A deep-learning-based SIoV framework in vehicle detection and counting system for Intelligent traffic management

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***Abstract*— The automatic detection and counting of vehicles can greatly contribute to improving traffic control and management. This is done by utilizing a deep neural network and classifying labeled data. The proposed model has three stages: first, to separate and count the vehicles; second, to determine whether the vehicle is slow or fast; and third, to make a decision about each vehicle. In the first step, vehicle images are analyzed using the YOLOv3 method, and the vehicles detected are counted. In the next stage, the labeled data is classified into two classes, slow and fast, using a recurrent neural network. Finally, considering the road type, number of cars, and the class of each car, a decision is made about the existing traffic situation. The proposed method was evaluated on two datasets, GRAM and HighwayII, and the experimental results show an accuracy of about 98%, which is better than other existing approaches.**

Keywords—Detection, Counting, SIoV, Deep learning

I. INTRODUCTION

Artificial Intelligence (AI) is a technology that can quickly process large amounts of data, thereby simplifying tasks for humans [1]. It has made significant progress in recent years and continues to evolve rapidly. AI has made remarkable advancements in areas such as traffic management, accident prevention, autonomous vehicles, smart parking, and smart cities. The Internet of Things (IoT) has played a significant role in these advancements. It is an advanced form of the internet that integrates thousands of AI components. It can perform tasks with greater precision and speed than humans.

The IoT is a technology that allows devices and objects to connect and work together [2]. One of the most useful applications of IoT is in vehicular networks. When drivers need quick access to services or information to avoid potential damage, they can interact with other vehicles in a social network. This allows them to share information quickly and effectively. The IoT collects data and information from the surfaces of objects and vehicles. These data can then be used for better decision-making processes and predictions.

The Internet of Vehicles (IoV) is a sophisticated system that connects vehicles to the internet using advanced technologies [3]. IoV allows vehicles to connect to road networks and receive real-time traffic data, which helps improve navigation, driving safety, and communication between vehicles. IoV relies on various sensors, GPS, cloud data, and wireless networks to enhance fuel efficiency and traffic management. The concept of IoV has evolved from Vehicle Ad-Hoc Networks (VANETs) [4]. VANETs were used for Vehicle-to-Vehicle (V2V) or Vehicle-to-Infrastructure (V2I) communication, but with the advancements in IoV, VANETs have transformed into a more sophisticated system. Nowadays, every new vehicle and Roadside Unit (RSU) are equipped with internet connectivity and communicate with each other using Dedicated Short-Range Communications (DSRC). An RSU is a communication unit installed alongside or in proximity to roads, which can gather information about traffic, road conditions, accidents, and other relevant data related to the road and send it to central systems [5].

The infrastructures mentioned pave the way for the expansion of the Social Internet of Vehicles (SIoV), which addresses many of the issues and shortcomings found in previous models. The communication between vehicles through V2V technology has been enhanced, allowing for better coordination as information and features can be exchanged. To enable the socialization of internet-connected vehicles, stable infrastructures are required to enhance communication between them.

One of the primary objectives of connecting vehicles to the internet is to provide them with awareness of their surroundings. This connectivity enables vehicles to share information, creating a social network. Vehicles can share information about their interests and locations, and innovative tools use real-time traffic data collected through various sensor methods. These tools can assist drivers in selecting better routes. Examples of such tools include Waze, Google Live Traffic on Google Maps, and recently launched apps such as Uber and Lyft [6], which allow users to share their vehicles with others traveling to similar destinations. With image processing models, more comprehensive data can now be provided to drivers and SIoV systems. Images captured from highways and busy roads can help drivers determine better routes. However, the intelligence of self-

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driving vehicles presents challenges when processing information captured through cameras while in motion on the roads. When multiple self-driving cars intend to enter the same area, there may be errors in prioritizing which vehicle enters first, leading to accidents. In some countries, the responsibility for these vehicles is not yet clearly defined.

Section 2 discusses previous work. Section 3 presents the proposed work. Section 4 reviews the results and experiments. Finally, Section 5 provides a general conclusion of the article.

