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Development of a Virtual Weigh-In-Motion System for Enhanced Pavement System Management

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16. Abstract

Weigh-in-Motion (WIM) is a promising solution to regulate weight-related violations but has high installation and recurring maintenance costs. Also, the requirement of installing induction loops for vehicle presence detection may cause damage to pavement structure and lead to early deterioration of the pavement surface. Recently, virtual weigh-in-motion (V-WIM) techniques consisting of WIM scales, traffic surveillance videos, and other sensors have become a new technological trend that has attracted interest from state DOTs to deal with size and weight enforcement that reaches beyond the WIM's conventional role in data collection. Accurate detection of the specific vehicle-type information to activate the WIM sensors is a major step for the V-WIM from roadside-captured images/videos containing vehicles. This project evaluated the machine learning–based You Only Look Once (YOLO) algorithm trained on a custom dataset as a potential automatic vehicle detection process to work on existing traffic surveillance videos/images as the vehicle sensor data source. The results showed that the trained model could detect vehicles close to the camera with high confidence. The findings and outcomes may support the development of viable and functional V-WIM as well as increase the applications of traffic surveillance videos in transportation infrastructure management.

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CHAPTER 1

Introduction

BACKGROUND

The continuous economic development in the United States has led to a rapid increase in road traffic volume. It is anticipated that commercial vehicles may move 100 percent more freight tonnage in 2035 compared to 2004 with the fast expansion of online shopping activities (Capecci et al. 2009). However, the growing amount of vehicles that exceed weight limits can cause damage to the pavement structure and substantially reduce the stability and service period of the road (Pederson 2007). To sustain the serviceability of the road, the application of weigh stations for weight regulations has been implemented to deal with weight-related violations and assist in enhancing the stability and durability of the pavement and bridge structure (Luskin and Walton 2001). However, high operational costs, user delays, labor intensity, size, and lack of coverage are the main drawbacks of applying conventional weigh stations. Moreover, weigh stations are commonly operated to enforce weight restrictions that check vehicle weight by stopping them. As a result, intense rutting and shoving can develop in the proximity of the weigh station resulting from the braking and turning of vehicles (Harvey et al. 2002). This intense rutting and shoving of the pavement surface can lead to premature disintegration of the structure and increase the maintenance costs as more treatments are required to maintain the serviceability of the structure.

Weigh-in-motion (WIM) technology managed to alleviate some of these issues, as it involves no stopping of vehicles and reduces rutting and shoving problems caused by vehicles stopping and turning at weigh stations. WIM has been recognized as a prominent technique for measurement of gross vehicle weights (GVWs) of commercial vehicles, but the high costs of WIM sensor installation, calibration, and maintenance have caused reluctance to its widespread implementation (Kwon 2016). Moreover, the installation of induction loops for vehicle presence detection in WIM can initiate early deterioration of the pavement surface and increase the maintenance cost.

At Virginia Tech, the PI Linbing Wang's research team has developed a low-cost, reliable piezoceramic sensing system to address the high cost of present piezoelectric sensors in installation and maintenance. The team has also developed an energy harvester (a macro sensor) using typical piezoelectric material known as piezoceramic lead zirconate titanate (PZT) disks. The piezoelectric energy harvesters were fabricated and installed in a real pavement for site evaluations. The installed energy harvesters had functioned for more than one year under highway traffic and the voltage output and spectrums from the energy harvesters can be used for predicting traffic information, such as axle loading, number of axles, the distance between axles, vehicle speeds, and number of vehicles. The developed system presents the benefits of being much lower cost (for a four-lane roadway, it only costs $10,000–13,000 in comparison to conventional WIM that costs at least $100,000), waterproof, and resistant to fatigue. Figure 1 presents (a) the design of the harvester, (b) the site installation, and (c) the output of the harvester or macro sensor.

Figure 1. The prior developed piezoelectric sensor system.

Recently, virtual weigh-in-motion (V-WIM) has become a technological trend that has attracted the interest of state DOTs. The V-WIM system consisting of WIM scales and other sensors turns out to be an innovative approach to deal with pavement management issues that reach beyond the traditional WIM's role in data collection and vehicle weight measurement. This system may consist of WIM scales, surveillance videos, electronic transponders, wireless communications, and other sensors and devices to support better pavement management. Machine learning and computer vision techniques are used to analyze the video streams to detect the vehicle, vehicle speed, axle configuration, and type of vehicle. As a result, the V-WIM system can collect real-time information such as weight, speed, type, and axle configuration of specific passing commercial vehicles to transportation agencies. Also, the data generated from the surveillance video can be synchronized with the data generated from the WIM scales for improving the accuracy of the system. Figure 2 presents a typical V-WIM setup on the roadway.

