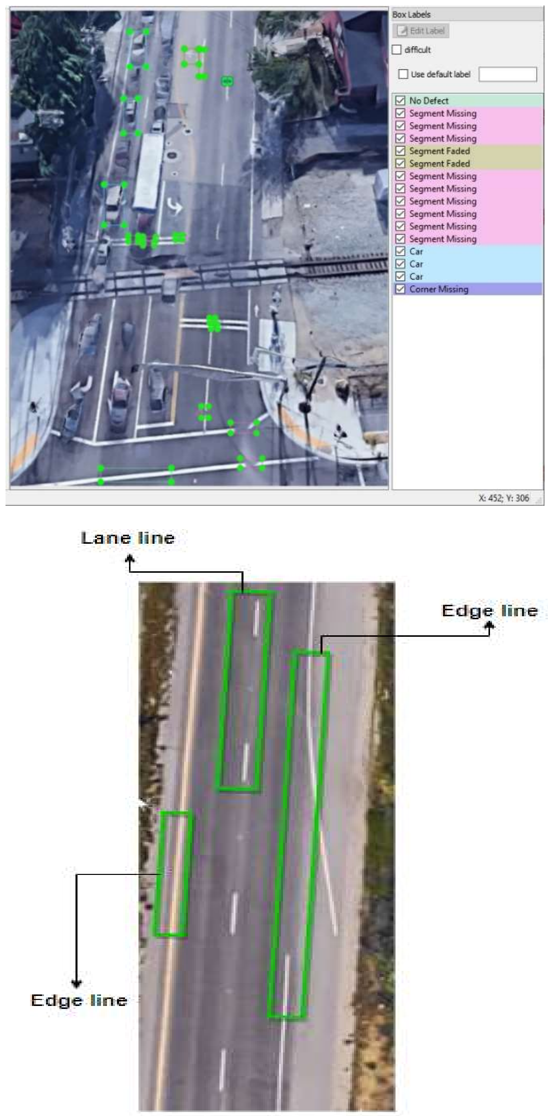


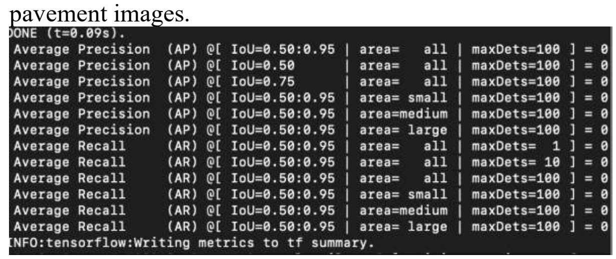
Figure 2. Pavement Marking Annotation and Data Preparation for Model Training

For purposes of this study, lane type identification was added to ensure that the labeling algorithms can differentiate between spacing between dashed center lines and faded sections along a continuous edge line. As seen in Fig. 2 a multilevel classification software was employed in this study in order to annotate the features of the road segment onto the image. This step is essential in developing a reliable and consistent algorithm-based system for future automated classification of roads. The annotations made must be precise and consistent to increase confidence levels. The second round of annotations classifies the markings based on defect types from Table 1. The pavement markings from the training and testing data must be fully categorized to be processed correctly according to MUTCD standards.

3.3 Model Development and Data Processing

3.3.1 Model Development

The model used to detect the objects in the test images was based on a region proposing convolutional neural network (RCNN) written in python. This model initially had the original settings of a pre-trained model called the "faster_rcnn_inception_v2" model from tensor flow's library of packaged models open to anyone for usage and particular implementation. The layers of the neural network were pre-defined for optimal speed and result, and required weights adjusted and optimized for the pavement images.



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DONE (t=0.09s).
 Average Precision  (AP) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0
 Average Precision  (AP) @[ IoU=0.50      | area=   all | maxDets=100 ] = 0
 Average Precision  (AP) @[ IoU=0.75      | area=   all | maxDets=100 ] = 0
 Average Precision  (AP) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0
 Average Precision  (AP) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0
 Average Precision  (AP) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=  1 ] = 0
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets= 10 ] = 0
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0
 Average Recall     (AR) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0
 Average Recall     (AR) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0
INFO:tensorflow:Writing metrics to tf summary.
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Figure 3. Deep Learning Model Precession Data

3.3.2 Model Training

For this study, this model was trained to identify the specific features of the pavement images. The model was trained using a dataset named pavement marking images (PMI). The model was fed aerial images from Google Maps, which are accessible to all and contain data from roads all over the world. These are updated about every 1-3 years, which renders the satellite-images mostly accurate. Images were captured along the highways of San Luis Obispo County, CA, which were manually inspected and annotated according to the lane type, as seen in Fig. 1, and the defects identified. A multi-level classification program was used in this process.

To train this model, each image's data is passed through the network. Once all the images go through the network, this is considered an epoch. After each epoch, the weights of the network are changed slightly to yield better predictions on all of the data. 100 training images were collected and annotated and 50 images more were selected for testing.

3.4 Model Testing

The model was only given 80 training images and 20 test images. A snapshot of the model results is shown in Fig. 3. The results of the Validation Data are outlined in the Preliminary Results and Analysis section of this report.

Once all the training and testing images have been processed, the images captured by a UAV, or similar technology, can be automatically processed using complex computer vision algorithms to extract multiple features from the images captured. If these images are annotated consistently and with reduced background noise, the output should be accurate and reliable. The coded data from the collection and classification stage is processed, and its output informs what type of defect, if any, is found along a given road segment.

