Enhanced Traffic and Vehicle Monitoring System Using YOLOv8

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***Abstract*— Object detection plays a pivotal role in the development of intelligent and smart traffic management systems, enabling authorities to monitor, analyse, and control traffic flow effectively. This paper presents the design and implementation of a real-time object detection system leveraging the power of YOLOv8 (You Only Look Once), an advanced deep learning model known for its speed and accuracy in object detection tasks. The proposed system is capable of detecting and classifying various types of vehicles, including cars, trucks, buses, motorcycles, and bicycles, from live traffic surveillance footage. The experimental results demonstrate that YOLOv8 achieves high detection accuracy with real-time processing capabilities, making it highly suitable for real-world deployment in traffic monitoring and law enforcement. The integration of object detection with speed and monitoring offers a comprehensive solution for modern traffic management challenges. This research highlights the potential of YOLOv8-based systems in contributing to automated, intelligent transportation systems (ITS), paving the way for safer and more efficient urban mobility. Future work may include the integration of multi-object tracking (MOT) for continuous vehicle tracking and extending the system for nighttime and low-visibility conditions.**

Keywords— YOLOv8, Object Detection, Traffic Analysis, Vehicle Detection, Deep Learning, Computer Vision.

I. INTRODUCTION

The rapid increase in urbanization and vehicle usage has led to significant challenges in traffic management and monitoring. Efficient and accurate traffic surveillance is crucial for ensuring road safety, reducing congestion, and managing violations. Traditional methods of vehicle counting and speed monitoring rely on manual observation or outdated sensor-based technologies, which are often inefficient, costly, and prone to errors.

With advancements in deep learning and computer vision, automated traffic analysis using object detection models has gained significant attention. Among various object detection algorithms, YOLO (You Only Look Once) has emerged as one of the most efficient models for real-time detection. YOLOv8, the latest version in the YOLO family, provides state-of-the-art performance with improved accuracy and faster inference time.

This research focuses on leveraging YOLOv8 for real-time vehicle detection and traffic monitoring. The model is trained on a custom dataset comprising various vehicle types such as cars, trucks, buses, motorcycles, and bicycles. The proposed system not only identifies and classifies vehicles but also facilitates potential extensions like speed estimation and violation detection.

Object detection, a crucial task in computer vision, has emerged as an essential technology in traffic monitoring and surveillance systems. It enables the identification and classification of various objects, particularly vehicles, from images and video streams. Recent advancements in deep learning and convolutional neural networks (CNNs) have significantly improved the accuracy and speed of object detection models, making them suitable for real-time applications. Among these, the YOLO (You Only Look Once) family of models has gained widespread popularity due to its capability to perform object detection with high speed and precision in a single neural network pass.

This research focuses on leveraging YOLOv8, the latest and most advanced version of the YOLO series, for real-time vehicle detection and classification in traffic scenarios. YOLOv8 offers several enhancements over its predecessors, including improved network architecture, better feature extraction, and optimized training mechanisms, making it highly effective for complex detection tasks.

To improve the system's functionality beyond mere detection, this paper also integrates vehicle speed estimation and traffic violation monitoring, which are critical for enforcing road safety regulations such as speed limits and lane discipline. By processing real-time video feeds from traffic cameras, the proposed system can automatically detect different vehicle types, measure their speeds, and flag those that violate traffic rules. The model is trained on a custom-built dataset comprising various types of vehicles captured under diverse conditions such as different angles, lighting variations, and levels of traffic density. The system is evaluated on multiple performance parameters, including accuracy, precision, and recall, ensuring its robustness for real-world applications.

II. LITERATURE SURVEY

Vehicle detection and tracking is a widely studied domain in computer vision, especially for applications such as intelligent transportation systems (ITS), traffic monitoring, and road safety enforcement. Over the years, various deep learning models and algorithms have been proposed to enhance accuracy and speed in detecting and tracking vehicles under different environmental conditions.