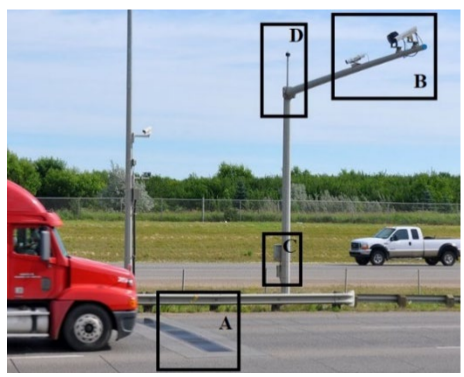


Figure 2. Typical setup of a V-WIM system [adapted from International Road Dynamics Inc. (2022)].

(Legend: A. WIM scales, B. Surveillance camera, C. Roadside controller, D. Communication.)

As illustrated in Figure 2, when a vehicle approaches the virtual weigh station, it collects the vehicle's weight while in motion on the WIM scales. The vehicle's pictures are also taken for additional information extraction. The screening software incorporates data from the WIM and surveillance video and readily processes them into information such as weight, speed, axle configuration, and type of the passing vehicle for further analysis. State DOTs such as Florida DOT, Indiana DOT, NY State DOT, and California DOT have led efforts in developing and deploying V-WIM to support overweight truck detection and generate traffic data for use in current highway performance monitoring and future highway planning. However, the development of V-WIM is still at its infancy stage with limited functions, as the applied technologies and sensors are not fully exploited. The current V-WIM system has yet to be powerful enough in harvesting rich data collection by a diversity of sensors to yield holistic insights for pavement system management.

OBJECTIVES

The overarching goal of this research was to leverage the data collected by P-WIM developed by the PI Wang and streams captured by the traffic surveillance video from the state DOTs to develop a low-cost and powerful V-WIM system based on analytical, computer vision, and machine learning techniques. This system is capable of capturing a diversity of actionable information of moving vehicles on roadways that will enhance the pavement management system. In addition to the P-WIM system that captures weights of passing vehicles, the V-WIM system provides functions including vehicle detection, speed measurement, identification of vehicle axle configurations, recognition of vehicle types, and measurement of volumes of different types of vehicles that have passed the installation location of the system within a certain period of time.

In this project, the specific objective was to develop a computer vision-based method that applies machine learning algorithms trained on a custom dataset as a potential automatic vehicle detection process to work on existing traffic surveillance videos/images as the vehicle sensor data source. This way, the proposed system will eliminate the need of the induction loop installation in the pavement for vehicle presence detection.

DATA AND DATA STRUCTURES

To train the commercial vehicle detection system, vehicle data were collected from the publicly available image dataset and Google images. The images were randomly selected to avoid similarity among the pictures and then labeled. To evaluate the performance of the model in processing images in complex scenarios and in cases of different resolutions, data augmentation and preprocessing were not used. The images were collected from multiple sources to ensure views from different angles. To eliminate the model bias during the training process, the collected pictures were rearranged chronologically based on the time they were taken (e.g., daytime or nighttime) and then evenly divided into the training and validation datasets at the ratio of 7:3. In addition to this, other surveillance videos downloaded from the internet were used to test the model and understand the performance of the trained model in real-world traffic settings. All of the collected images were manually labeled by the software LabelImg. Details of the established vehicle dataset are given in Table 1.

Table 1. Statistics of established vehicle dataset.

Data	Car (day)	Car (night)	Bus (day)	Bus (night)	Truck (day)	Truck (night)	Total
Training	504	298	405	147	422	136	1,912
Validation	164	95	170	65	145	81	720
Testing	43	26	44	18	40	29	200

CHAPTER 2

Methodology

INTRODUCTION

A major part of V-WIM system development is detection of commercial vehicles in terms of presence and classification. In this study, commercial vehicle detection was achieved utilizing machine learning–based algorithms. In this chapter, the algorithms used and the developed method are presented in detail.

OVERVIEW OF PROPOSED METHOD

In this study, the You Only Look Once (YOLOv5) network was utilized to achieve commercial vehicle detection. Meanwhile, DarkNet-53 was utilized as the backbone for the YOLOv5. This network architecture reinforced the entire convolution process and restored the preceding version of the direct-connected convolutional neural network with the residual network. Benefitting from this, it has been demonstrated that YOLOv5 outperforms its predecessor YOLOv4 in terms of detection accuracy and processing speed. The flow of the vehicle detection and classification method is illustrated in Figure 3.

