VISION BASED REAL-TIME VEHICLE VOLUME CLASSIFICATION AND COUNTING SYSTEM USING DEEP LEARNING

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Abstract
Currently, deep learning techniques are widely used in most applications. They work well with unstructured data, generate features automatically, and have the advantage of self-learning. Conventional approaches for vehicle classification often lack accuracy, require considerable processing time, and are not suitable for real-time scenarios. In the proposed work, we have created a dataset of vehicles and applied YOLOv3 (You Only Look Once) to identify, categorize, and count multiple vehicle types. The proposed system is successful in accurately performing vehicle detection, recognition, and counting with 99.78% accuracy. The achieved accuracy verified the effectiveness of the developed methods and YOLOv3 in the task of vehicle classification.
Keywords: Deep Learning; YOLO; Vehicle Classification; Traffic Volume

I. Introduction

Vehicle detection and classification in highways plays a significant role in intelligent traffic control and highway management. Vehicle detection and counting also helps in accurate measurement of the traffic volume. Prediction of traffic flow is a challenging task as it differs between cities, regions, and nations. In addition, it also varies across the daytime, seasons, festival time etc. The heterogeneity of traffic volume can be estimated with Passenger Car Unit (PCU). The PCU is weighted conversion of varied traffic volume into an equivalent homogeneous quantity keeping Car as ONE unit [1]. It varies depending on the traffic characteristics, geometric design, and intersection design of the road. Accurate estimation of PCU is crucial to efficiently manage and control the traffic. Since a decade, the highways sector in India is seeing a drastic boost in terms of investment and performance. Share of GDP on logistics and transportation accounts for 15%. Precise evaluation of traffic flow plays a vital role in the planning, development, and upkeep of transportation infrastructure [2].

As per the current trends, by 2030 it is estimated that the number of fatalities due to road accidents will be ranked 5th in the total deaths across the world [3]. Availability of traffic volume count also helps in analyzing the cause of accidents and facilitates better prevention. Due to rapid urbanization in India, it is becoming increasingly difficult to manage huge population, infrastructure, and traffic in major cities. Smart cities require Advanced Traffic Management Systems (ATMS) and Intelligent Transport Systems (ITS) to integrate the real-time traffic information, analyses and take appropriate actions based on the existing traffic and transportation problems. In addition, these systems need to accurately predict the future state of traffic across the city so that the city corporation or governments can plan for new infrastructure [4]. Traffic prediction is broadly divided into short-term and long-term forecasting. Short-term models utilize recent traffic patterns to estimate traffic conditions typically within the next 5–30 minutes [5]. Long term forecasting targets for one or more days in future and generally utilized for managing futuristic traffic congestions [6]. Effective implementation of ATMS and ITS depends on precise vehicle detection, classification and counting mechanisms adopted by traffic management agencies.

Vehicle classification (VC) is an important task especially in traffic surveillance. Classifying the vehicles based on their types, size, colour, purpose etc can be achieved using computer vision techniques. Some of the application of vehicle classification are designing the futuristic roads, identifying the stopped vehicles, over speeding vehicles, ambulance detection etc. VC is a challenging task due to low inter-class variation and high intra-class variation amongst the vehicles [7].

Vehicle detection is required for accurate vehicle counting. Traditionally various sensors and hardware devices such as microwave detectors, ultrasonic detectors, laser detectors, radar detectors, inductive loop detectors were utilized for vehicle counting. However, the accuracy of these sensors was largely affected by environmental conditions and were expensive to maintain. Currently, video-based detection methods are being utilized as they are more accurate, less expensive and easy to maintain [5]. Vehicle detection can be performed using various methods such as frame differencing, background detection and optical flow etc. Nevertheless, these methods are inefficient, inaccurate and ineffective in terms of object detection [6]. Recently, deep learning techniques are excessively being utilized for vehicle detection and counting purposes. In deep learning, the cumbersome process of feature extraction and modelling steps are performed automatically. They are capable to scale large amounts of data without any overfitting [8].