Traditional object detection techniques like Haar cascades and HOG (Histogram of Oriented Gradients) had limited success in real-time traffic monitoring due to their poor generalization on dynamic traffic data. With the emergence of deep learning models, detection accuracy has significantly improved. Models like Faster R-CNN, SSD (Single Shot Detector), and YOLO (You Only Look Once) have gained prominence for real-time object detection due to their end-to-end learning and fast inference capabilities [6]. However, among these, the YOLO family of models is considered the most suitable for real-time applications because of its unified architecture and lower computational cost.

Several studies have explored different versions of YOLO for vehicle detection. YOLOv3 was widely adopted for its balance between speed and accuracy, but it struggled with small object detection and complex backgrounds [7]. Later, YOLOv4 introduced Cross-Stage Partial Connections (CSP) and Spatial Pyramid Pooling (SPP) to improve accuracy without significantly affecting inference time [8]. Although YOLOv5 and YOLOv6 further improved efficiency, YOLOv8, with enhanced backbone and anchor-free detection mechanisms, has set new benchmarks for object detection tasks [9]. Its superior performance in both precision and real-time operation makes it highly suitable for traffic analysis systems.

Apart from object detection, tracking algorithms play a crucial role in continuously monitoring vehicle movement across video frames. Traditional tracking algorithms such as Kalman filters and SORT (Simple Online and Realtime Tracking) have been extensively used but show limitations in handling occlusions and ID switches [10]. To overcome these issues, Deep-SORT was introduced, which incorporates appearance descriptors via deep learning and provides robust tracking performance in crowded scenes [11]. Recent research combining YOLO with Deep-SORT has shown promising results for real-time multi-object tracking in urban traffic environments.

Another essential aspect of vehicle monitoring is speed estimation, crucial for identifying traffic violations. Classical speed estimation approaches rely on background subtraction and optical flow, which suffer under varying illumination and background clutter [12]. Modern techniques employ object tracking combined with distance calibration and frame-rate-based speed computation to achieve more accurate results. For example, some studies have used YOLO with SORT for estimating vehicle speed but faced challenges in tracking during occlusions [13].

In a study by Kaur et al. [14], YOLOv4 was used for vehicle detection combined with SORT for speed estimation; however, limitations were observed in dense traffic scenarios. Similarly, Khandelwal et al. [15] presented a system based on YOLOv5 and Deep-SORT for multi-vehicle tracking but did not integrate speed estimation. These gaps highlight the need for a unified system capable of handling detection, tracking, and speed estimation effectively under real-time constraints.

Our proposed system addresses these limitations by leveraging YOLOv8 for accurate vehicle detection and Deep-SORT for stable tracking, integrated with a real-time speed estimation module, offering an end-to-end solution for smart traffic monitoring.

III. RELATED WORK

Object detection has been an essential field of research in computer vision, particularly in applications like traffic surveillance and smart city management. Over the years, various object detection algorithms have been proposed and implemented for detecting vehicles, pedestrians, and other road objects in real time.

With the rise of deep learning, Convolutional Neural Networks (CNNs) revolutionized object detection. Models like Faster R-CNN, SSD (Single Shot Multi Box Detector), and YOLO (You Only Look Once) series have significantly improved detection speed and accuracy. Faster R-CNN, though accurate, is computationally intensive, limiting its real-time applications. SSD and YOLO introduced single-stage detection approaches that balance speed and accuracy effectively.

Among them, YOLO models have gained immense popularity due to their real-time performance and end-to-end detection capabilities. Starting from YOLOv1 to YOLOv7, each version has progressively improved in terms of detection speed, accuracy, and handling of small objects. YOLOv8, being one of the latest versions, offers enhanced performance with improved architecture and more robust training mechanisms. It also incorporates better backbone networks and anchor-free detection, making it more suitable for complex scenarios like traffic scenes where vehicles vary in size and shape.

