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A Novel Framework for Vehicle Detection and Classification Using Enhanced YOLO-v7 and GBM to Prioritize Emergency Vehicle

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Abstract: In the modern era, accurate vehicle detection and classification has become one of the key challenges due to the rapid increment in the number of varied size vehicles over the roads, particularly in urban regions. There have been explored and implemented promiscuous models for vehicle detection and categorization in the last few years. However, existing advanced frameworks have several issues related to the correct identification of the vehicles due to the shadow problem, which results in lower identification accuracy for prioritization of emergency vehicles. Further, these models consume more time in execution as well as intricate to implement and maintain in real-time. In this research work, a new framework for vehicle detection and classification has been proposed. This novel framework is based on Yolo-v7 and a Gradient boosting machine (GBM) to prioritize emergency vehicles in a faster and more accurate manner. For alleviating huge traffic as well as safety concerns, this suggested framework centers on the accurate identification of vehicles class in intelligent transportation system (ITS) for assigning priority to emergency vehicles to get a clear path. The findings of the suggested framework are highly optimal as well as enhanced in comparison to the previous models. The evaluated performance metrics i.e. accuracy, precision, recall, and F1-score of the suggested enhanced Yolo-v7 and GBM-based model are 98.83%, 96%, 97% and 98%respectively. This proposed research work can be extended in the future for more accurate vehicle identification to handle multifarious challenging circumstances, namely snow and rainy conditions or during the night.

Keywords: *Emergency Vehicles, GBM, Shadow Detection, Vehicle Detection, YOLO-v7*

1. Introduction

The recognition and vehicle classification is considered very critical for traffic surveillance as well as effective administration for assigning priority to emergency vehicles in real-time. The vehicle data is being acquired for vehicle supervision as well as management, data analytics, visualization as well as ITS improvement[1], [2]. For instance, the correct location of the vehicle along with the weight is vital for weight limit assessment. Moreover, the correct vehicle numbers count as well as categorization is essential for ITS for precise performance assessment. Traffic congestion is constantly becoming a very severe issue worldwide due to the quick increment in several vehicles. However, several models based on machine learning (ML), as well as deep learning (DL) methods, have been implemented earlier in ITS for effective traffic management in real-time[3]–[5].

There have been identified various challenges to urban traffic in the modern era such as the large number of cars which should be managed very effectively for traffic minimization. To manage the traffic in real-time, it is very essential to detect as well as classify the vehicle classes precisely for prioritization of the emergency vehicles. The correct identification of a particular class vehicle is an important task to manage the high volume of traffic employing ITS, in the modern era for obtaining high accuracy[6]. In numerous settings, the increased speed at the expenditure of correctness is acceptable; however, an enhanced identification scheme reduces the overall trade-off through recognition and prioritization of the most significant class of vehicle for detection. Shadow cast is still a major threat in correct vehicle detection as it is misidentified as vehicle components which leads to making distinct object loss and distortion[7]. Shadow elimination in a precise manner has been ignored by multifarious techniques including ML and DL[8].

Vehicle identification and categorization is one of the most vital research subjects in the areas of ITS and Advanced Driver Assistant Systems (ADAS). There has been carried out wide spread investigation on vision-rooted vehicle identification as well as categorization owing to the technological advancement in the field of pattern recognition and image processing as machine vision technology is very convenient, cheaper as well as non-contact. Vehicle recognition is a procedure to extract the targets of the vehicles via a region of interest (ROI)

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in the sequence of video to picture as means of multifarious image processing protocols[9].

The collection and generation of the correct data about multiple vehicles in an urban traffic surveillance setting is a fundamental job of the ITS, which requires massive efforts and attention to access the information[10]. As urbanization is at a fast pace at present owing to this vision-rooted automobile identification faces a massive challenge. Furthermore, due to the encounters of outdoor visualized processing namely alteration in illumination, bad meteorological conditions, shadow as well as diverse cluttered backgrounds, the precise identification of the vehicle through the fixed scanner also gets hindrance through its unique encounter[11], [12]. The increasing traffic congestion is becoming very common in urban areas, and as a consequence, numerous vehicle identification methods which apply motion data for detecting automobiles are not correct, as high traffic congestion reasons automobiles to slow down and minimizes the overall moving speed [13].

The key contribution of this experimental research work is described as follows.