There are various studies carried out in the recent past regarding vehicle detection-based computer vision techniques. Lately, Jagannathan et al. [9] worked on detection and classification of moving vehicles using machine learning algorithms. The proposed ensemble deep learning method achieved the classification accuracy of 99.13% and 99.28% on two standard vehicle datasets. Similarly, Lin Li et al. [10] utilized Fusion part model with active learning-based method for multi-view vehicle detection. The implemented method achieved better accuracy compared to state-of-the-art techniques on the same dataset. In another work, a deep learning framework was developed to detect and track vehicles that too in adverse weather conditions. In the proposed work, Hassaballah et al. also proposed visibility enhancement scheme which improved the performance of the developed method [11]. Likewise, an algorithm was developed to detect and count the number of vehicles using vision based and deep learning techniques in highway scenes. The authors utilized YOLOv3 and ORB algorithms on a large image dataset to achieve 83.46% of detection accuracy and 93.2% of counting accuracy.

Many studies have focused on automatically identifying different vehicle types such as cars, trucks, and two-wheelers. Ambardekar et al. [12] examined five object-recognition techniques and several of their hybrid combinations to perform vehicle classification. Their method utilized Principal Component Analysis (PCA) along with Scale-Invariant Feature Transform (SIFT) features to distinguish between vehicle classes, demonstrating high recognition performance across three vehicle categories. Similarly, Wang et al.[13]introduced a real-time vehicle classification system built with a deep convolutional neural network architecture. They implemented the Faster Region-Based Convolutional Neural Network (Faster R-CNN) model and achieved classification accuracies of 90.65% for cars and 90.51% for trucks, indicating strong effectiveness of their approach.

II. System Design

A. *Dataset Information*

Dataset is the collection of data, which is in the form of videos, images, files, documents, etc. It is one of the most important information which is required in data science or machine learning. In the proposed work, we captured the videos of the moving vehicles and later extracted frames for next level processing. Later, we created the image dataset in such a way that it can be easily accessed, managed and manipulated. The dataset of vehicle images was divided into training and testing set. We used computer vision algorithms to train the data set. Mostly, data sets are trained by labelling it with their class names. We have selected the portion (Region of Interest) of an image and labelled it with its name. The HP W200 digital webcam was used to capture images and videos. Specification of the of the digital webcam used is as follows: W200, Model name: HP W200, Video capture: 720p, Lens Type: Zoom, Media Type: Video8 and Mounting Hardware: Webcam.

B. *Deep Learning Model:*

In the proposed work, YOLO (You Only Look Once) V3. It utilizes Convolution Neural Networks (CNN) for real time object detection. Yolo processes images very fast. YOLO takes image as input and generates bounding box. It has class labels attached to it. YOLO shows the existence of any object by using a bounding box. YOLO is based on the idea of dividing the images into smaller images. It splits the images into S×S grid and each grid predicts and bounding boxes and confidence.

In general, deep learning-based object detection algorithms are implemented in 2 stages: The Region of Interest in an image needs to be selected and the algorithm classifies these regions using CNN. But the solutions provided by utilizing this approach can be slow because we must run predictions for every selected region. So, the proposed system uses YOLO for fast image processing, high accuracy and better performance in real time [14]. It can process 45 fps to 150 fps videos. The general architecture of YOLO architecture is given in Fig.1

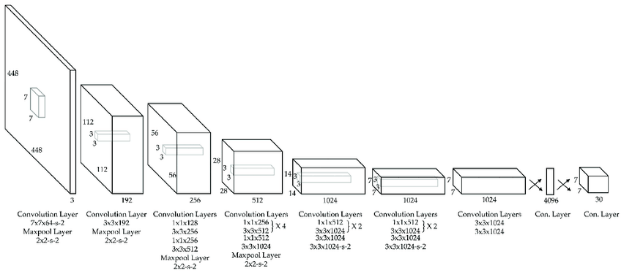

Fig.1: General YOLO architecture for object detection and localization [15]

C. *Methodology*

In the proposed system, a series of systematic steps are performed to accurately detect and categorize vehicles :

