EMERGENCY VEHICLE PRIORITIZATION AND DETECTION WITH ENHANCE YOLO-V7 AND GBM

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By

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BONAFIDE CERTIFICATE

This is to certify that the seminar report on the topic "Emergency Vehicle Prioritization with Enhance YOLO-v7 and GBM" by IJAS AHAMMED (REG NO: SCM20CS063), submitted in partial fulfilment of the requirement for the award of the degree of Bachelor of Technology, is a Bonafide work carried out by him under supervision, the seminar, during the academic year 2023-2024.

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ABSTRACT

In the present day, the detection and classification of vehicles has become a major challenge due to the rapid increase in the number of vehicles of varying sizes on the roads, especially in urban areas. In the last few years, we've seen a lot of research and development into promiscuous models for detecting and categorising vehicles. Unfortunately, these models have some problems with the accuracy of identifying the vehicles, like the shadow issue, which makes it harder to prioritise emergency vehicles. Plus, these models take more time to set up and keep up with in real-time, so they're not as easy to use.

A new vehicle detection and classification framework is proposed in this research work. This framework is based on the Yolo v7 and the Gradient boost machine (GBM). The objective of this framework is to prioritise emergency vehicles faster and more accurately. The proposed framework focuses on the precise identification of vehicle class in ITS for the purpose of prioritising emergency vehicles to gain a clear path.

The results of the framework are really good, and they're even better than the older models. The performance metrics - accuracy, accuracy, recall, F1 score - are all pretty good, with 98.83, 96%, 97%, and 98% respectively. This research work could be expanded in the future to make it easier to identify vehicles that can handle all kinds of tough conditions, like snow and rain, or even during the night.

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ABBREVIATIONS

ADAS	Advanced Driver Assistant Systems
CNN	Convolutional Neural Networks
DL	Deep Learning
GBM	Gradient Boosting Machine
ITS	Intelligent Transportation Systems
ML	Machine Learning
UA-DETRAC	University at Albany DEtection and TRACking
YOLO	You Only Look Once

CHAPTER 1: INTRODUCTION

1.1 OVERVIEW

In the contemporary landscape of urbanization and rapid technological evolution, the precise detection and classification of vehicles stand as a critical imperative for effective traffic surveillance and administration. Managing the escalating number of vehicles, particularly in urban regions, requires advanced models capable of overcoming challenges inherent in existing frameworks. Despite the strides made in machine learning (ML) and deep learning (DL) methodologies, the accurate identification of vehicles remains a formidable task, hindered by issues like the persistent shadow problem and the complexities associated with real-time implementation. The intersection of these challenges accentuates the need for innovative solutions that not only enhance accuracy but also expedite the identification process, especially for prioritizing emergency vehicles.

The study under consideration, addresses the aforementioned challenges through the proposition of a novel framework grounded in YOLO-v7 and a Gradient Boosting Machine (GBM). The overarching goal is to revolutionize vehicle detection and classification, prioritizing emergency vehicles with unprecedented speed and accuracy. In contrast to existing models, the proposed framework meticulously addresses the shadow problem, ensuring optimal performance metrics. The emphasis on real-time implementation and improved accuracy aligns with the broader objectives of Intelligent Transportation Systems (ITS), where the correct identification of vehicle classes is pivotal for efficient traffic management and emergency response prioritization.

The unique contributions of this experimental research encompass the development of a model that not only enhances the YOLO-v7 framework but also integrates GBM for superior accuracy and efficiency. The proposed model excels in shadow elimination, a critical aspect often overlooked in existing techniques. Performance evaluations showcase exceptional metrics, including accuracy, precision, recall, and F1-score, positioning the model as a significant advancement in the realm of ITS and Advanced Driver Assistant Systems (ADAS).

1.2 ORGANIZATION OF REPORT

The rest of the report is organized as follows.

Chapter 2 delves into the multifaceted challenges encountered in vision-based vehicle identification. This section lays the groundwork by addressing critical issues that form the backdrop of the proposed research, providing context for the subsequent chapters.

Chapter 3 extensively reviews related work, engaging in a thorough examination of previous research endeavours, critically assessing their contributions and limitations. Major limitations and gaps in the existing literature are elucidated, providing a crucial foundation for understanding the evolution of vehicle identification methodologies and the motivations for the proposed novel framework.

The heart of this seminar report lies in Chapter 4, where the novel methodology for vehicle identification and categorization is unveiled. This chapter meticulously details the integration of YOLO-v7 and Gradient Boosting Machine (GBM), showcasing how the proposed model addresses the limitations of previous approaches. The methodology is presented with clarity, offering insights into the innovative techniques employed for enhanced accuracy and real-time performance.

In Chapter 5, the focus shifts to the outcomes of the experimental study. Key results and analyses derived from the implementation of the proposed framework are elucidated. Metrics such as accuracy, precision, recall, and F1-score are presented and analysed to provide a comprehensive understanding of the model's performance in real-world scenarios.

The seminar report culminates in Chapter 6. The conclusion summarizes the impact of the proposed framework and outlines its implications for the future of urban traffic management.