- In this experimental study, a novel model based on the enhanced YOLO-v7 and GBM has been suggested for vehicle detection as well as classification, precisely.
- Another objective of this proposed model is to classify emergency vehicles accurately and assign them a priority for path clearance in real-time.
- This proposed model is more effective in terms of removing the entire shadow cast from the image frame data for precise classification of the distinct class of moving vehicles in real-time.
- Furthermore, all the performance measure metrics of this suggested enhanced YOLO-v7 and GBM-based model are very finest and optimal in terms of accuracy, precision, recall and F1-score.

The overall organization of this experimental research article is summarized as follows. Section 1 presents the introduction. Related work has been explained with major limitations of the earlier research work in section 2. The novel proposed methodology for vehicle identification as well as categorization is demonstrated in section 3. Furthermore, the key results and analysis have been described in section 4. At last, the conclusion of this experimental study and the future scope of research are described in section 5.

2. Related Work

General features namely texture, distinct object corners, color variations, and edges are generally utilized for the representation of the distinct class vehicles [14], [15]. These determined features are to be offered to real-time deterministic classifiers for distinct vehicle identification. Owing to the inaccessibility of numerous categorization features in various instances, namely object occlusion partially, the key utility of such approaches may be restricted to certain specified applications only [16]. Numerous new research on part-rooted models is carried out for recognizing vehicle classes while preserving the effective performance under the various occluded settings [17]–[20]. By utilizing such techniques, an automobile is recognized to be made up of windows, multiple wheels, a roof, as well as distinct other components. Once the parts identification is done, the motion speed, as well as multifarious element models are generally utilized for vehicle detection [21].

In [22], P. Rosayyan et al. discussed an optimized control scheme to prioritize emergency vehicles in smart city settings as a means of the diverse Internet of Things (IoT) sensors and edge computing. The mission behind the smart city concept is to enhance the quality of life as well as economic development by utilizing information and communication technology (ICT). The prioritization of the emergency vehicle is one of the main IoT elements in the smart city that might secure numerous lives by providing an accurate manner green indication to a detected emergency vehicle namely a fire truck or an ambulance immediately. However, this optimized control scheme to prioritize the emergency vehicles in the smart city has diverse many limitations namely more average waiting time and lower accuracy in moving vehicles classification.

H. Wang et al. in [23], discussed another algorithm for vehicle identification which is rooted in the LiDAR cloud fusion approach. In the modern era, precise identification of vehicles is one of the utmost essential environmental perception jobs for distinct automated vehicles. The conventional vision-rooted vehicle identification techniques are not highly correct particularly for minor and occluded objects, on the other hand, light detecting and ranging (LiDAR) rooted techniques are pragmatic in identifying the objects, however, they consume more time, as well as offer low categorization rate for the distinct target class. A. Gomaa et al. in [24], proposed a scheme based on the faster convolutional neural network (CNN) for vehicle identification and counting tactic for a fixed number of multiple camera scenes. Automated counting and identification of automobiles in multiple videos is a crucial job and is a recognized significant application area for traffic surveillance and administration. This research work is focused to develop a YOLO-v2-based model for features points' movement assessment to identify and count the running vehicle in real-time. However, this YOLO-v2-based model has various drawbacks such as less accurate classification of the objects due to the shadow cast and more time taking in the average waiting period for diverse vehicles.

In [25], A. Farid et al. discussed a faster and more precise vehicle identification framework based on the DL for unconstrained settings. The DL-based detection and categorization protocol is emerging as a robust instrument for vehicle identification in modern ITS. This experimental research proposed the identification and categorization of the distinct class of automobile on the publicly accessible database as means of a novel developed YOLO-v5 model. Though, this developed model has multiple downsides such as a high average waiting time, lower vehicle classification accuracy in high congestion settings, inefficient shadow cast elimination and high computing cost.

H. Haritha et al. in [26], discussed a modified DL-based framework for vehicle identification in the traffic surveillance system. The deployment of satisfactory supervision, as well as secrecy measurement, is very vital in the modern world. This suggested framework is developed for handling the observation which determines the automobiles present within the traffic. The performance computation of this suggested model is determined by comparing it with previous techniques namely YOLO-v2 as well as MS-CNN. However, this suggested model has very limited performance evaluation metrics as well as more time taken in the training as well as testing settings. Further, this proposed framework is ineffective for the complete elimination of the shadow cast for precise classification of the vehicle class.