1. Image capturing: This system use camera for capturing images of vehicles for classification. The camera can be placed at locations, such as entrance of institution, parking lots and traffic roads. In our work, the web camera was placed at the entrance of TKIET Warananagar (Autonomous), Kolhapur, Maharashtra. The camera was placed in such a location where the accurate view of vehicles was captured.
2. Pre-processing: The captured images were pre-processed to improve quality of detection process. Here, we reduced the frame size to reduce image size and for faster processing. Other pre-processing techniques can be applied for noise reduction, missing values etc.
3. Object/Vehicle detection: In this step, objects were identified from the frames. In order to achieve this process, we used YOLO V3.0 algorithm.
4. Vehicle feature detection: For vehicle classification, system needs to extract features from images. Features may include texture, size, shape, and color.
5. Vehicle classification: For vehicle classification YOLO uses OpenCV and deep learning libraries. This system has trained on large dataset for better analysis and classification of vehicles.
6. Output: In final output, system indicates the type of vehicle in video. These systems also provide information about time.
7. Evaluation: Model performance is evaluated using metrics like: Accuracy (for classification) Precision, Recall, F1-score (for detection) Mean Average Precision (mAP). Testing is done on multiple videos under different lighting and traffic conditions

Overall, an intelligent vehicle classification system can improve parking management system, traffic management and classify vehicles in real time.

III. Result Analysis

In this section, we have described the performance of the proposed system in terms of accuracy. This analysis was done in TKIET Warananagar (Autonomous), Kolhapur, India on 14/10/2025. The camera was placed on the road divider, the videos captured consisted of the vehicles travelling both the directions i.e., vehicles entering the campus and vehicle that are leaving the campus.

Table 1 provides the details of the vehicle types and the accuracy achieved. The ground truth was generated by manually counting the number of incoming and outgoing vehicles.

Vehicles	Machine Counts in Nos.	Manual Counts in Nos.
Car	104	104
Motorcycle, Scooter	450	451
Bus	11	11
Truck	01	01
Mini Bus	08	08
Total	**573**	**575**

Table 1: RESULTS OBTAINED

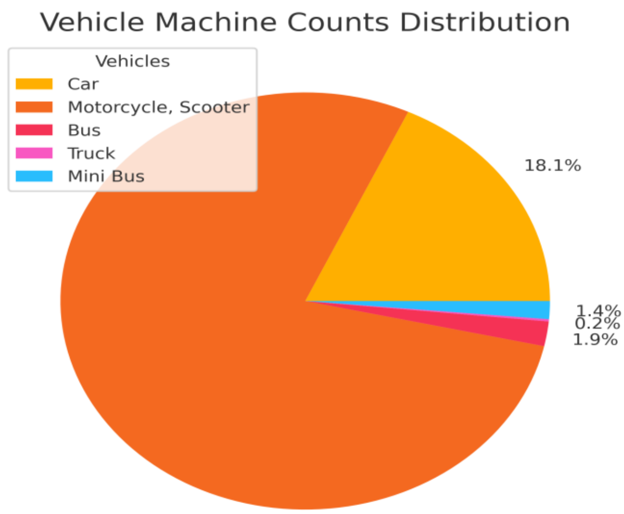

Fig. 2: Percentage Classified Distribution of Vehicles

From Table 1, it can be observed that out of 575 vehicles, 573 were successfully detected, classified, and counted. The developed algorithm was unsuccessful to detect only one out of 575 motorcycles that were manually counted.

Fig. 2 depicts vehicle detection, classification and counting.

Fig. 3: Vehicle detection and classification

In Fig.2, it can be observed that all the three vehicles that are visible in the frame are identified and classified correctly.

The proposed system identified all the vehicles with 99.82% classification accuracy. From the obtained results, it is evident that the developed model with YOLO V3.0 is effective in identifying, classifying, and counting the vehicles in real-time conditions.

The parking management strategies used in this study are summarized in Table 2.

