A New Era in Transportation Infrastructure Contrition Evaluation with Connected Vehicles

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ABSTRACT: Gathering pavement data has always been a tedious task for highway agencies. Researchers and Practitioners have always looked for a cost-effective and continuous method for pavement monitoring. With vehicles being equipped with Information and Communication Technologies (ICT), Connected Vehicles (CVs) are now available in the market. In this paper an architecture for CV-based pavement evaluation was proposed. Next a model was developed for distress detection and implemented on vehicle using a raspberry pi. The model was capable of detecting 8 different pavement distresses with a Mean Average Precision (mAP) of 58.8%, a precision of 74.2%, and a recall of 52.1%. Due to the low computation time, the model could be run on the onboard mini-computer to detect anomalies in real time. It was concluded that the model could be used on vehicles to gather condition data.

1 INTRODUCTION

Highways, as strategic and essential infrastructures, allow for the social development in a country. However, factors such as traffic loads, temperature, and moisture will result in the degradation of highway pavements, consequently bringing about large economic losses (Li et al. 2019). For instance, pavement distresses impose $ 130 billion of additional vehicle repair costs to US motorists (ASCE, 2019). It is therefore important periodically assess pavement condition and then develop pavement maintenance scenarios. If the maintenance operations are carried out in the right time and without delay, budget expenditures of the road authorities are reduced (Ji et al. 2020).

The current practice in pavement evaluation involves using vehicles equipped with high-tech sensors such as laser scanners, black-box cameras, and accelerometers. Along with the technical equipment, Deep Learning (DL) algorithms such as Convolutional Neural Networks (CNNs) are employed to automatically analyze the collected data (Gopalakrishnan, 2018). The collected information includes inventory data (road geometrics and amenities such as drainage) and condition data (pavement distresses, roughness, and skid resistance) (Sholevar et al. 2022). Although automatic road surveyors offer many advantages, there are challenges in using them for network-wide monitoring. Provision, maintenance, and operation of the equipment impose high expenses to the highway agencies. Thus, the agencies can only afford to provide one or two automatic profilers and implement them on limited areas of the network. The other shortcoming is long inspection periods. With the small number of surveyors available, road authorities are not able to cover all the network and can only concentrate on major roads (Chen et al. 2022). As relying on Road Surface Profilers (RSPs) for pavement monitoring is not feasible and cannot provide timely data, researchers have tried to devise alternative health monitoring systems with commercial-grade tools and capable of automatic evaluation in short time.

In this regard, Linton & Fu 2016 proposed a structure for winter road surface condition evaluation using CVs. Bridgelall et al. 2019 concentrated on the enhancement of CV signals and improvement of distress localization. Entezari & Golroo 2023 conducted a thorough review on the applications of CVs in pavement evaluation. According to the research, evaluation of many pavement distresses (including raveling, weathering, potholes, alligator cracks, along with manholes and faded markings), though well evaluated in the literature using advanced road surface profilers and surveyors, have not been investigated in a CV-environment by taking advantage of computer vision techniques. In the present article, the 8th version of YOLO object detection algorithm (Redmon et al. 2016) is used to detect pavement distresses in a CV environment.

In the following sections of the present article, first an architecture for CV-based pavement evaluation is proposed based on Edge computing. Then,

the case study carried out based on the architecture is discussed. Finally, the strategies for future research are proposed.

2 METHODOLOGY

The system architecture in an Intelligent Transportation System (ITS) is presented in Figure 1. In such a system, data obtained from vehicles is stored on a backend server. Data could be transmitted to the data processing center through Roadside Units (RSUs). Each vehicle is equipped with an Onboard Unit (OBU) to send, receive, or process data (Jadaan et al. 2017).

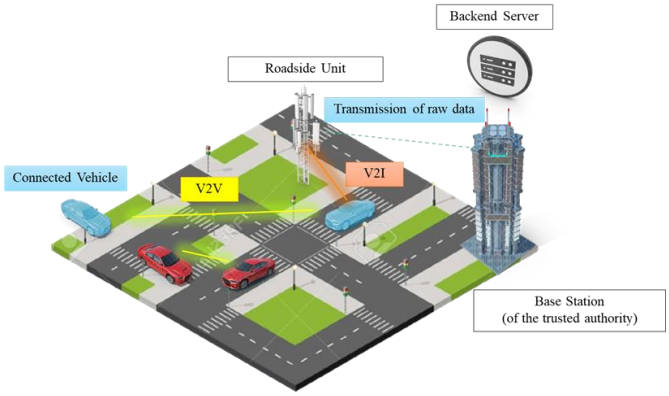

Figure 1. The architecture and components in an intelligent Transportation System

To grasp more deeply how such an architecture could be deployed to assess pavement condition, the details of the architecture is demonstrated in the workflow in Figure 2. According to the workflow, first, vehicles traverse the roads and gather data by different sensors, including visual sensors such as the rear-view camera. The data are processed by onboard computer which is programmed to analyze the input data. The obtained information is then sent to RSUs. Subsequently, the data is transferred to the data processing center from RSUs. Various information obtained from the fleet of vehicles such as pavement distresses could then be used to have an understanding of the asset condition. The information can be used by experts to calculate pavement performance indices and address the required maintenance operations.