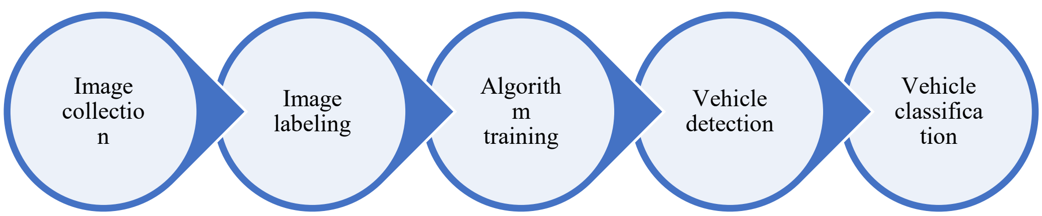


Figure 3. The flow of the method.

ALGORITHM TRAINING

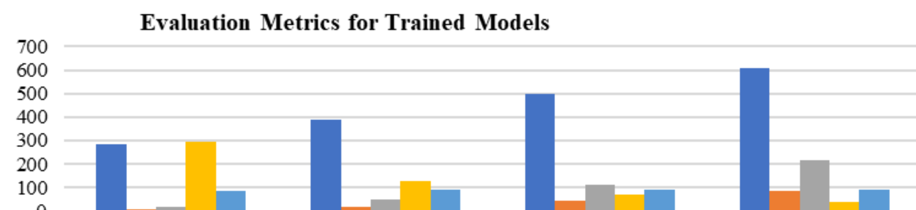
The model training and performance evaluation for vehicle detection and classification was conducted on the platform of Google Colab, which provides free access to powerful GPUs and requires no configuration. The GPU provided by the Google Colab was Tesla T4, 15109.75MB. There are four versions/models available for YOLOv5, that is, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x. Each model was first pre-trained on the ImageNet dataset and then finetuned on the customized vehicle dataset as listed in Table 1. The hyperparameters, that is, learning rate, momentum, weight decay, and batch were set to 0.01, 0.94, 0.0005, and 2 for each model during the training process.

CHAPTER 3

Findings

RESULTS

Figure 4 presents a comparison of the performance of four different trained YOLOv5 models on the validation dataset. As can be seen, YOLOv5m has the comparably highest overall performance in terms of processing speed (128 fps) and detection and classification accuracy (91.8%) in comparison to the other three models. Therefore, the model YOLOv5m was utilized in this study for vehicle detection and classification. Table 2 illustrates the details of the architecture and implementation of YOLOv5m.



	YOLOv5s	YOLOv5m	YOLOv5l	YOLOv5x
Layers	283	391	499	607
Parameters (Million)	7	21	47	87
FLOPs (Billion)	16.4	50.4	114.3	217.4
Inference Time (FPS)	294	128	69	40
mAP@.5 for all class (%)	88.7	91.8	92.6	93.2

Figure 4. Evaluation metrics for trained models.

Table 2. Details of the architecture/implementation of the network.

Detector	YOLOv5m
Feature extractor	Darknet-53
Layer	53
Epoch	500
Pre-trained on	ImageNet
Shape of detection kernel	1 x 1 x (B x (5 + C)), where B is the number of bounding boxes a cell on the feature map can predict, '5' is for the 4 bounding box attributes and one object confidence and C is the no. of classes.
Process of classification loss calculation	Binary cross-entropy

Figure 5 plots the different types of losses and average mean average precision of YOLOv5m during the training process. There were three different types of loss shown in Figure 5: box loss, objectness loss, and classification loss. The box loss illustrates how closely the algorithm can locate the center of an object and how effectively the predicted bounding box encompasses an object. Objectness loss is a measure of the probability that an object exists in a proposed region of interest. If the objectness is high, this means that the image window is likely to contain an object. Classification loss presents a notion of how effectively the algorithm can predict the correct class of a given object.