CHAPTER 2: CHALLENGES

Accurate counting and categorization of vehicles stand as pivotal challenges in the realm of ITS, where precise performance evaluation is paramount. The ability to effectively manage a substantial number of cars is not only crucial for minimizing traffic congestion but also forms the foundation for optimizing the overall functionality of modern transportation systems. Achieving high accuracy in ITS hinges on the precise identification of vehicle classes, a critical task that ensures the system's capability to handle heavy traffic seamlessly.

A persistent challenge in the landscape of vehicle detection is the issue of shadow cast. This phenomenon introduces a significant hurdle as shadows are often misidentified as vehicle components, leading to object loss and distortion in the detection process. Overcoming the complexities introduced by shadow cast is imperative for enhancing the overall accuracy of vehicle detection systems.

Moreover, the challenges are further compounded by the ongoing process of urbanization, which introduces dynamic elements such as varying illumination, adverse weather conditions, and cluttered backgrounds. These environmental factors add layers of complexity to the collection of data, making it a multifaceted task. Addressing these challenges becomes essential for the continued evolution of Intelligent Transportation Systems, ensuring their adaptability and effectiveness in the face of the ever-changing dynamics of urban environments.

CHAPTER 3: RELATED WORKS

Several recent studies have explored the use of Convolutional Neural Networks (CNNs) for vehicle identification and counting in traffic surveillance scenarios. Gomaa et al. [2] proposed a scheme based on the Faster CNN, specifically tailored for a fixed number of multiple camera scenes. Their focus was on automated counting and identification of vehicles, a critical task for traffic surveillance and administration. However, the YOLO-v2-based model they developed had limitations, including less accurate classification of objects due to shadow casting and an increased average waiting period for diverse vehicles.

In a different vein, Farid et al. [1] introduced a faster and more precise vehicle identification framework based on DL for unconstrained settings. Their DL-based detection and categorization protocol, employing a novel YOLO-v5 model, aimed to address the challenges faced in modern ITS. Despite advancements, this model exhibited drawbacks such as a high average waiting time, lower vehicle classification accuracy in high congestion settings, inefficient shadow cast elimination, and elevated computing costs.

Haritha et al. [4] contributed to the discourse with a modified DL-based framework for vehicle identification in traffic surveillance systems. Emphasizing the significance of supervision and security in modern traffic observation, their framework aimed to determine the presence of automobiles within traffic. However, the suggested model faced challenges, including limited performance evaluation metrics, extended time requirements for training and testing, and ineffectiveness in completely eliminating shadow cast for precise vehicle class classification.

This research seeks to build upon these works, addressing existing drawbacks and pushing the boundaries of efficiency and precision in traffic surveillance systems.

CHAPTER 4: METHODOLOGY

4.1 UA-DETRAC DATABASE

The foundation of the proposed framework lies in its reliance on the enhanced YOLO-v7 and GBM for robust vehicle detection and classification, with a specific emphasis on prioritizing emergency vehicles for real-time path clearance. To validate the efficacy of the model, comprehensive training and testing were conducted utilizing the UA-DETRAC (University at Albany DEtection and TRACking) dataset, a widely acknowledged benchmark in the realm of object identification and surveillance in traffic scenes.

The UA-DETRAC database, recognized as a benchmark and extensively utilized in novel model training and testing, offers a rich array of video sequences capturing real-time traffic scenarios. This diverse dataset serves as a representative collection of various communal traffic conditions and classes, encompassing settings such as T-junctions, metropolitan highways, and other urban locations. Comprising multifarious traffic scenes, the UA-DETRAC dataset provides a realistic portrayal of dynamic environments, essential for evaluating the proposed model's performance.

With over 140,000 frames and meticulous annotations, including automobile class, truncation, weather conditions, automobile bounding box, and occlusion, the UA-DETRAC database stands as a pragmatic asset for assessing the effectiveness of models in object recognition and surveillance within traffic scenes. The comprehensive nature of this dataset ensures that the proposed framework undergoes rigorous testing under diverse conditions, enhancing its reliability and applicability in real-world traffic management scenarios.

4.2 VIDEO SEQUENCES AND DATA SPLITTING

In the context of this research study, a video sequence is defined as a single picture displayed on the screen, forming the fundamental unit of motion in a video. Video sequences are constructed by showcasing a series of frames in rapid succession, creating the illusion of motion. The frame rate of a video denotes the number of frames displayed per second, a crucial parameter influencing the perception of motion smoothness.

For the purpose of testing and validating the proposed model in real-time, a curated selection of 20 distinct videos was employed. These videos serve as a diverse and representative dataset, allowing for a comprehensive evaluation of the model's performance across various scenarios.

To facilitate the splitting of data into training and testing sets, the group k-fold cross-validation method was adopted. This method was chosen for its effectiveness in providing accurate estimations of model performance, especially when dealing with datasets organized into distinct groups. The utilization of this data splitting approach ensures a robust assessment of the proposed model's generalization capabilities.

4.3 PRIORITY SCENARIO AND VALIDATION

Table 1 encapsulates the priority scenario designed for a varied class of vehicles in emergency situations. Priority values, ranging from 0 to 4, are assigned to different vehicle classes, namely ambulance vehicles, police vehicles, fire control truck vehicles, bus vehicles, and car vehicles. This prioritization schema serves as a foundation for the validation of the proposed model, allowing for a systematic evaluation of its ability to accurately prioritize and identify emergency vehicles in real-time scenarios.