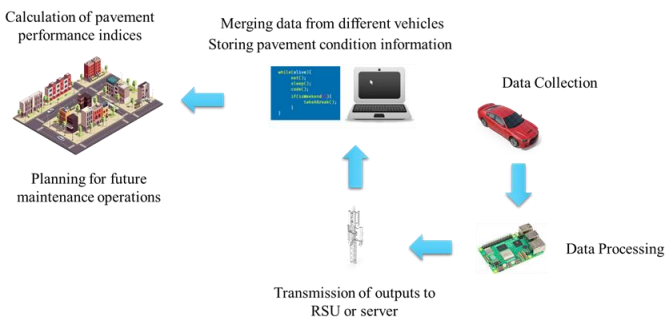

Figure 2. Pavement monitoring and maintenance planning in a CV environment

In the architecture presented in this article, the OBU is advised to be made of two main parts. The first part is a radio communication unit which broadcasts messages to other CVs or the RSUs. The information sent to the RSUs will finally reach the backend server in order to fulfill the authority's database. The second part of the OBU is a processing unit which performs data analysis models on the collected data. To automatically process the data, the application of DL models is necessary.

In order to comply with the essence of Edge computing, a pavement distress detection model was developed in this research and implemented on Raspberry pi 3B+ device. To develop the model, YOLOv8 algorithm was used. YOLO is a one-stage object detection model based on Convolutional Neural Networks (CNNs) which is run on Python and installed using a PIP package (Zheng et al. 2024). The original Yolo architecture was built up from 24 convolution layers followed by two fully connected layers.

To train the model, a dataset of 600 pavement images were gathered and annotated. The data, collected via Raspberry pi during daylight, is available online (Fahmani et al. 2024) with a wider quantity of data and a sample image is presented in Fig. 3. The distresses labeled on the images included linear cracks, alligator cracks, lane shoulder drop-off, weathering, raveling, patching, and potholes. Also, faded lane markings were labeled in the dataset.

Figure 3. Sample image from the pavement distress dataset

The available data were divided into 3 different groups of training data (70%), validation data (15%), and Testing data (15%). Google Colab platform was used for model training. In order to evaluate the model, 3 performance indices were investigated: Recall, Precision, and mAP. The formulations of the first two are presented in Equations 1 and 2:

$$Recall = \frac{TP}{TP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

where *TP* = True Positive; *FN* = False Negative; and *FP*= False Positive.

The formulation of mAP is also presented in Equation 3:

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \quad (3)$$

where AP_K = Average Precision of the Kth group; and n = number of groups.

3 RESULTS AND DISCUSSION

The performance indices obtained for the distress detection model after a 300-epoch training process were an mAP of 58.8% (Fig. 4), a Precision of 74.2%, and a Recall of 52.1% (Fig. 5).

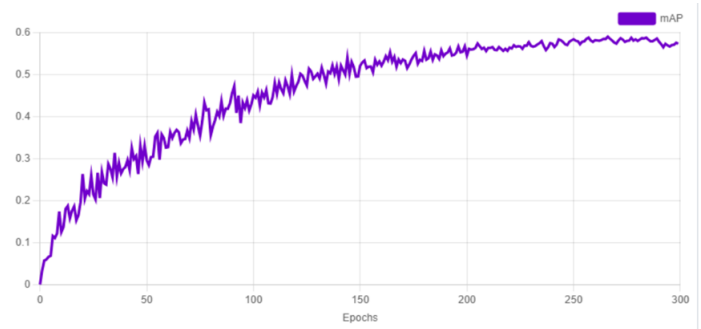

Figure 4. The increase in model's mAP through 300 iterations of the training process