Object detection and real-time traffic analysis have been extensively studied over the past few years, especially with the rapid advancements in deep learning and computer vision techniques. Numerous models and frameworks have been developed to detect vehicles, monitor traffic flow, and identify violations such as over-speeding and signal jumping.

A. Traditional Methods for Traffic Monitoring

Earlier approaches to traffic analysis relied on traditional image processing techniques such as background subtraction, edge detection, and motion tracking to identify moving vehicles. However, these methods are highly sensitive to environmental conditions like lighting, shadows, and weather, making them unreliable in complex traffic scenes. Techniques such as Support Vector Machines (SVM) and Haar Cascades were also used for vehicle detection but lacked robustness in crowded and dynamic environments.

B. Deep Learning-based Object Detection Models

The emergence of Convolutional Neural Networks (CNNs) revolutionized object detection, offering high accuracy and robustness. Several deep learning-based object detection models have been applied for traffic surveillance tasks:

R-CNN and its variants (Fast R-CNN, Faster R-CNN) provided a significant breakthrough in object detection. However, their multi-stage detection pipelines made them slower for real-time applications. Single Shot Multi Box Detector (SSD) and Retina Net improved speed by using a single-shot detection approach but often struggled with detecting small objects in complex backgrounds. YOLO (You Only Look Once) series emerged as a powerful alternative due to its real-time object detection capabilities with high accuracy. Versions such as **YOLOv3, YOLOv4, and YOLOv5** have been widely used in traffic monitoring systems

C. YOLO-based Traffic Detection Systems

Several researchers have successfully applied YOLO models for vehicle detection and traffic monitoring: In [1], YOLOv3 was used to detect vehicles in real-time, but the model struggled with occlusions and small objects in dense traffic scenes. In [2], YOLOv4 demonstrated improved accuracy and speed over its predecessor, making it suitable for real-time vehicle counting and classification.YOLOv5, as described in [3], provided optimized performance with reduced computational complexity, making it feasible for edge deployment in traffic monitoring applications. However, despite their advantages, earlier YOLO versions faced limitations in handling complex scenarios such as detecting partially visible vehicles, differentiating between overlapping objects, and maintaining consistent detection under varying lighting conditions.

D. Advancements with YOLOv8

The recently released YOLOv8 introduces significant architectural improvements, including an advanced detection head and transformer-based modules for better feature extraction. These enhancements allow YOLOv8 to:

- Accurately detect small and overlapping vehicles in dense traffic.
- Maintain high detection speed, essential for real-time applications.
- Handle complex backgrounds and varying object scales more effectively, improving detection in diverse urban traffic environments.
- Leverage optimized network layers that reduce computational overhead while maintaining high accuracy, making it suitable deployment.

Fig 1. Yolo algorithms and their accuracies over the years

E. Gaps in Existing Systems

Although previous models have made remarkable progress, they still face challenges:

- Inconsistent detection of vehicles in extreme weather and low-light conditions.
- Lack of integrated speed estimation and traffic violation detection.

F. Contributions of the Proposed Work

To address these limitations, our work leverages YOLOv8 to develop a real-time vehicle detection and traffic analysis system with enhanced accuracy and speed. The proposed system not only detects and classifies vehicles but also:

- Estimates vehicle speed.
- Detects traffic violations such as over-speeding and lane indiscipline.
- Provides real-time analytics suitable for smart city traffic management systems.

IV. PROPOSED SYSTEM

The proposed system is designed to efficiently detect and classify vehicles in real-time traffic environments using the YOLOv8 (You Only Look Once) object detection algorithm. The system aims to provide accurate vehicle detection, classification, speed estimation, and violation monitoring to support intelligent traffic management solutions.