3. Methodology

3.1. *Dataset Used:*

This proposed framework is based on the enhanced YOLO-v7 and GBM for vehicle detection and classification to prioritize the emergency vehicle for path clearance in real time. The proposed model has been trained and tested on widely acknowledged datasets namely the UA-DETRAC. This UA-DETRAC database is a benchmark and most recognized dataset for novel model training and testing for multiple object identification and surveillance in traffic scenes. This dataset comprises multifarious video sequences which are clicked through real-time traffic scenes and represents numerous communal traffic condition and classes, including T-junction, metropolitan highway, and many more places. Furthermore, this UA-DETRAC database comprises more than 140,000 frames along with enhanced annotations which include automobile class, truncation, weather, automobile bounding box, and occlusion. Therefore, the UA-DETRAC dataset is a pragmatic asset for the performance evaluation of the models to object recognition and surveillance in traffic scenes.

3.2. Sample Size:

In a video sequence, a frame denotes a single picture that is shown over the screen. Every video is built on a series of frames which are shown in faster succession for creating an illusion of motion. A video frame rate indicates the overall frames which are shown per second. In this research study, 20 distinct videos have been selected for proposed model testing and validation in real-time. For data splitting into the train and test data, the group k-fold cross-validation method has opted because this data splitting method offers a highly correct estimation of model performance in a scenario where the dataset is in groups. Table 1 illustrates the priority scenario for a varied class of vehicles in emergencies. The assigned priority value to the diverse vehicle classes i.e., ambulance vehicles, police vehicles, fire control truck vehicles, bus vehicles, and car vehicles are given 0, 1, 2, 3 and 4, respectively for proposed model validation.

Table 1: Illustrates the priority scenario for a varied class of vehicles.

Sl. No.	Type of Vehicles	Assigned Priority Value
1	Ambulance Vehicles	0
2	Police Vehicles	1
3	Fire Control Truck Vehicles	2
4	Bus Vehicles	3
5	Car Vehicles	4

3.3 System Setup:

This experimental research work was carried out using a computing machine that comprises of described system settings: 64 bits operating system (OS), RAM: 16 GB, DDR4and Graphic Card: GeForce GTX 1650 NVIDIA, integrated processor: Intel Core i5 and installed with the Window 11.In this work, the Google Colab environment has been utilized as it is a cloud-rooted platform for writing, running and sharing Python language code within Jupyter Notebook.

3.4. System Architecture:

Vehicle detection and classification in an accurate and precise manner is a challenging job nowadays, owing to a rapid increase in vehicles. The previously developed models for vehicle detection and classification have various flaws related to model accuracy, precision, model execution time, and many more. To settle these threats, in this work a novel model is developed for vehicle detection and classification using enhanced YOLO-v7 and GBM to prioritize emergency vehicles for immediate path clearance. Figure 1 illustrates this suggested system architecture for vehicle identification as well as categorization using enhanced YOLO-v7 and GBM. The working method of this novel model is described as follows. In the first phase of the proposed model implementation, the dataset pre-processing and data augmentation is done effectively. In the data pre-processing multiple important operations have been performed on the data i.e., noise removal, as well as data integration, along with data reduction, and data transformation. The noise removal process eliminates unnecessary or irrelevant information from the data. The data integration process combines raw data accessed from diverse sources with unique data for effective training and testing. Data decrease is a process in which multiple attributes or records are reduced within the dataset while ensuring that minimized dataset originates a similar outcome as the real dataset. The data transformation normalizes and aggregates the received dataset as per the requirement of the data in model training. Further, the data augmentation approach has been utilized for increasing the amount of the dataset as means of creating a novel, transformed version of the original dataset.

In the data augmentation segment, multifarious operations have been performed namely random rotation, color modification, cropping as well as zooming to the received datasets. The key objective of the data augmentation in the suggested model was to enhance the overall framework performance as means of offering more distinct as well as representative datasets in the training and testing phase. In the next phase, this pre-processed and augmented dataset is translated to the background edge extraction framework for shadow detection and removal with the help of the K-Means clustering protocol. The K-means clustering protocol has been utilized as a part of the color-rooted segmentation scheme for eliminating the shadows from the image frames. In this technique, the K-means protocol was chosen for clustering the pixel in the picture rooted in the color values. Furthermore, the clusters corresponding to shadow areas may then be recognized as well as eliminated from the pictures effectively in real-time. In the following phase, the hierarchical clustering technique is used for cluster analysis which seeks to make hierarchical clusters for effective training and validation of the proposed model. Hierarchical clustering is done aiming to merge the same data within N number of distinct clusters such that the same dataset within a hierarchical cluster comes close to one other.