4 Preliminary Results and Analysis

This study presented preliminary results of the proposed system that automatically predict the pavement marking condition. The proposed deep learning model was trained with a sample of annotated images, and another sample was used for testing purpose. The model was able to predicate road segments with and without pavement marking defects. A group of the defects classified as corner faded and missing were identified with an accuracy of 50% to 80% as shown in Figure 4. Although the model was intended to generate preliminary results using machine learning technique, the results still showed promising trends and levels of confidence for expansion and fine-tuning. The model projected higher accuracy in detecting larger features than small and medium ones. This was expected because larger objects in the image contain more pixels which inform the object detector of what defect it might be, than small and medium-sized features. These results will guide the manual annotation of additional sets of data to enhance the model prediction algorithm. Annotating defects in images, and ensuring less noise within the boundary circling the defects was found to be critical for the model accuracy.

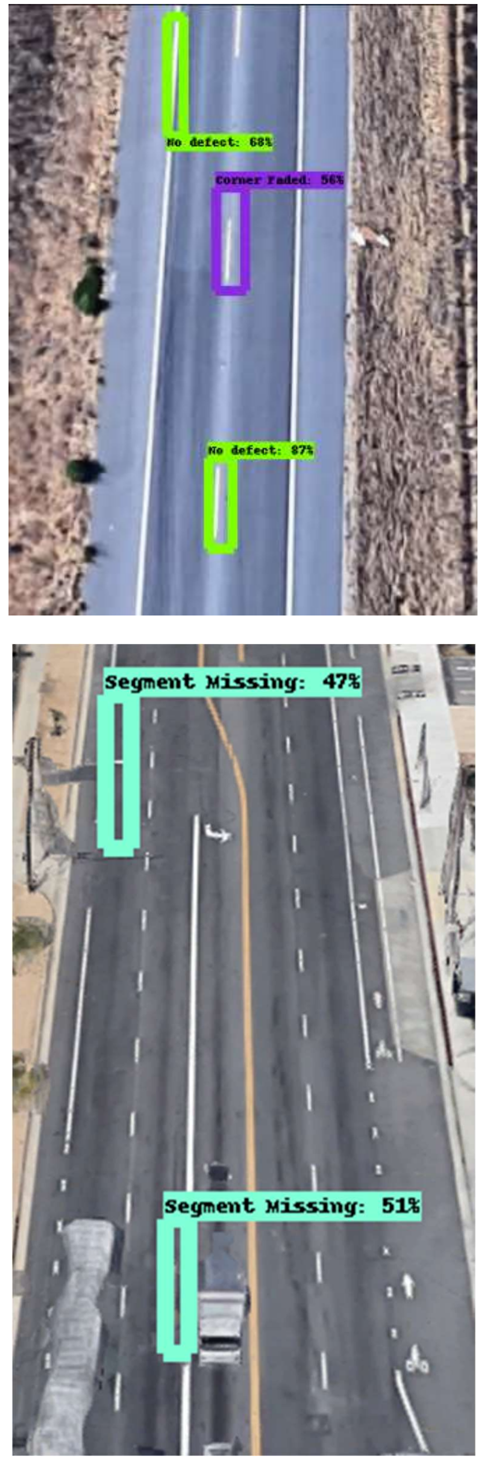

Figure 4. Defects Detection by the Deep Learning Model

Despite the small number of data sets used to train and test the model, the deep learning model was able to predict road pavement defects with over 50% confidence. In some instances, it predicted the defects with 80% confidence, as shown in Fig. 4. These results also yield increased confidence in identifying pavement markings without defects. This was expected since faded segments vary in levels of marking deterioration and visibility, while pavement markings in good condition are similar in contrast to the pavement in their clean-cut edges. The results of the model were validated manually by comparing the model outcomes with the manually annotated images.

These results inform us of the current condition of pavement markings in the area, as well as which road segments require immediate attention, and which should be monitored. The preliminary state of these results cannot replace traditional methods for pavement marking inspection, but it can still inform road agencies of which road segments output the most defects in an initial site survey using a drone. By expanding the training and testing data, these results could be used to predict the remaining service life of each road segment captured.

Lastly, the results of this pavement marking identifier tool are expected to show an increase in safety, a reduction of labor and equipment-associated costs, a fast identification of defects, and expedited repairs.

5 Conclusion

In this paper, a method for assessing and predicting pavement marking defects using machine learning was presented. Images extracted from a satellite imagery web-mapping service were processed to create a dataset of over 100 annotated images. For image optimization, images compiled were carefully annotated to ensure noise reduction, consistency, and proper labeling. The method employed in this paper used images in PASCAL VOC in a multi-level classification program. For image annotations, tighter rectangles enclosing road features were found to produce results that are more accurate. The preliminary results show higher accuracy and detection for larger segments and most common features. These show potential in an integrated manual identification of pavement marking defects and a python-based image extractor software. Future research will be focused on integrating retroreflectivity analysis and reading into the model to better resemble the standard maintenance protocols used by departments of transportation. This will result in a comprehensive system for assessing, monitoring, and maintaining roads. By implementing this model, drones can automatically detect and classify the pavement marking defect classes. The machine-learning-based methods employed in this research are accessible, cost-effective, and relatively safe to conduct pavement marking assessments and evaluations. With enough data and proper annotation, the model developed can detect marking defects from an aerial view using different camera views. This reduces labor and equipment costs otherwise incurred from manual inspection and reduces the risk of construction-related accidents from placing workers in high-speed roads. The improvement of machine learning models for maintaining pavement markings up to standard is essential for the digital maps integrated into the programming of AV's to detect road surface markers (RSMs). By maintaining roads up to MUTCD standards, AV machine learning can detect the necessary road features to allow for the integration of autonomous vehicles on our roads. Improved roads pave the way for improved cars, transportation systems, and societies.

In the future, this study will be extended to address the relationship between road defects and road pavement marking defects. Many studies suggest that the causes that contribute to pavement defects also contribute to pavement marking defects.

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