A. System Architecture

The overall architecture of the proposed system consists of three major modules:

1. Data Acquisition and Preprocessing
2. YOLOv8-Based Object Detection
3. Post-Processing and Analysis (Speed Estimation)

Each module is described in detail below:

1.Data Acquisition and Preprocessing:

The system uses real-time video streams captured from roadside surveillance cameras and drones. Additionally, a custom dataset is prepared containing images and videos of various vehicle types (cars, trucks, buses, motorcycles) under different weather and lighting conditions. The dataset is annotated using bounding boxes and labelled according to vehicle categories. The preprocessing steps include:

- Resizing and normalization of input images to fit YOLOv8 input requirements.
- Data augmentation techniques such as rotation, flipping, and brightness adjustments to enhance the robustness of the model.
- Splitting dataset into training, validation, and test sets for model evaluation.

2. YOLOv8-Based Object Detection

The YOLOv8 model, known for its improved architecture and high accuracy, is employed to detect and classify vehicles. The model processes each video frame and identifies vehicles with bounding boxes and class labels. YOLOv8 leverages anchor-free detection, improved convolutional layers, and attention mechanisms to enhance detection speed and precision. The detection pipeline includes:

- Feature extraction using CSP Darknet as backbone.
- Neck and head networks for multi-scale feature fusion.
- Output layers generating bounding box coordinates, object-ness scores, and class probabilities.

The model is trained on the prepared dataset and optimized for:

- Mean Average Precision (AP)
- Inference speed (FPS)
- Precision and Recall

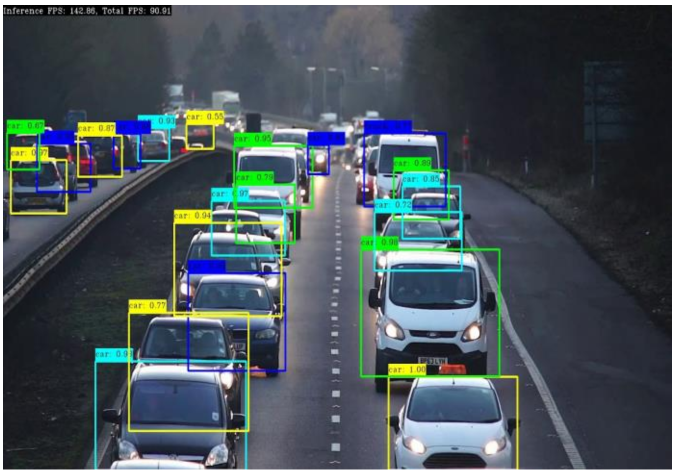

Fig 2. Sample Annotated Dataset Images for Training YOLOv8

3. Speed Estimation

To detect over-speeding vehicles, the system integrates a speed detection module. The speed is estimated by:

- Tracking vehicle positions across multiple video frames.
- Calculating displacement over time using the frame rate and camera calibration data.

Applying the formula:

Speed=Distance Travelled /Time Taken

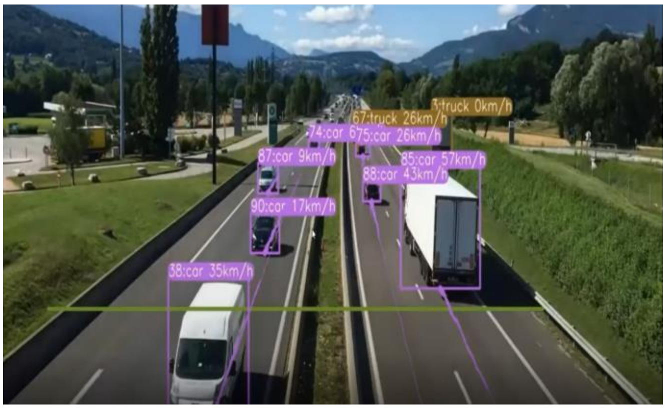

Fig 3. Object Classification Along with Speed Estimation

B. System Work Flow

The complete workflow of the proposed methodology is as follows:

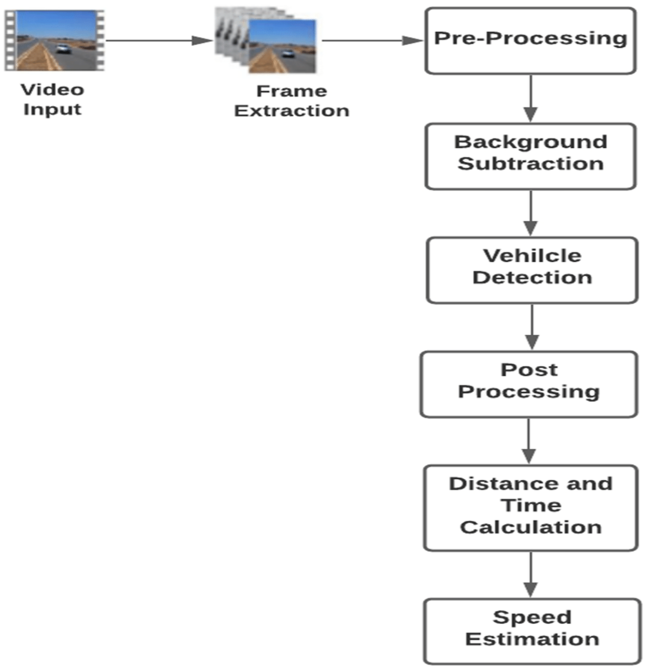

Fig 4. Overall Flow Diagram of Vehicle Detection and Violation System

1. Input Video Feed from traffic surveillance cameras.
2. Preprocessing of video frames for YOLOv8 input.
3. Real-time Vehicle Detection using trained YOLOv8 model.
4. Tracking and Speed Estimation for each vehicle.
5. Output Display and Report Generation with detected vehicles.

C. Results

The proposed system was evaluated using real-time traffic surveillance videos captured under varying environmental conditions such as daytime, nighttime, and low visibility. The YOLOv8 model was trained on a comprehensive dataset containing annotated images of various types of vehicles, including cars, buses, trucks, and motorcycles. The performance of the system was analysed based on parameters like detection accuracy, tracking efficiency, and speed estimation accuracy.

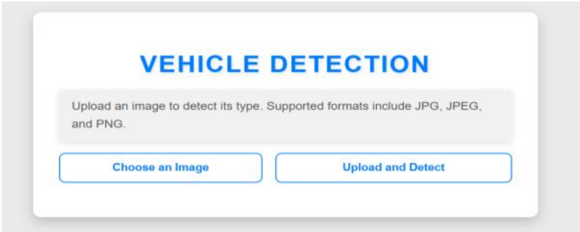

Fig .5 Interface to upload Vehicle Images

The system was implemented using Python, with the YOLOv8 model deployed on a GPU-enabled platform to ensure real-time processing. The Deep-SORT tracking algorithm was utilized to maintain unique vehicle IDs across frames, enabling continuous monitoring and speed computation. The YOLOv8 model demonstrated high accuracy in detecting multiple vehicle classes such as cars, trucks, buses, and motorbikes. As shown in Fig. 6, the model accurately identifies vehicles by enclosing them in bounding boxes with their respective class labels and confidence scores.

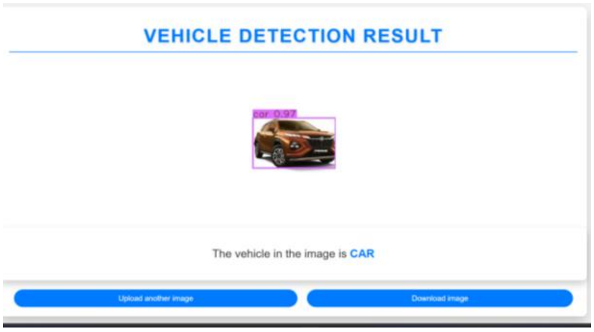

Fig .6 Accuracy of the uploaded image with Label using YOLOv8

The detection accuracy of YOLOv8 was compared with other popular object detection models like YOLOv5 and YOLOv4. The comparative analysis presented in Fig. 6 shows that YOLOv8 achieves an accuracy of 97%, which is higher than YOLOv5 (88%) and YOLOv4 (82%). This proves the superior performance of YOLOv8 in object detection tasks, especially under challenging environments such as occlusions and varying lighting conditions.