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

Table 4.1: Illustrates the priority scenario for a varied class of vehicles.

4.4 SYSTEM SETUP

The experimental research work was conducted on a computing machine configured with specific system settings to ensure optimal performance. The system specifications included a 64-bit operating system, 16 GB DDR4 RAM, and a GeForce GTX 1650 NVIDIA graphic card. The integrated processor for this setup was an Intel Core i5. The entire system operated on the Windows 11 platform, providing a stable and efficient environment for the execution of the proposed methodology.

To facilitate the implementation and execution of the research code, the Google Colab environment was employed. Google Colab, being a cloud-rooted platform, offers a collaborative and accessible space for writing, running, and sharing Python language code within a Jupyter Notebook. Leveraging the capabilities of Google Colab ensured seamless integration with the proposed model, allowing for efficient development, testing, and validation of the system under consideration. The cloud-based nature of Google Colab also contributed to the scalability and accessibility of the experimental setup, facilitating collaborative research efforts.

4.5 SYSTEM ARCHITECTURE

The landscape of accurate and precise vehicle detection and classification faces formidable challenges in the current era, primarily attributed to the rapid proliferation of vehicles. The inadequacies observed in previously developed models, such as deficiencies in model accuracy, precision, and execution time, underscore the pressing need for innovative solutions. In response to these challenges, this work introduces a novel model for vehicle detection and classification, leveraging enhanced YOLO-v7 and GBM to prioritize emergency vehicles and facilitate immediate path clearance.

The novel model's architecture is elucidated through a comprehensive system setup, as illustrated in Figure 1. At its core, the system employs enhanced YOLO-v7 and GBM to enhance accuracy, precision, and reduce model execution time.

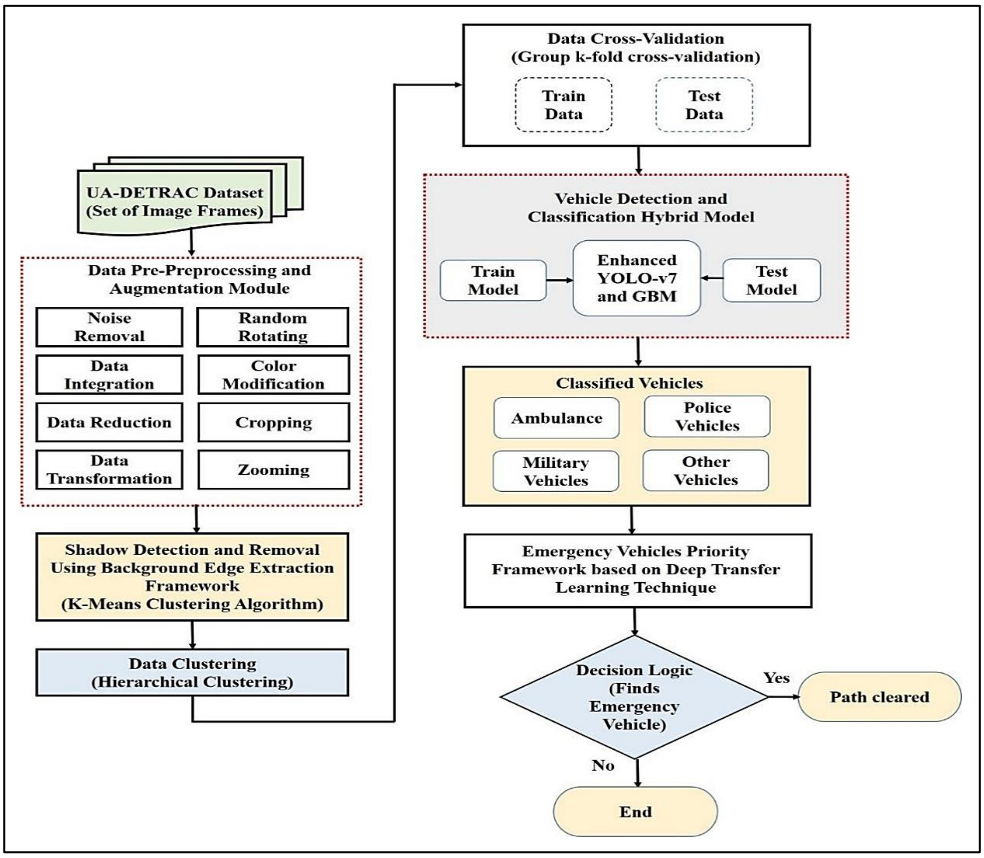


Fig 4.1: Proposed system architecture for vehicle detection and classification using enhanced YOLO-v7 and GBM.

4.5.1 Data Pre-Processing and Augmentation Module

The initial model implementation phase centers on essential dataset pre-processing and augmentation, laying the groundwork for effective training and testing. This section outlines key operations to enhance dataset quality and diversity.

Firstly, a meticulous noise removal process refines the dataset by eliminating irrelevant information, ensuring its purity for accurate model outcomes. The data integration step combines raw data from diverse sources with unique data, enriching the dataset for more effective training and testing scenarios. Strategic data reduction minimizes attributes while preserving essential characteristics, maintaining similar outcomes to the original dataset.