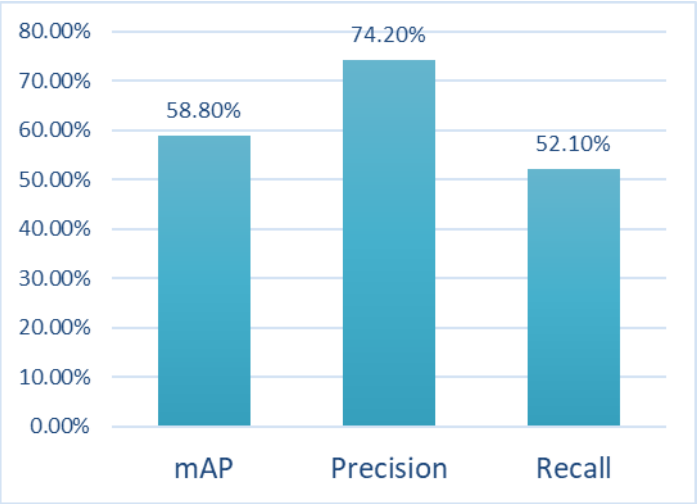

Figure 5. Obtained performance indices for the distress detection model

It is presumed that the low mAP is perhaps due to the low number of instances for each category. It could also be attributed to the quality of crowdsourced cameras, not fully capturing the texture of the pavement and making it hard to detect weathering defects. As the model merits from a high precision index, but has a low recall, it can be realized that the model misses some of the distresses, but correctly classifies the ones that it detects. Missing of some distresses could be due to their diverse forms. The faded marking category reached the highest precision, as the white color of the shapes helped the model for an easier detection. The Average Precision obtained for each group is presented in Table 1.

Table 1: Average Precision obtained by the model for the 8 detected classes

Distress	Average Precision
Linear crack	55.5%
Alligator crack	61%
Weathering	59.5%
Shoulder drop-off	71%
Patching	50%
Raveling	66%
Pothole	33%%
Faded Marking	74.5%

To make sure whether the presented solution is compatible for a CV-environment, the duration of analysis for each picture on the raspberry pie was evaluated. As the videos were first preprocessed and then sent to the model, the analysis period of each frame was about 2 seconds. A sample analyzed frame is presented on Figure 6.

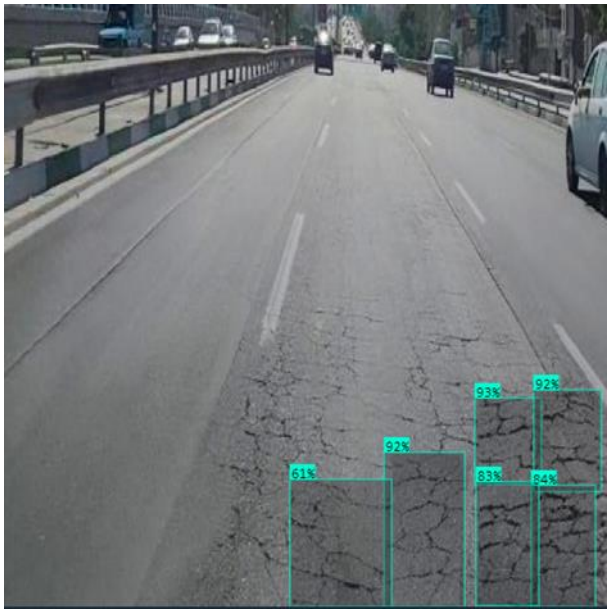

Figure 6. A sample frame analyzed by the distress detection model

4 CONCLUSION

Pavements are adversely affected by axle loadings, environmental factors and interaction with underneath layers. As a result, the serviceability of the

infrastructure is lowered by the appearance of distresses (such as linear cracks, alligator cracks, weathering, and faded markings) and roughness. Thus, road authorities continuously monitor pavements of the wide road network. The collected information includes condition data and inventory data. Automatic pavement surveyors such RSPs are the current technology implemented by highway agencies to collect pavement data. For this purpose, they traverse road segments by the surveyor vehicles. As the equipment is highly expensive, each agency can afford to purchase very few automatic surveyors. As it is not possible to traverse the whole network by the available vehicles, road agencies can only concentrate on major roads and even these high-priority roads are evaluated only once a year. In such a system maintenance planning is difficult as the data is delayed and timely data is not at hand. To come up with a new framework for pavement evaluation, connected vehicles have proven to fulfill the requirements of a pavement health monitoring system. These vehicles consistently move in the network and evaluate pavement using cost-effective sensors. As the vehicles are able to communicate with each other and with the infrastructure, the obtained data can be used to both complete the database of the road authority and to alert drivers of intense distresses. In this article an architecture was proposed for evaluating pavement by CVs and a specific design for the OBU was suggested. Next, as a case study, pavement distress detection was performed on the vehicle, detecting 8 different pavement anomalies including linear crack, alligator crack, raveling, weathering, shoulder drop-off, patching, pothole, and faded marking. The case study included collection and annotation of 600 pavement images, training a distress detection model using Yolo V8 algorithm, and implementing the model on a raspberry pie. The model reached an mAP of 58.8%, a precision of 74.2%, and a recall of 52.1%. It was concluded that pavement distress detection could be applied on vehicles. It was suggested that the developed system could be improved in future research by implementing radio communication technologies for broadcasting the results, increasing the number of instances in the model for higher accuracy, and comparing the performance of other detection models such as SSD with the current model. More sophisticated case studies may include RSUs, receiving data from the vehicles in their range and sending the information to data processing center.

5 ACKNOWLEDGMENT

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