For data cross-validation, to split data into train and test data, Group k-fold cross-validation method has been utilized. The group k-fold cross-validation is an extended version of the k-fold cross-validation which is more effective in terms of improving the accuracy of the framework. For training and testing of the proposed model, the split data are divided into the train and test groups i.e. 80% dataset is utilized for the model training, and the rest of the 20% of data is utilized for model testing. For vehicle detection and classification, a hybrid model based on the enhanced YOLO-v7 and GBM is integrated with the train and test model. Further, this proposed model accurately detects and classifies the vehicles into multiple classes i.e., emergency vehicles such as ambulances, police vehicles, military vehicles, and other vehicles such as buses, cars, trucks, and motorbikes etc. In the next phase, this classified dataset is translated to the emergency vehicle priority framework which is based on the deep transfer learning technique. The fundamental of deep transfer learning is the features generality inside the trained model. While, the emergency vehicle priority framework, determines the emergency vehicle based on deep transfer learning, the path is cleared in real-time for assigning priority to the emergency vehicle, otherwise, in the case of a normal vehicle, the priority framework terminates the priority assigning process.

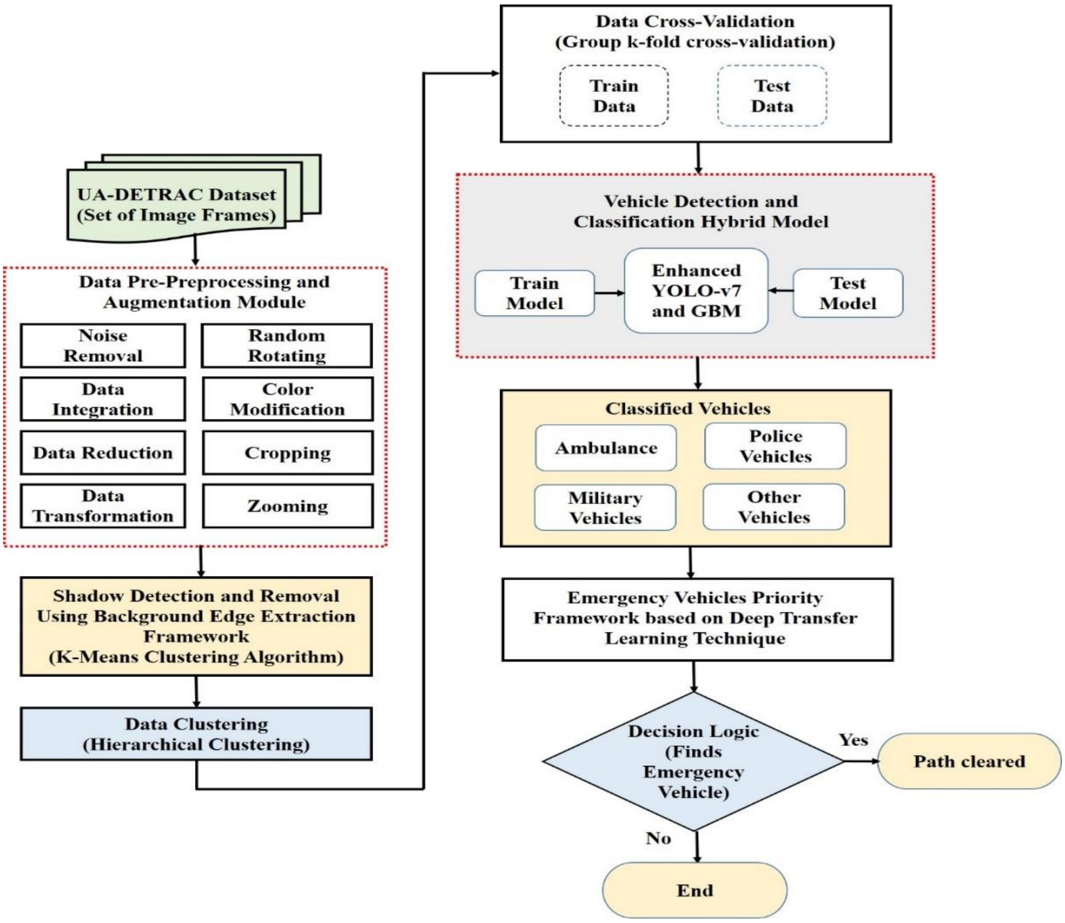


Fig 1: Illustrates the proposed system architecture for vehicle detection and classification using enhanced YOLO-v7 and GBM.