Data transformation involves normalizing and aggregating the dataset to align with specific model training requirements. This step optimizes the dataset for subsequent model phases. Data augmentation, achieved through operations like random rotation, colour modification, cropping, and zooming, increases dataset volume and diversity. The primary goal is to enhance overall framework performance by introducing diverse datasets during training and testing, making the model more resilient and adaptable to real-world scenarios.

4.5.2 Shadow Detection and Removal

In the next phase of the methodology, the pre-processed and augmented dataset undergoes a crucial step involving background edge extraction for shadow detection and subsequent removal. This is facilitated by implementing the K-Means clustering protocol, integral to the colour-rooted segmentation scheme.

The K-Means clustering protocol is chosen for its effectiveness in addressing shadow challenges in image frames. Operating within a colour-rooted segmentation scheme, it clusters pixels based on their colour values, enabling nuanced analysis of shadowed regions. The protocol plays a central role in identifying shadow areas by differentiating colour values, initiating a real-time elimination process to effectively remove shadows from the images.

This method ensures not only the detection but also the immediate removal of shadowed areas, contributing to overall dataset enhancement. The integration of the K-Means clustering protocol within the colour-rooted segmentation scheme exemplifies a sophisticated approach to mitigating shadow impacts in image frames, refining the dataset for subsequent stages in the proposed model.

4.5.3 Data Clustering

Moving to the subsequent phase, the implementation incorporates the hierarchical clustering technique for cluster analysis, a pivotal step in enhancing the proposed model's effectiveness. Hierarchical clustering is deployed with the objective of creating hierarchical clusters that contribute to more efficient training and validation processes.

Hierarchical clustering operates by merging similar data within a specified number, denoted as N, of distinct clusters. The essence of this technique lies in the proximity of the same dataset within a hierarchical cluster, ensuring that similar data elements are grouped together. This strategic clustering not only facilitates a streamlined and organized dataset but also promotes effective training and validation of the model. The hierarchical clustering approach aims to optimize the model's understanding of intricate relationships within the dataset, contributing to its overall robustness and performance.

4.5.4 Data Cross-Validation

In data cross-validation, the Group k-fold cross-validation method is employed, surpassing traditional k-fold techniques for improved framework accuracy. This extended approach proves effective in refining and validating the proposed model.

For model training and testing, the split data is divided into distinct train and test groups. Approximately 80% of the dataset is dedicated to training, ensuring robust learning, while the remaining 20% is reserved for meticulous model testing. This strategic allocation optimizes the training process and enables a comprehensive evaluation of the model's performance, showcasing the efficacy of the Group k-fold cross-validation method in enhancing accuracy and reliability.

4.5.5 Hybrid Model for Vehicle Detection and Classification

For vehicle detection and classification, a hybrid model, combining enhanced YOLO-v7 and GBM, is seamlessly integrated into the training and testing phases. This innovative model goes on to achieve precise detection and classification of vehicles across diverse classes.

The proposed model demonstrates exceptional accuracy in detecting and categorizing vehicles, distinguishing between emergency vehicles like ambulances, police vehicles, and military vehicles, and other common vehicles including buses, cars, trucks, and motorbikes. This integrative approach ensures a comprehensive and accurate identification of vehicles, showcasing the effectiveness of the hybrid model in handling various classes with precision.

4.5.6 Emergency Vehicle Priority Framework

Advancing to the subsequent phase, the categorized dataset undergoes translation into the emergency vehicle priority framework, leveraging the deep transfer learning technique. At the core of deep transfer learning lies the generality of features within the trained model.

The emergency vehicle priority framework employs deep transfer learning to discern emergency vehicles. In real-time, this determination results in the immediate clearing of the path to assign priority to the identified emergency vehicle. Conversely, for regular vehicles, the priority framework promptly concludes the priority assignment process. This strategic utilization of deep transfer learning underscores the framework's adaptability and efficiency in prioritizing emergency vehicles in dynamic scenarios.

4.6 MODEL EVALUATION METRICS

The evaluation of the proposed model, rooted in enhanced YOLO-v7 and GBM, is meticulously conducted using a diverse set of performance metrics. These metrics, namely accuracy, sensitivity (recall), precision, and F1-score, play a pivotal role in gauging the model's effectiveness.

The accuracy metric assesses the proportion of accurate predictions made by the suggested model, providing a comprehensive measure of overall correctness. Precision, another critical metric, evaluates the proportion of true positive predictions out of the total positive predictions made by the proposed model. This insight is invaluable in understanding the model's precision in positive predictions.

Moreover, recall or sensitivity measures the proportion of true positive predictions out of the total actual positive occurrences in the dataset. This metric is essential for comprehending the model's ability to identify positive instances. Lastly, the F1-score, a performance computation metric, serves as a weighted average of recall and precision, striking a balance between these two distinct aspects. This balanced metric provides a nuanced understanding of the model's overall performance, ensuring a comprehensive evaluation across multiple dimensions.