II. RELATED WORK

It is important to practice smart and safe driving to avoid any potential dangers on the road. This not only reduces the number of accidents but also helps in better management. The IoV approach has been introduced in [4] to enhance smart and safe driving. This approach discusses the connected vehicle architecture that can be used to improve control and prevent accidents, as well as monitor private or public transportation services. The Smart-Eye camera is used to share real-time images of incidents or traffic, which can promote smart and safe driving in the automotive markets. Additionally, the article [7] mentions the use of Raspberry Pi architecture as a control system for cars. In this model, the cloud server stores encrypted data related to brakes, location, and motion indicators. The Pi sensor is used to convert mechanical vibrations into electrical signals.

Various tools have been introduced in the field of Smart SIoV. The SocialDrive tool is introduced in [3], which helps drivers share their trip updates on social media platforms in real-time. It provides information on driving patterns to drivers and assists them in better understanding their driving habits to improve their driving style. In [8], a network uses a small on-board microcontroller and a DigiMesh radio to transmit and receive erratic driving behaviors of nearby vehicles. The system generates driver alerts using a Dynamic Time Warping (DTW) algorithm on sensor data obtained from each vehicle's OBD-II interface, including excessive speed, lane departure, sudden braking, and sudden acceleration. SIoV tools are not restricted to driving. In [9], a framework was proposed to help prevent widespread viral diseases in smart cities. The proposed framework consists of a physical distance notification system using deep learning and the IoVs. Each vehicle is equipped with a switching camera system through thermal and vision imaging. In this model, the physical distance violation between objects of the same class was measured and detected using the Faster R-CNN algorithm. VSN (Vehicle Social Networks) was created to integrate social networks and the IoVs to create social relationships. The primary focus of VSN in [10] is on safety-related and infotainment applications, multimedia services distribution, and provision based on the interests of drivers or passengers. These data-driven applications play a significant role in VSNs. Vehicle information in mobile computing systems in vehicles and smart devices can be used to generate and estimate vehicle motion in specific scenarios, and repeated movement patterns of vehicles can help predict their future movements and paths.

Various types of data like images, video, velocity, GPS, etc. can be included in an SIoV system. However, studies indicate that the data in the SIoV system is not integrated yet. Integrating the existing data can create numerous new applications for intelligent transportation, including traffic monitoring, intelligent navigation, and autonomous driving. While most of the focus has been on deep neural networks, a new approach has been developed using Convolutional Neural Networks (CNN) to evaluate the score of social relationships between pairs of vehicles. The effectiveness of this approach for evaluating road topology is evaluated using extensive simulations that include performance metrics such as content dissemination, energy, and social score. The proposed approach enables more efficiency in using the IoT in a mobile environment, and its effectiveness has been confirmed through simulation. An innovative framework called ADLIoB has been proposed in [11]. This framework is a complex deep learning framework for the Internet of Behavior (IoB) which imports sensor data such as images, time series, and charts. The framework provides an IoB decision set as output. To reduce communication bottlenecks and protect the privacy of car user data, in [12], a deep learning algorithm based on conditional selection probability has been proposed. This algorithm introduces elements of inter-user trust to describe the vehicle connectivity network from the perspective of vehicle-user communication.

The SIoV is a complex system that requires different layers to complete various tasks. In a previous study [13], a solution was proposed for the SIoVs embedded in deep learning, which addressed priority ambiguity in social recommendations and provided online data enrichment. The proposed system includes a persistence layer, a display layer, a processing layer, and an application layer. These layers work together to provide a flexible environment for data management, scheduling, and execution of collaborative social computing tasks. The persistence layer performs pre-processing tasks on the source data, sorts the data, and fills in missing content. The Transmission Control Protocol is the standard data transmission across the social Internet. The representation layer represents the social network as a composite social graph. The features of nodes and edges in both subgraphs are jointly transformed into two separate representative vectors. The application layer connects the core functions of the SIoVs to end-users and provides a content delivery platform for platform operators, social users, and other end-users.