Pseudo code: The pseudo-code for the proposedYOLO-v7 and GBM-based model for vehicle classification and assigning priority to the emergency vehicles are described as follows:

Input: Set of image frames(IF_1, IF_2, IF_3,…..IF_N)

Output: Classified emergency vehicle (CE_v)

Step 1: Multiple sets of image frames (IF_1, IF_2, IF_3,…..IF_N**)** are aggregated.

Step 2: To input(IF_1, IF_2, IF_3,…..IF_N), for data pre-processing and augmentation module for obtainingIF_{AD}.

Step 3: To apply IF_{AD} to K-Means algorithm for shadow detection and removal to obtainSD_{EE}.

Step 4: To repeat step 3, till theSD_{EE} are in pre-defined goals i.e. (PD_{G1}, PD_{G2}).

Step 5: Initialize the hierarchical clustering for obtaining ($HC_1, HC_2, HC_3, HC_4, \dots \dots . HC_N$).

Step 6: To apply($HC_1, HC_2, HC_3, HC_4, \dots \dots . HC_N$) on group k-fold cross-validation to obtain, (TR_{d1}, TD_{d2}).

Step 7: To separate the (TR_{d1}, TD_{d2}) for model training and testing.

Step 8: Initialize the training on TR_{d1} using enhanced trained model based on YOLO-v and GBM.

Step 9: Initialize the testing on TD_{d2} using enhanced trained model based on YOLO-v and GBM.

Step 10: Perform the classification using the trained model to obtain classified vehicles i.e., (AM_B, PL_V, ML_V, OT_V).

Step 11: To apply decision logic using deep transfer learning for finding classified emergency vehicles (CE_v) for path clearance.

3.5. Model Evaluation Metrics:

The performance evaluation of the proposed model which is based on the enhanced YOLO-v7 and GBM has been computed by using multifarious metrics namely accuracy, sensitivity or recall, precision as well as F1-score. These aforementioned metrics play a vital role in the performance evaluation level of the model in an effective manner. The accuracy performance computation metric evaluates the proportion of accurate predictions made via this suggested model. The precision performance computation metrics evaluate the true positive prediction proportion out of the total positive predictions made by this proposed model. Further, the recall or sensitivity determines the true positive prediction proportion out of total real positive occurrences in data. Lastly, theF1-score performance computation metrics is a weighted average of recall and precision that offers a balance among these two distinct metrics. The accuracy metric is described in equation 1.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

The recall or sensitivity may be computed as the mean of the following equation

$$Recall\ or\ Senstivity = \frac{TP}{TP+FN} \qquad (2)$$

The precision metric can be evaluated by using the subsequent equation 3.

$$Precision = \frac{TP}{TP+FN} \qquad (3)$$

The F1-score measure may be computed by utilizing the below-defined equation 4.

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision+Recall} \qquad (4)$$

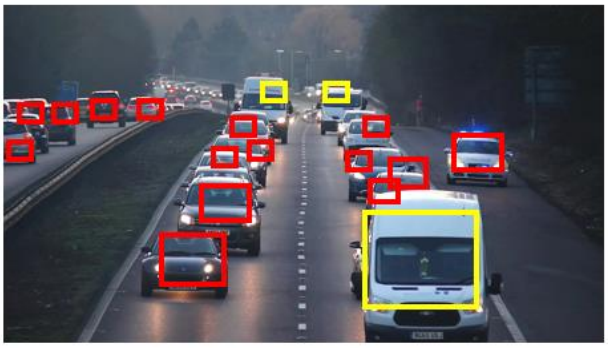
4. Results and Discussion

The ITS framework has been attentive to the utilization of the recent information technology (IT) for implementation of the assets allocation scheme to improve the community service capacities effectively. Nowadays, traffic is increasing very rapidly globally due to the constant advancement in the automobile sector for providing convenient vehicles to users. However, effective traffic management is still a key issue in the ITS owing to the less vehicle detection and classification accuracy to prioritize the emergency vehicle for providing a clear path. To resolve these defined key challenges, this research work is focused to develop and implement a novel framework for vehicle detection and classification using the enhanced YOLO-v7 and GBM technique for emergency vehicle prioritization and path clearance in real-time.