Equation 4.1 outlines the calculation for the accuracy metric. Similarly, equation 4.2 delineates the computation method for recall or sensitivity. For precision evaluation, equation 4.3 can be employed. The F1-score measure is determined by utilizing the formula defined in equation 4.4.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.1}$$

$$Recall\ or\ Sensitivity = \frac{TP}{TP + FN} \tag{4.2}$$

$$Precision = \frac{TP}{TP + FP} \tag{4.3}$$

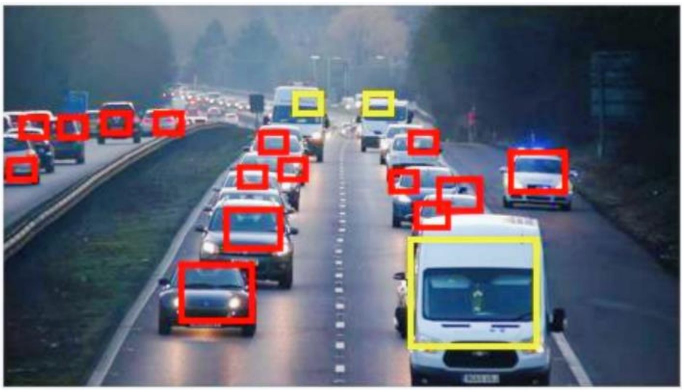
$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4.4}$$

CHAPTER 5: RESULTS

The Intelligent Transportation System (ITS) has strategically embraced recent Information Technology advancements, deploying them to optimize asset allocation schemes and enhance community service capacities. In the contemporary global landscape, the proliferation of vehicles due to constant advancements in the automobile sector has led to a rapid surge in traffic. Despite these advancements, effective traffic management remains a significant challenge within the ITS, primarily due to shortcomings in vehicle detection and classification accuracy, particularly in prioritizing emergency vehicles for unimpeded passage.

In response to these critical challenges, this research work is dedicated to the development and implementation of a groundbreaking framework for vehicle detection and classification. Leveraging the enhanced YOLO-v7 and GBM technique, this novel framework is meticulously designed to address the pressing need for accurate emergency vehicle prioritization and real-time path clearance. Through the integration of advanced technologies, this research aims to contribute significantly to the efficacy of traffic management within the ITS, ensuring a safer and more streamlined experience for road users.

(a)



(b)

Fig 5.1: Illustrates the correct vehicle detection by the proposed framework in real-time

Figure 5.1 serves as a testament to the precision of the proposed framework in real-time vehicle detection. In (a), the illustration captures the movement of vehicles on a highway, while (b) showcases vehicles navigating a metropolitan area near a traffic light. The accuracy of vehicle detection and classification is of paramount importance, particularly in scenarios where emergency vehicles require high-priority clearance, minimizing delays.

The depicted results in Figure 5.1 affirm the proposed model's capability to accurately detect and classify diverse vehicle classes, even amid the swift motion of vehicles in the queue. Notably, the model excels in prioritizing distinct vehicle classes during emergencies. Assigning priority values, ranging from 0 to 4, for various vehicle classes such as ambulances, police vehicles, fire control trucks, buses, and cars, the proposed model undergoes validation for precise performance evaluation. This detailed approach ensures a more nuanced and accurate assessment of the model's effectiveness in real-world scenarios.

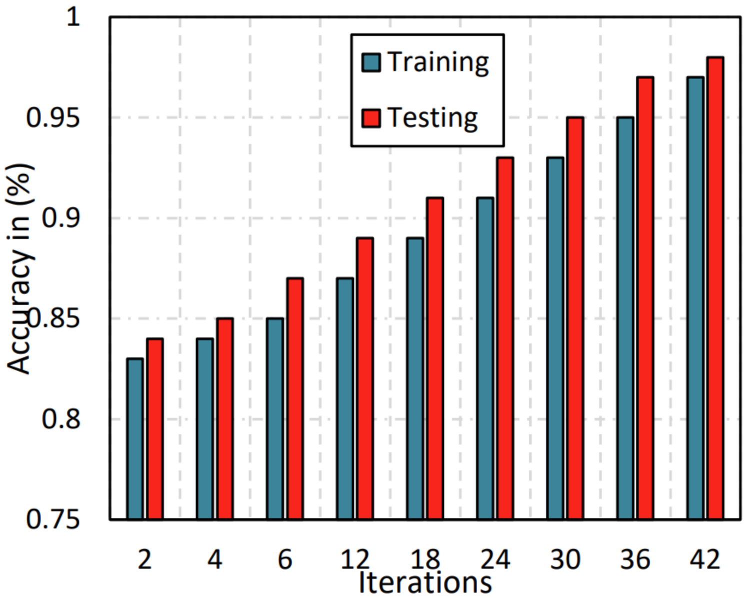


Fig 5.2: Accuracy measured in the training as well as testing segment of this suggested model.

Figure 5.2 presents a visual representation of the accuracy observed in both the training and testing phases of the proposed YOLO-v7 and GBM-based model. Throughout iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42, the training accuracy steadily increases, measuring 0.83%, 0.84%, 0.85%, 0.87%, 0.89%, 0.91%, 0.93%, 0.95%, and 0.97%, respectively.

Similarly, the testing accuracy during these iterations demonstrates a parallel upward trend, measuring 0.84%, 0.85%, 0.87%, 0.89%, 0.91%, 0.93%, 0.95%, 0.97%, and 0.98%, respectively. This observed improvement in both training and testing accuracy levels across distinct iterations underscores the model's proficiency and optimal performance in real-time validation.