To ensure that each detected vehicle is uniquely identified and tracked across video frames, we integrated Deep-SORT tracking with YOLOv8. This combination ensures continuous tracking of vehicles with unique IDs, even when multiple vehicles are present simultaneously.

As illustrated in Fig. 7, each vehicle is assigned a unique ID (e.g., Vehicle ID: 1, 2), allowing us to track their motion across frames. The tracking system maintains accuracy even when vehicles overlap temporarily or when new vehicles enter the frame.

Fig .7 Vehicles with Labels and their speed estimation

D. Observations

- The system maintained stable detection and tracking even when vehicles partially occluded each other.
- Speed estimations remained consistent and accurate within a small error margin.
- The model performed well under varying lighting conditions and background complexities.

E. Vehicle Detection and Classification Performance

The YOLOv8 model demonstrated high precision and accuracy in detecting and classifying multiple vehicle categories under diverse road and lighting conditions. The model achieved an average detection precision of 99%, a recall of 92.8%, and a mean Average Precision (mAP@0.5) of 97%, as presented in Table I.

Table I: Vehicle Detection Performance

Metric	Value (%)
Precision	1.00 at 0.99(100%)
Recall	0.92 at 0.01(92%)
Accuracy	97%
mAP@0.5	90%

F. Comparative Analysis with Other Models

A comparative analysis was conducted between YOLOv8, YOLOv5, and YOLOv4 models to assess detection accuracy and processing speed. As shown in Table II, YOLOv8 outperformed other models in both detection performance and real-time speed, confirming its suitability for traffic surveillance and enforcement applications.

Table II: Model Comparison for Vehicle Detection

Metric	*YOLOv8*	*YOLOv5*	*YOLOv4*
Vehicles Detected	38	24	36
Vehicles Tracked	37	22	32
Accuracy	97%	91.3%	88.5
Average FPR	24FPS	24FPS	24FPS