Table 2: Parking Management Strategies

Based on Design	Improve parking facility design and operations to help solve problems and support parking management
Unbundle Parking	Provide parking facilities separately from building space
Smart Growth	More compact, multi-modal development must be encouraged to allow more parking development.
Overflow Parking Plans	Proper plans must be developed to manage peak parking demands.

Parking facilities are generally categorized into on-street parking, off-street parking, and special parking systems. On-street parking refers to vehicle parking along the road margin, typically at the curb, on roadside strips parallel to the carriageway, or within public road areas such as squares. Common on-street parking configurations include parallel, perpendicular, angled, and pay-and-display parking. In this work, angle parking is recommended, as it offers the most efficient on-street layout, allowing vehicles to be positioned at an angle to the roadway. Table 3 presents the parking space requirements, while Table 4 lists the Equivalent Car Space (ECS) values [16].

Table 3: Parking Space Requirement

Vehicle	Space Required (in m^2)
Car	20-36 sq. m
Two Wheelers	02-03 sq. m
Buses	55-60 sq. m
Mini Busses	35-40 sq. m
Trucks	55-60 sq. m
3 Wheelers	10-15 sq. m

Table 4: Equivalent Car Spaces (ECS) [16]

Vehicle Type	ECS
Car/Taxi	1.00
Two-Wheeler	0.25
Auto Rickshaw	0.50
Bicycle	0.10
Trucks/Buses	2.50
Emergency Vehicles	2.50

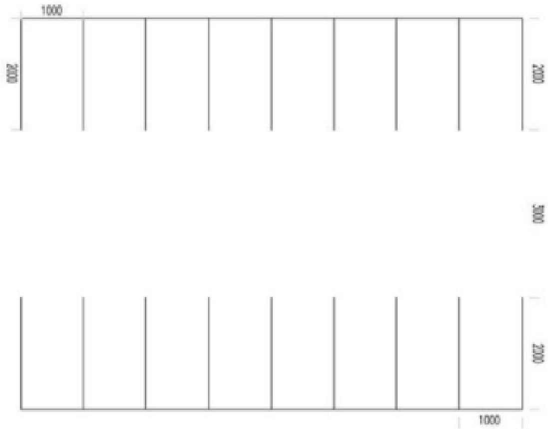

Fig. 4: Parking Layout Design for Two Wheelers

From the figure we can calculate space required for 451 Two-Wheeler as follows:

For 1 Two-Wheeler, space required is 2 sq. m. Hence for 451 Two-Wheelers, space required is 902 sq. m.

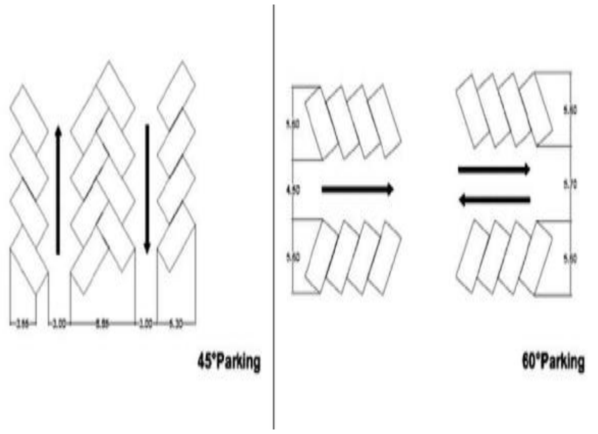

Fig. 5: Parking Layout Design for Cars

Analysing the above figure, we suggest 60° Car Parking for On-Street Parking. From the figure we can calculate space required for 50 cars as follows: For 1 car, space required is 20 sq. m. Hence, for 104 cars, space required is = 2080 sq. m.

IV. Conclusions

Vehicle counting and classification play a key role in designing an effective parking system for an educational campus.

The essential objectives of a parking policy are outlined as follows:

1. Ensure maximum utilization of the available parking area.
2. Increase the turnover rate of parking slots.
3. Optimize and manage the parking space efficiently.
4. Provide park-and-ride facilities for bicycle users to enable smooth mode interchange.
5. Use the designated parking spaces to their highest operational and economic efficiency.

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