Table 2 illustrates the system setup details, which are utilized in this experimental study. The entire implementation work of this proposed model is done employing a computing machine set up with the described configuration, OS: 64-bits, RAM: 16-GB, DDR5, Clock Speed: Up to 3200 MHZ, Graphic Card installed: GeForce GTX 1650 NVIDIA, Core Processor: Intel i5, and Window Platform selected: Window 11. Furthermore, in this work, the programming environment is utilized the Google Colaboratory which is generally called the Google Colab. This is a cloud-rooted open-access platform offered by Google for diverse machine learning and deep learning-based model training and validation in real-time with very less computational complexity. Lastly, the Python 3.11.3 version has been utilized for the programming purpose in this model development process.

Table 2: Illustrates the system setup details.

Sl. No	System Setup	Configuration
1	Operating System (OS) Selected	64-Bits
2	RAM	16 GB, DDR5, Clock Speed: Up to 3200 MHZ
3	Graphic Card	GeForce GTX 1650 NVIDIA
4	Processor	Intel Core i5
5	Window Platform	Window 11
6	Programming Environment	Google Colab
7	Programming Language	Python 3.11.3



(a)

(b)

Fig 2: Illustrates the correct vehicle detection by the proposed framework in real-time (a) shows moving vehicles over a highway and (b) moving vehicles in a metropolitan nearby a traffic light area.

Figure 2 illustrates the correct vehicle detection by a proposed framework in real-time (a) shows moving vehicles over a highway and (b) moving vehicles in a metropolitan nearby a traffic light area. Accurate vehicle detection and classification is a very critical job, particularly in a scenario where emergency vehicles need to assign a high priority for passing over the road quickly without any long delay or effort. Figure 2 depicts that this proposed model accurately detect and classify distinct vehicle class whether it's a similar kind of car or other vehicles very precisely even while fast-moving vehicles are in the queue. Furthermore, this proposed model is capable to prioritize the distinct vehicle classes in emergencies. The assigned priority value to the diverse vehicles classes i.e., ambulance vehicles, police vehicles, fire control truck vehicles, bus vehicles, and car vehicles are given 0, 1, 2, 3 and 4, respectively in the proposed model validation for performance evaluation in a more precise and accurate manner.

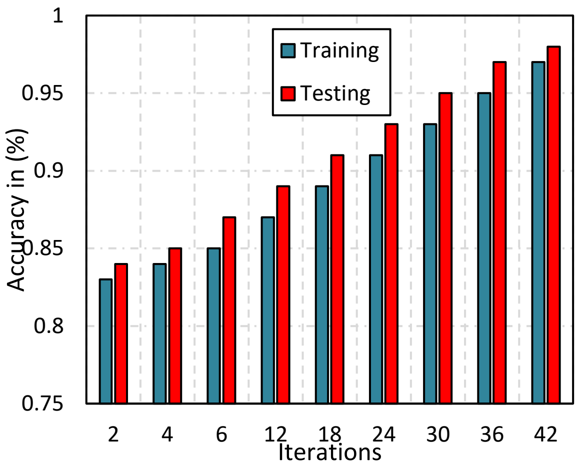


Fig 3: Accuracy measured in the training as well as testing segment of this suggested model.

Figure 3 depicts the accuracy measured in the training as well as the testing segment of the suggestedYOLO-v7 and GBM-based model. The training accuracy of this proposed YOLO-v7 and GBM-based model on iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42, is measured 0.83%, 0.84%, 0.85%, 0.87%, 0.89%, 0.91%, 0.93%, 0.95%, 0.97%, respectively. Further, the testing accuracy of this proposed model on iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42, is measured 0.84%, 0.85%, 0.87%, 0.89%, 0.91%, 0.93%, 0.95%, 0.97%, 0.98%, respectively. The measured training and testing accuracy level over distinct iterations is found improvised and optimal in real-time validation of the proposed model.

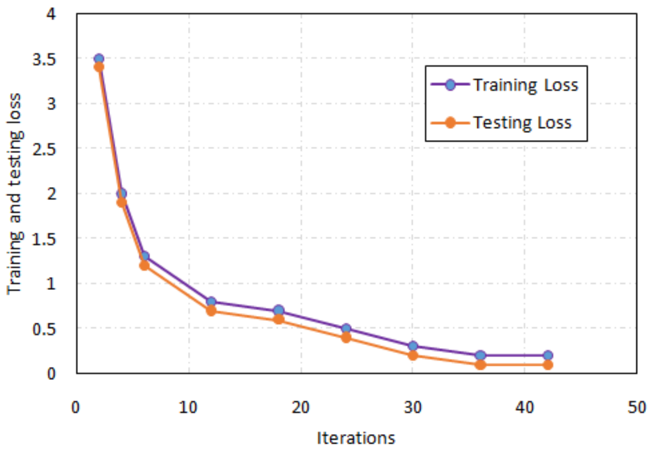


Fig 4: Depicts the evaluated training as well as testing loss for the suggested YOLO-v7 and GBM based model.