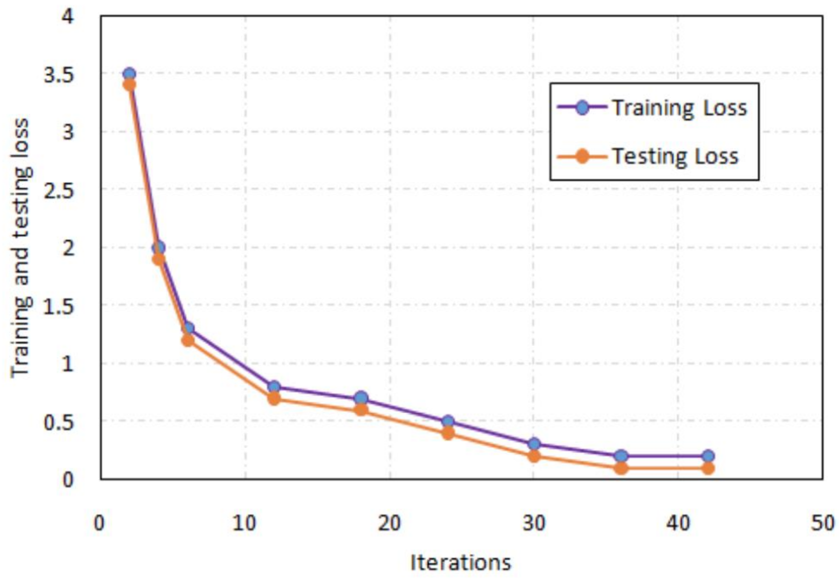


Fig 5.3: Depicts the evaluated training as well as testing loss for the suggested YOLO-v7 and GBM based model.

In Figure 5.3, the training and testing loss for the proposed YOLO-v7 and GBM-based model are illustrated. During training iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42, the recorded training loss progressively decreases, measuring 3.5, 2, 1.3, 0.8, 0.7, 0.5, 0.3, 0.2, and 0.2, respectively.

Concurrently, the testing loss, evaluated during iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42, follows a similar downward trend, registering values of 3.4, 1.9, 1.2, 0.7, 0.6, 0.4, 0.2, 0.1, and 0.1, respectively. The minimal and optimal training and testing loss values observed in real-time implementation underscore the robust performance of the proposed YOLO-v7 and GBM-based model.

In Figure 5.4, an accuracy comparison between the proposed YOLO-v7 and GBM-based model and existing models (C. Bao et al. [3], R. Ma et al. [6], and Z. Qiu et al. [8]) is presented. The existing models achieve accuracies of 84.5%, 98.6%, and 80.1%, respectively. In contrast, the novel proposed model outperforms these benchmarks by achieving an impressive accuracy of 98.33% during the testing phase. This significant enhancement establishes the proposed model as a pragmatic solution for real-time vehicle detection and classification. Its ability to prioritize emergency vehicles efficiently, coupled with immediate path clearance based on assigned priorities, positions it as a superior choice in comparison to previous models.

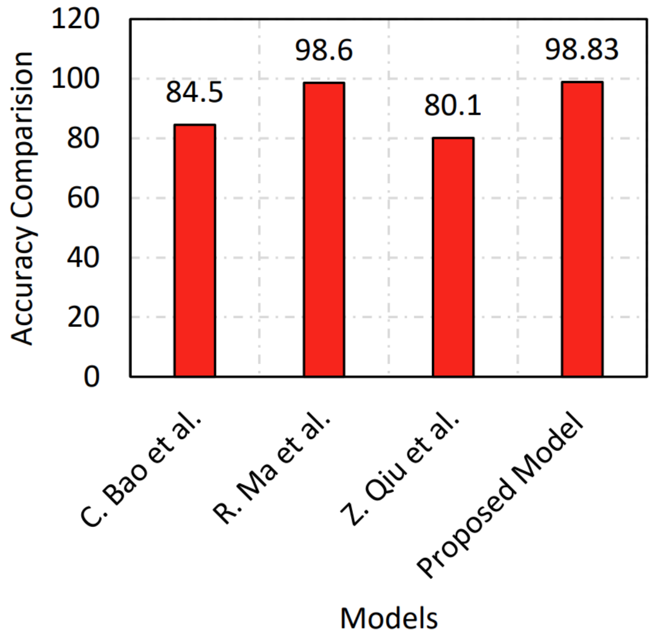


Fig 5.4: Accuracy comparison of the suggested model along with previous frameworks