In the world of IoT, a common issue arises regarding the accuracy of sensor data. This can lead to the loss of some records, which is evident in the SIoVs. The usage of two or more sensors with the same characteristics is insufficient to address this challenge, as there will still be shortcomings in the system. However, if two or more sensors with different characteristics can be integrated, it can increase productivity. In [14], various features and sensors are introduced, while [15] uses these features for security in the SIoVs. In [16], a deep network model for vehicle separation based on image and video is presented. It appears that the SIoV system's ability to utilize different sensors enhances its capabilities.

III. PROPOSED METHOD

In this section, we will introduce the proposed model for a vehicle recognition and counting system. The data collected by recognition systems and vehicle numbers in SIoV are usually diverse, so the proposed model is designed to process heterogeneous data. The model starts by analyzing the input data. If the data is an image, a convolutional neural network is used to process it. On the other hand, if the input data consists of speed, acceleration, and GPS information, it is analyzed and classified with the help of a recurrent neural network. The outputs from both neural networks are then integrated, and a decision is made for each vehicle. Finally, the decisions are transmitted to the driver with the help of an RSU. Fig. 1 illustrates the proposed model.

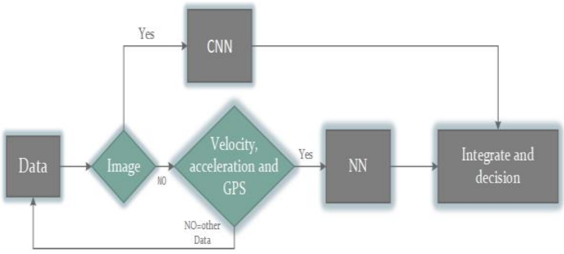

Fig. 1. Overview of the proposed model.

A. Vehicle Detection

To ensure that the data is accurately processed without any interference, it is labeled based on its type. The data is classified either as an image or non-image type. If the input data is an image, the deep neural network will process it and initiate the detection operation. During this process, the road surface is extracted and divided. The YOLOv3 learning [16] detection method is used to detect any vehicle objects present. Once the vehicles are detected, they are separated and their number is counted.

The road surface segmentation method is used to extract the road area, which is divided into two sections - far and near - depending on the camera location. The YOLOv3 object detection algorithm is used to detect vehicles in both road areas. The input image features are extracted using a convolutional neural network and are divided into 8x8 grids based on the feature map size. The YOLOv3 network structure is Darknet-53 [17], which uses the full convolution method and residual structure to ensure the integrity of image feature information, reduce training complexity, and improve recognition accuracy.

B. Neural network-based clustering

The proposed model aims to improve traffic management by automatically classifying vehicles based on their speed, acceleration, and GPS data received by the RSUs. The first part of the model detects and counts cars, but to manage traffic effectively, other factors such as the speed and location of each vehicle need to be considered. Therefore, the cars detected in the first part are classified into slow, medium, and fast classes in the second part of the model. An MLP-based classifier using standard DSM and BP training algorithms is employed to classify the cars based on the extracted features. The system model consists of computing servers and an IoV network. The IoV devices are randomly deployed across the area, and the network is divided into clusters to facilitate data collection from the devices.

C. Integrate and decision

In the final stage, the proposed model is integrated by dividing the vehicles detected in the images into two groups based on their position, speed, and acceleration - slow and fast. The first part involves not only vehicle recognition but also vehicle counting. Based on the number of vehicles on each type of road where the RSU unit is placed and the classification of the vehicles, instructions to slow down or increase speed can be given. This will lead to better traffic management.

IV. EXPERIMENTAL RESULTS

To model traffic behavior, data is initially categorized as either image or non-image data. Non-image data must be thoroughly reviewed, and incomplete data will be removed. Data that exceeds or falls below the specified limits, such as a speed exceeding 180, will also be removed. The proposed method underwent comparison with various advanced algorithms for detection and evaluation. The resulting analyses were presented in tables and figures, including Tables 1 and 2 and Fig. 3 and Fig. 4.