Figure 4 depicts the evaluated training as well as testing loss for the proposed YOLO-v7 and GBM-based model. While training this model on iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42, the training loss is recorded 3.5, 2, 1.3, 0.8, 0.7, 0.5, 0.3, 0.2, and 0.2, respectively. Further, while testing this model on iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42, the testing loss is recorded 3.4, 1.9, 1.2, 0.7, 0.6, 0.4, 0.2, 0.1, and 0.1, respectively. The evaluated training, as well as testing loss, are found very minimal and optimal in real-time implementation of the suggested YOLO-v7 and GBM-based model.

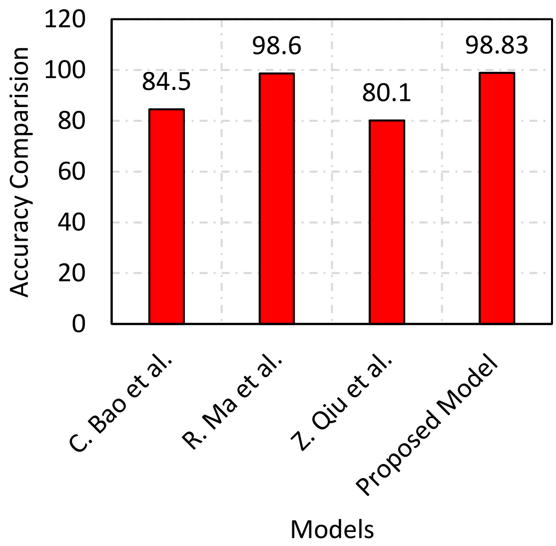


Fig 5: Accuracy comparison of the suggested model along with previous frameworks [27]–[29].

Figure 5 depicts the accuracy comparison of the suggestedYOLO-v7 and GBM-based model along with the existing models [27]–[29]. The existing models C. Bao et al., R. Ma et al., and Z. Qiu et al. obtain an accuracy 84.5%, 98.6%, and 80.1%, respectively. While, this novel proposed model obtains an accuracy of

98.33% in the model testing phase, which is more enhanced as well as finest in comparison to the previous models. Therefore, this proposed model is a pragmatic one for real-time vehicle detection and classification to prioritize the emergency vehicles in a quick manner and immediate path clearance following the assigned priority to the emergency vehicles.

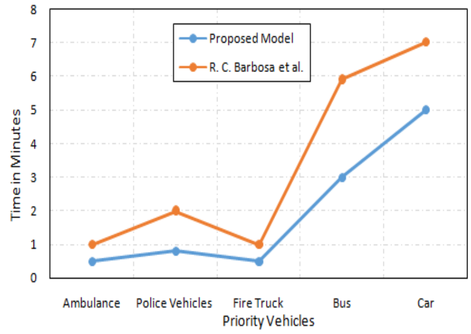


Fig 6: Illustrates average waiting period taken by the proposed YOLO-v7 and GBM-based model and existing model[30].

Figure 6 illustrates the average waiting period taken by the proposed YOLO-v7 and GBM-based model and existing model [30]. The existing model proposed by R. C. Barbosa et al. [30], consumes an average waiting time for diverse priority vehicles such as ambulances, police vehicles, fire truck vehicles, bus and car vehicles,1 minute, 2 minutes, 1 minute, 5.9 minutes ,and 7 minutes, respectively. However, this novel proposed model consumes, an average waiting time for diverse priority vehicles such as ambulances, police vehicles, fire truck vehicles, bus and car vehicles, 0.5 min., 0.8 min., 0.5 min., 3 min., and 5 min., respectively. Therefore, the average waiting period comparison of the suggested and previous frameworks for distinct vehicle classes clearly states that this suggested framework takes a very minimal average waiting period in comparison to the existing model[31].

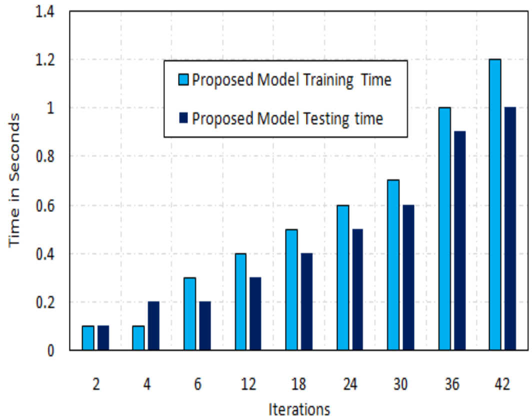


Fig 7: Illustrates proposed model training and testing time consumption on diverse iterations in real-time model implementation.