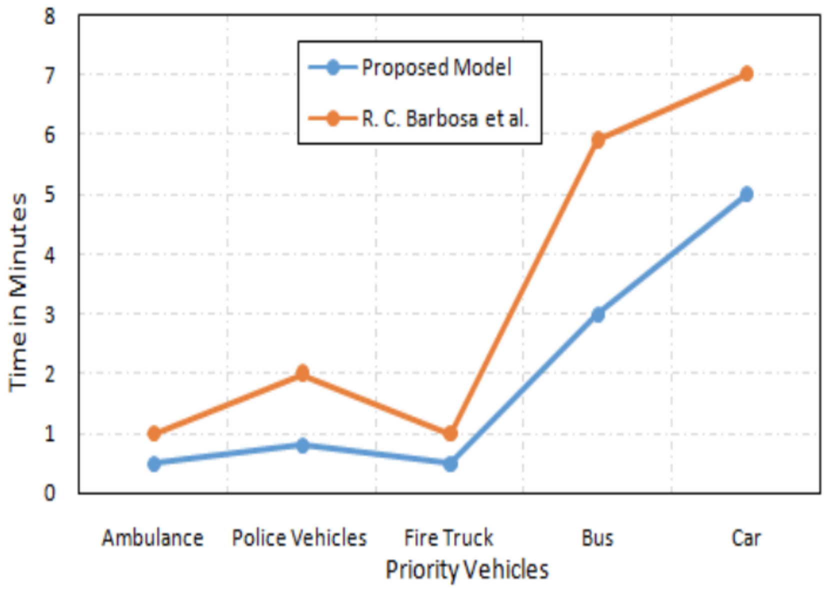


Fig 5.5: Illustrates average waiting period taken by the proposed YOLO-v7 and GBM-based model [7] and existing model [5].

In Figure 5.5, the average waiting period comparison between the proposed YOLO-v7 and GBM-based model and the existing model [5] (R. C. Barbosa et al.) is depicted. The existing model's average waiting time for various priority vehicles—ambulances, police vehicles, fire trucks, buses, and cars—is 1 minute, 2 minutes, 1 minute, 5.9 minutes, and 7 minutes, respectively.

In contrast, the novel proposed model showcases a significant reduction in average waiting times, with values of 0.5 minutes, 0.8 minutes, 0.5 minutes, 3 minutes, and 5 minutes for ambulances, police vehicles, fire trucks, buses, and cars, respectively. This comparative analysis underscores the effectiveness of the suggested framework, indicating substantially reduced average waiting periods in comparison to the existing model [5].

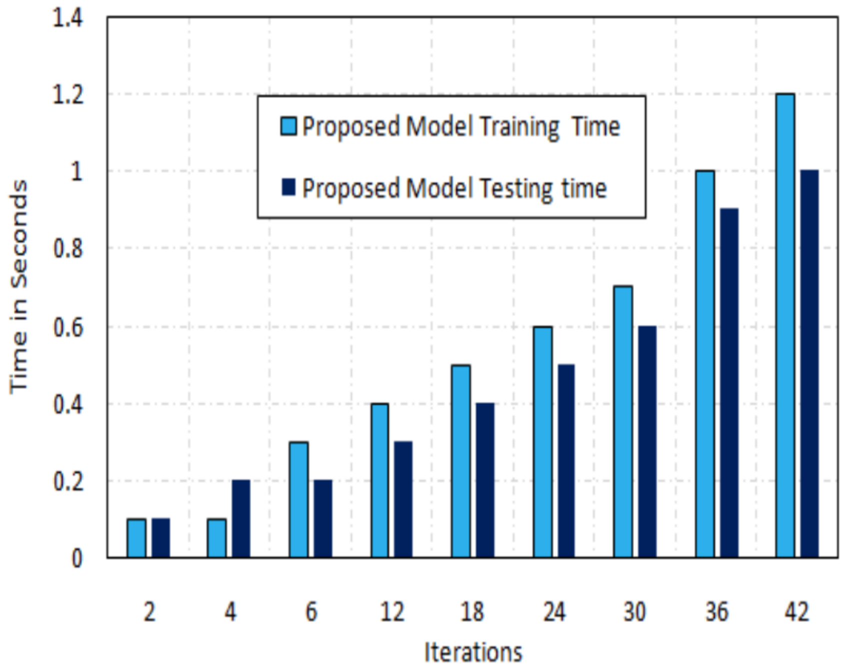


Fig 5.6: Illustrates proposed model training and testing time consumption on diverse iterations in real-time model implementation.

Figure 5.6 presents the training and testing time efficiency of the proposed YOLO-v7 and GBM-based model across different iterations in real-time implementation. During iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42, the training time for the enhanced YOLO-v7 and GBM-based model ranges from 0.1 sec. to 1.2 sec.

Similarly, the testing time for the model during these iterations varies from 0.1 sec. to 1 sec. The recorded training and testing times demonstrate superior efficiency, being both minimal and optimal for the proposed enhanced YOLO-v7 and GBM-based model.