A. Dataset

To evaluate and compare with other techniques, datasets were collected that contained vehicle objects along with their unique characteristics. Two video datasets, GRAM [18] and HighwayII were used for this purpose. Initially, the datasets were labeled with the relevant information, after which speed, acceleration, and GPS data were added to each vehicle. An example of the available datasets can be seen in Fig. 2.

Fig. 2. Datasets. a) GRAM dataset. b) HighwayII video dataset

To evaluate and compare with other techniques, datasets were collected that contained vehicle objects along with their unique characteristics. Two video datasets, GRAM [18] and HighwayII [19] were used for this purpose. Initially, the datasets were labeled with the relevant information, after which speed, acceleration, and GPS data were added to each vehicle. An example of the available datasets can be seen in Fig. 2.

The HighwayII video [19] was captured over two days using a stationary camera that was positioned above I-5 in Seattle, WA. The recorded video was manually classified into three categories based on the traffic density - light, medium, and heavy. These categories correspond to free-flowing traffic, traffic that moves at a reduced speed, and traffic that has either stopped or is moving very slowly. It's important to note that the first frame of the original video is corrupted with another video signal. Therefore, while processing the video, it's necessary to begin from the second frame.

In each image, the vehicle's speed, acceleration, and GPS specifications are recorded in a separate table assigned to the vehicle based on the image number and type.

B. Performance measures

The proposed method allows for detecting and counting vehicles. To evaluate its performance, we will compare its detection and counting results with those of other approaches. The accuracy of detection has been measured using precision and recall, which are quantitative performance measures. Formulas 1 and 2 are the evaluation criteria used for this purpose [20].

(1) $Precision = \frac{|TP|}{|TP|+|FP|}$

(2) $Recall = \frac{|TP|}{|TP|+|FN|}$

Here, TP (True Positive) is the number of correctly detected vehicle pixels, FP (False Positive) is the number of falsely detected pixels, and FN (False Negative) is the number of correctly undetected pixels.

C. Detection and counting

The available datasets in the SIoV field include road camera images. Real-time counting of vehicles helps the SIoV system to better manage. In order to count the vehicles, the detection should be done according to the available images, and then the detected vehicles should be counted. Fig. 3 is an example of vehicle detection and counting for the GRAM dataset.

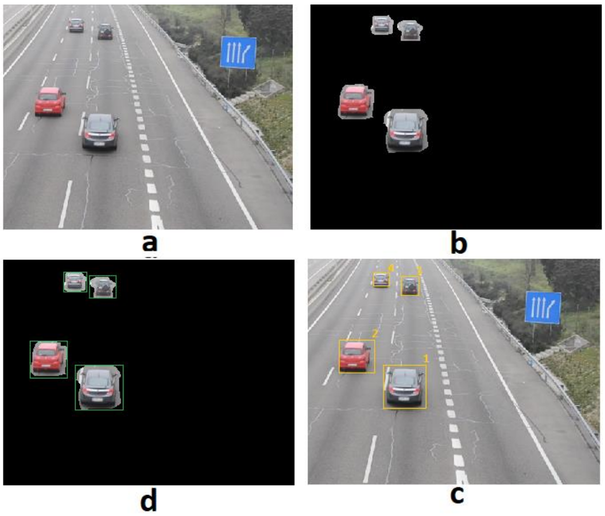

Fig. 3. Detection and counting in GRAM Dataset. a) Original Image in Dataset. b) Remove background. c) Detection of vehicle. d) Counting of vehicle