Figure 7 illustrates the proposed model training and testing time consumption on diverse iterations in real-time model implementation [33][34]. The training time for the enhanced YOLO-v7[35] and GBM-based model on iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42 are measured 0.1 sec., 0.1 sec., 0.3 sec., 0.4 sec., 0.5 sec., 0.6 sec., 0.7 sec., 1 sec., and 1.2 sec. However, the testing time for the enhanced YOLO-v7 and GBM-based model on iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42 are measured 0.1 sec., 0.2 sec., 0.2 sec., 0.3 sec., 0.4 sec., 0.5 sec., 0.6 sec., 0.9 sec., and 1 sec., respectively. The computed training and testing time for the proposed enhanced YOLO-v7 and GBM-based model is the finest and very minimal.

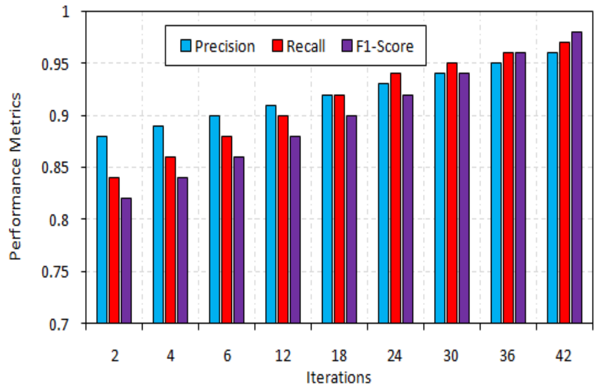


Fig 8: Illustrates measured precision, recall, and F1-score for this suggested YOLO-v7 and GBM based framework.

Figure 8 illustrates measured precision, recall, and F1-score for this suggested YOLO-v7 and GBM based framework. The measured precision values of the suggested enhanced YOLO-v7 and GBM-based model on diverse iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42 are obtained 0.88%, 0.89%, 0.9%, 0.91%, 0.92%, 0.93%, 0.94%, 0.95%, and 0.96%, respectively. Furthermore, another performance metric i.e., recall value on diverse iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42 are obtained0.84%, 0.86%, 0.88%, 0.9%, 0.92%, 0.94%, 0.95%, 0.96%, and 0.97%, respectively. Moreover, the computed F1-score metric of the proposed enhanced YOLO-v7 and GBM-based model on diverse iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42 are obtained0.82%, 0.84%, 0.86%, 0.88%, 0.9%, 0.92%, 0.94%, 0.96%, and 0.98%, respectively. Therefore, the outcome of this proposed model is very much optimal and the finest in terms of distinct performance metrics i.e., precision, sensitivity or recall, and F1-score.

5. Conclusion

In the modern ITS system, distinct vehicle accurate detection has become a fundamental encounter owing to miscellaneous reasons such as faster increment in the vehicles, shadow issues, and low accuracy in the correct identification of the similar size of the moving vehicles. This experimental research work is focused to resolve these aforementioned key issues in a significant manner. In this work, a novel framework for vehicle detection and classification using enhanced YOLO-v7 and GBM has been developed for prioritizing the emergency vehicle in real-time for immediate path clearance based on the assigned priorities to a distinct class of vehicles. The supervision of real-time traffic is one of the critical use cases for video-rooted observation systems. During the last decade, the investigators had worked on vision-rooted ITS, effective planning of transport, as well as distinct traffic engineering, and improved applications for the extraction of important and precise traffic information. While the vehicle identification process is performed in a complex scene, it becomes very important for removing the entire shadow cast from the image frames data for further classification of the vehicle. Correct and precise shadow detection and removal is a vital phase to recognizing the running vehicles in real-time traffic. All the measured performance metrics of the proposed enhanced YOLO-v7 and GBM-based model are very pragmatic and improved. The calculated accuracy, recall or sensitivity, precision and F1-score of the proposed model are obtained 98.83%, 97%, 96%, and 98%, respectively. This experimental research work may be extended in the future for highly accurate vehicle detection and recognition for handling various challenging circumstances, such as snow, rain conditions, or night.

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