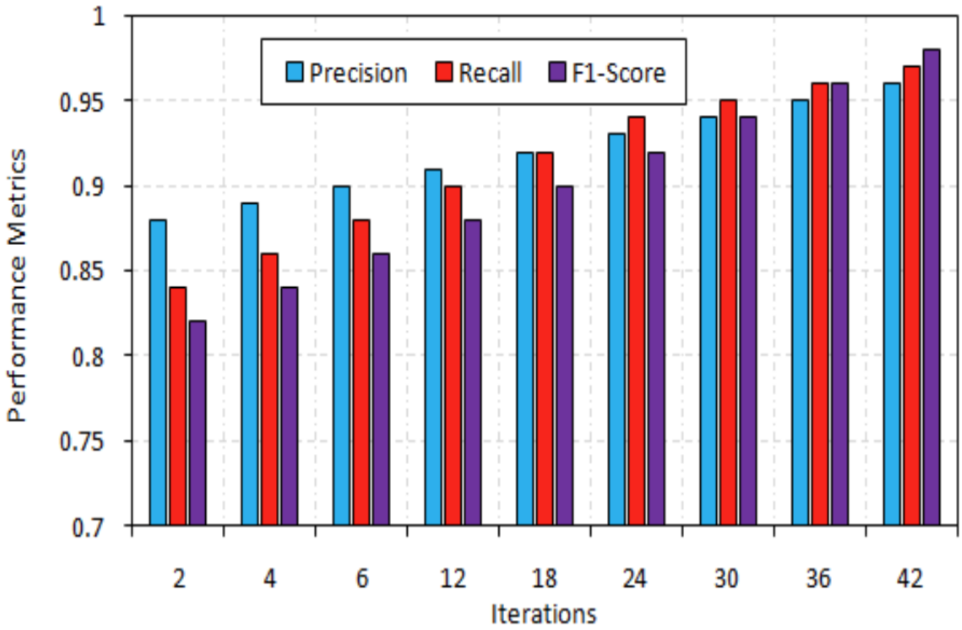


Fig 5.7: Illustrates measured precision, recall, and F1- score for this suggested YOLO-v7 and GBM based framework.

In Figure 5.7, the precision, recall, and F1-score measurements for the proposed YOLO-v7 and GBM-based framework are depicted. Precision values for the enhanced model during iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42 are recorded at 0.88%, 0.89%, 0.9%, 0.91%, 0.92%, 0.93%, 0.94%, 0.95%, and 0.96%, respectively.

Additionally, recall values during the same iterations are observed at 0.84%, 0.86%, 0.88%, 0.9%, 0.92%, 0.94%, 0.95%, 0.96%, and 0.97%, respectively. The computed F1-score metrics for the proposed enhanced YOLO-v7 and GBM-based model during iterations 2, 4, 6, 12, 18, 24, 30, 36, and 42 are reported as 0.82%, 0.84%, 0.86%, 0.88%, 0.9%, 0.92%, 0.94%, 0.96%, and 0.98%, respectively. These outcomes affirm the optimal performance of the proposed model across various metrics, including precision, recall, and F1-score.

Table 5.1 provides a comprehensive summary of the precision, recall, and F1-score metrics at different iterations for the proposed YOLO-v7 and GBM-based framework, showcasing its optimal performance across diverse evaluation criteria.

Iteration	Precision (%)	Recall (%)	F1-Score (%)
2	0.88	0.84	0.82
4	0.89	0.86	0.84
6	0.9	0.88	0.86
12	0.91	0.9	0.88
18	0.92	0.92	0.9
24	0.93	0.94	0.92
30	0.94	0.95	0.94
36	0.95	0.96	0.96
42	0.96	0.97	0.98

Table 5.1: Performance metrics measured at various iterations for the proposed framework.

CHAPTER 6: CONCLUSION AND FUTURE SCOPE

In conclusion, the modern Intelligent Transportation System (ITS) faces significant challenges in accurately detecting vehicles due to the rapid increase in their numbers, shadow-related issues, and inaccuracies in identifying similarly sized moving vehicles. This experimental research aims to address these critical issues by introducing a novel framework for vehicle detection and classification, leveraging enhanced YOLO-v7 and GBM. The primary focus is on prioritizing emergency vehicles in real-time, facilitating immediate path clearance based on assigned priorities to different vehicle classes.

The importance of real-time traffic supervision is underscored in contemporary traffic management systems, where video-based observation plays a crucial role. Over the past decade, researchers have devoted efforts to vision-rooted ITS, efficient transport planning, traffic engineering, and applications that extract precise traffic information. The complexity of vehicle identification in such scenes necessitates the removal of shadows from image frames, a critical step for accurate vehicle classification.

The proposed enhanced YOLO-v7 and GBM-based model demonstrates remarkable and practical improvements across various performance metrics. The calculated accuracy, recall or sensitivity, precision, and F1-score stand at 98.83%, 97%, 96%, and 98%, respectively. These results affirm the effectiveness of the developed framework in achieving highly accurate and reliable vehicle detection and classification in real-time traffic scenarios. The novel approach presented in this research holds promise for enhancing the efficiency of traffic management systems and ensuring prompt prioritization of emergency vehicles for seamless path clearance.

6.1 FUTURE SCOPE

The future scope of this experimental research work offers exciting possibilities for further advancements in highly accurate vehicle detection and recognition, particularly in addressing various challenging circumstances. One avenue for extension involves enhancing the model's robustness to diverse weather conditions, such as snow and rain.

Adapting the framework to effectively operate in adverse weather scenarios would significantly contribute to its real-world applicability and reliability.

Additionally, the proposed model can be extended to perform optimally during nighttime conditions. Improving the model's performance in low-light situations would broaden its scope of application, ensuring accurate vehicle detection and recognition irrespective of the time of day. Incorporating features and adaptations specifically designed for nocturnal scenarios would be a valuable direction for future research endeavours.

Moreover, the exploration of scalability and applicability to different urban landscapes and traffic scenarios could be another avenue for extension. The model's performance may vary across diverse environments, and further research can focus on optimizing and tailoring the framework for seamless integration into various real-world traffic settings.

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