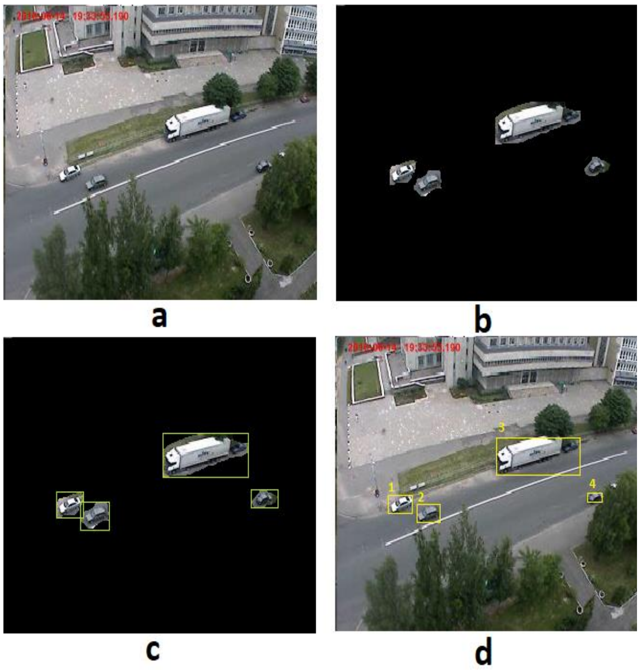

Fig. 4. Detection and counting in HighwayII video Dataset. a) Original Image in HighwayII video Dataset. b) Remove the background. c) Detection of vehicle. d) Counting of vehicle

GRAM dataset is a collection of images. Fig. 3a shows an original image from this dataset. Fig. 3b presents the separation of the background region from the vehicle. Fig. 3c displays the detection of vehicle areas, and Fig. 3d shows the counting of vehicles according to the detected boxes. Based on Fig. 3, it is evident that the proposed model has been successful in detecting and counting vehicles to a great extent. However, there are still some pixels in the detected spaces that can be further explored in future studies.

The HighwayII dataset is a collection of videos, which are converted to a series of images based on their frames. As shown in Fig. 4, the proposed model was able to detect vehicles quite well but struggled in areas where vehicles were closely clustered together. This dataset contains a similar number of vehicles as the GRAM dataset and the detection is based on identified areas.

D. Evaluation results

To compare with other vehicle counting techniques, we have used datasets that contain information about vehicle objects, including their speed, acceleration, and GPS. Our experiment focused on evaluating the accuracy and sensitivity of two datasets from GRAM, HighwayII video.

TABLE I. Assessment of accuracy for two datasets

	precision	**recall**
GRAM	98.75	98.02
HighwayII	95.33	95.67

Table 1 shows that the proposed method outperformed others in analyzing GRAM data.

Table 2 provides a comparison of the GRAM dataset and labeled data with recent techniques. Based on the table, it is evident that the proposed method has an advantage over other methods in terms of counting accuracy. The proposed method achieved the highest precision without missing any vehicle.

TABLE II. Vehicle counting accuracy for GRAM Dataset

	Precision	*Recall*
Yang et al. [21]	92.20	88.10
Quesada et al. [22]	97.41	92.86
Bouvie et al. [23]	89.62	88.10
Bouvie et al. [24]	89.62	88.10
Proposed Method	98.75	98.02

The results of Table 2 indicate that the proposed method outperforms recent methods in some cases, particularly in vehicle counting.

A comparison between the proposed method and recent techniques was conducted on the HighwayII dataset and labeled data. The results are presented in Table 3, which shows that the proposed method has the advantage of accurate vehicle counting. The method achieved the highest precision without missing any vehicle.

The results presented in Table 3 demonstrate the proposed method's superiority over recent methods in vehicle counting.

TABLE III. VEHICLE COUNTING ACCURACY FOR HIGHWAYII DATASET

	Precision	*Recall*
Yang et al. [21]	95.10	85.43
Quesada et al. [22]	91.30	92.10
Proposed Method	95.33	95.67

V. CONCLUSIONS

An innovative and robust approach to vehicle detection, counting, and management in SIoV has been introduced in this work. The selective approach comprises of three steps - diagnosis, review, and decision-making. Firstly, the method identifies labeled datasets using image and non-image-based techniques. The vehicles are then detected and counted using a CNN-based classifier called YOLOv3. The labeled vehicles are further classified into slow and fast categories, with the help of a recurrent neural network. Finally, a decision is made based on the available road space, and the driver is notified using RSU. The experimental results on different datasets demonstrated that the proposed strategy performs better than other existing methods.

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