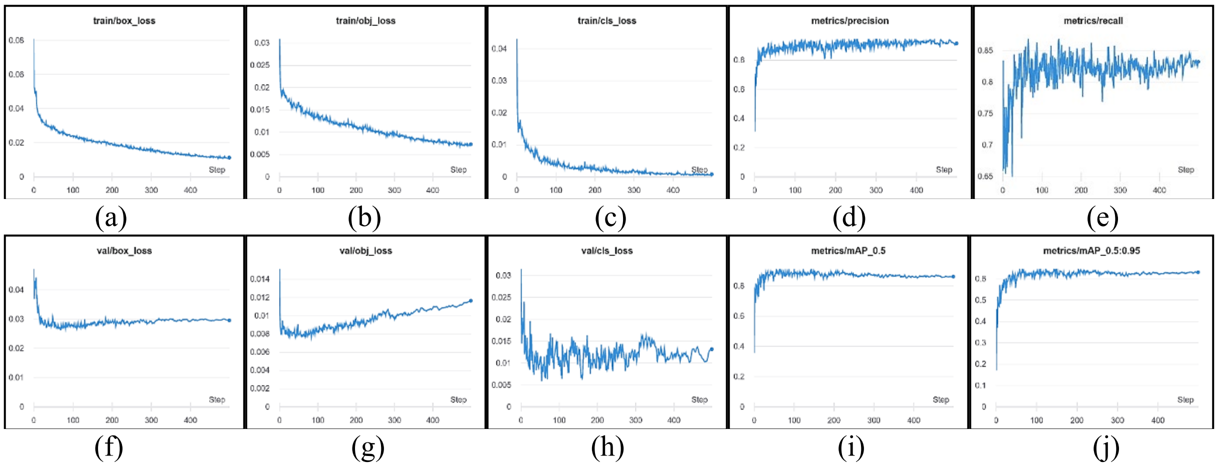
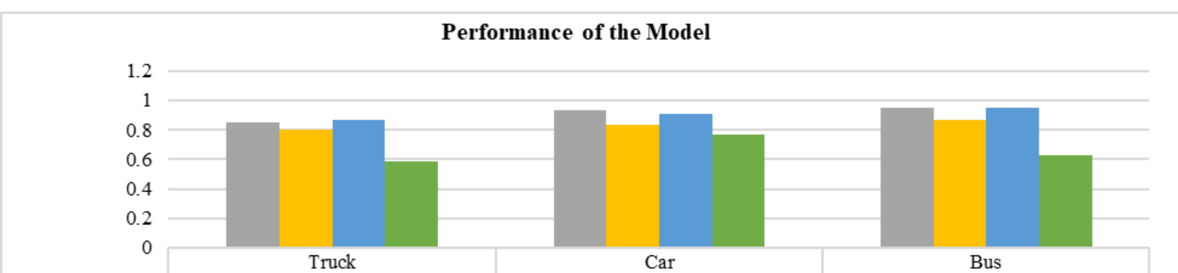


Figure 5. Plots of different types of losses in training and the validation process of the algorithm: (a) training box loss, (b) training objectness loss, (c) training classification loss, (d) precision, (e) recall, (f) validation box loss, (g) validation objectness loss, (h) validation classification loss, (i) mean average precision (mAP) 0.5, and (j) mAP 0.5–0.95.

As can be seen, the model performance progressed rapidly in terms of precision, recall, and mean average precision from the beginning. The box, objectness, and classification losses of the validation data also showed a rapid decline from the start of the training process. As the training proceeded, the performance of the model improved significantly and started to converge after 35 epochs. Particularly, the model trained at the 143rd epoch was selected and utilized for vehicle detection, as it has the highest value of mAP@0.5:0.95. Figure 6 represents the performance of the trained model for the detection and classification of different types of vehicles under the testing dataset. Among the three categories of vehicles, the bus showed the most anticipated value by mAP@.5, precision, and recall. The car showed superiority in detection at mAP@.5:.95. The difference among the three categories of vehicles was little.



	Truck	Car	Bus
Precision	0.849	0.931	0.952
Recall	0.804	0.836	0.868
mAP@.5	0.865	0.909	0.954
mAP@.5:.95	0.59	0.767	0.63

Figure 6. Performance of the model based on class detection.

To further understand the adaptability and applicability of the trained model in real-world traffic settings, the traffic surveillance images under different light conditions in the testing dataset were utilized for model performance evaluation, respectively. Figure 7 presents some samples of vehicle detection and classification results from traffic surveillance videos under different light conditions. The results show that the trained YOLOv5m model has better vehicle detection and classification performance for day conditions than for dusk/dawn and night conditions.

(a) Day (b) Night (c) Dusk/Dawn

Figure 7. Vehicle class detection from traffic surveillance videos under different light conditions.

CHAPTER 4

Recommendations

Some recommendations are summarized as follows:

The trained algorithm functioned competently, as it recognized and classified vehicles as expected. The algorithm could detect the front of a vehicle to a higher degree of confidence, as most of the train images contained the front face of the vehicles. However, it encountered inconvenience recognizing the rear end of a vehicle, especially when these were situated at a distance from the camera. Also, misjudged classification occurred in several images with low resolution and night condition. These misjudgments produced the conclusion about the potential space for boosting the performance of the algorithm in modifying the substantial data collection process and improving the capability in data labeling. Including more images in the dataset and labeling them appropriately could increase the accuracy of the algorithm. Images for all light and weather conditions could also improve the performance of the algorithm.

The three classes of vehicle instances in the dataset utilized in this study were unbalanced. Cars were overrepresented in the dataset, pointing out the evidence that the roads were mainly utilized by cars. Also, the number of images utilized for the night and dusk/dawn conditions should be increased, as detection of the vehicle in these conditions largely depends on the algorithm performance on learning from these images.

The incorporation of a supplementary algorithm to the analysis for recognition could also be advantageous. The additional algorithm could either detect other characteristic features of commercial vehicles that are simply visible from the side, such as wheels, or it could classify the images indicating the number of commercial vehicles.

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