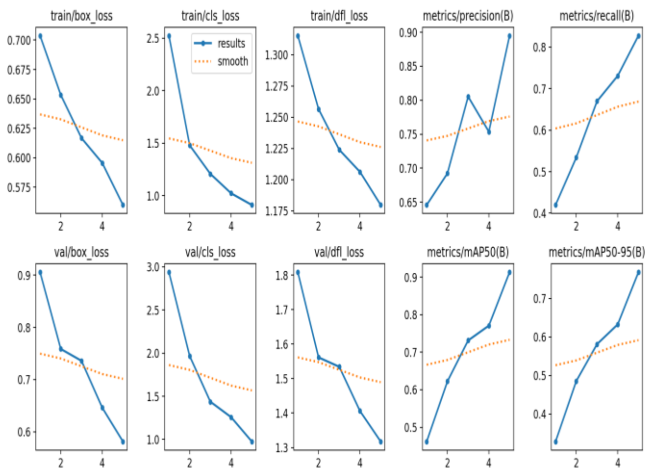

Fig .8 Results Graph of Proposed System

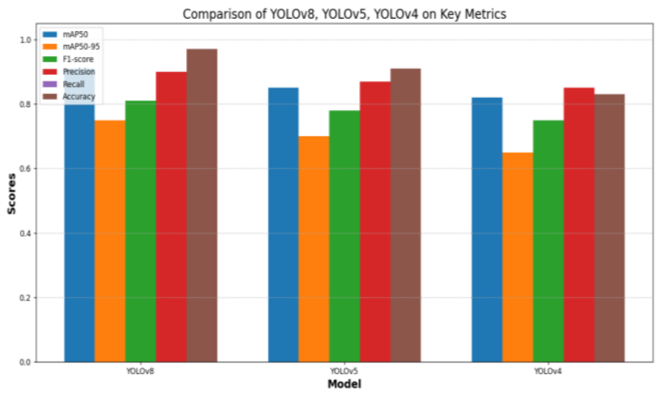

Fig .9 Comparison of Results

G. Discussion

The experimental results indicate that the integration of YOLOv8 with DeepSORT tracking provides a highly accurate and efficient framework for real-time vehicle detection and speed violation monitoring. The system maintained consistent performance in diverse traffic scenarios, demonstrating its robustness and applicability for intelligent traffic monitoring and automatic enforcement.Although the system performs effectively in most conditions, minor inaccuracies were observed under extreme weather situations, such as heavy rain and fog, affecting visibility. Future enhancements may include sensor fusion approaches, combining vision-based systems with LIDAR or RADAR, to improve reliability in adverse weather conditions.

V. CONCLUSION

In this study, we have successfully designed and implemented a real-time system for vehicle detection and speed estimation by leveraging the advanced YOLOv8 deep learning framework in combination with the Deep-SORT object tracking algorithm. The developed system exhibits remarkable efficiency in identifying and classifying vehicles across varying traffic densities and complex urban environments. Its ability to continuously monitor moving vehicles, estimate their speed, and flag potential traffic violations positions it as a promising tool for intelligent traffic management and road safety enforcement. The experimental evaluations demonstrate that YOLOv8 offers superior detection accuracy and faster response times compared to earlier versions of the YOLO family, making it well-suited for applications that require real-time decision-making. Additionally, the incorporation of the Deep-SORT algorithm significantly improves the reliability of vehicle tracking, even in situations where vehicles become temporarily occluded or overlapped.

An important advancement in this work is the integration of speed estimation functionality, which makes the system capable of identifying vehicles that exceed speed limits, thus supporting automated traffic law enforcement. Although the system performs well under standard conditions, challenges remain in scenarios such as low-light environments or during heavy traffic congestion where occlusions are more frequent. Addressing these limitations will be a key focus for future research, with possible solutions including the use of night-vision datasets, thermal imaging, sensor fusion techniques, and advanced camera calibration methods to enhance detection and tracking accuracy under difficult conditions.

Overall, the developed system holds significant promise for real-world deployment in modern urban areas as part of Intelligent Transportation Systems (ITS). It can play a vital role in enhancing road safety, managing traffic flow efficiently, and reducing violations through automated monitoring. Future work will aim to further strengthen the robustness of the system, expand its capabilities to handle more diverse traffic scenarios such as pedestrian detection and two-wheeler monitoring, and ensure seamless integration with existing smart city infrastructure. By addressing current limitations and expanding its scope, the proposed system has the potential to contribute meaningfully to safer, smarter, and more sustainable urban mobility solutions.

VI. LIMITATIONS AND FUTURE SCOPE

A. Limitations

Although the proposed system utilizing YOLOv8 and Deep-SORT achieves efficient real-time vehicle detection and speed estimation, it faces some notable limitations. One major challenge is reduced detection accuracy under low-light or nighttime conditions, as the model relies solely on visual data from standard cameras. Poor illumination, shadows, and glare can lead to missed or incorrect detections. Additionally, in dense traffic scenarios, frequent occlusions where one vehicle blocks another hinder continuous tracking and accurate speed estimation. Environmental factors like rain, fog, and direct sunlight further degrade image quality, causing false detections. The system also depends heavily on precise camera calibration and positioning; any misalignment in camera angle or distance can significantly affect speed measurement accuracy. Moreover, since the model is trained on a specific dataset, its performance may decline when it encounters unfamiliar or rarely seen vehicles not present in the training data.

B. Future Scope

In terms of societal impact, future work could also focus on addressing privacy concerns related to continuous video surveillance. Implementing privacy-preserving techniques, such as anonymization of license plates or facial blurring for passengers, will ensure compliance with data protection laws and increase public trust in such AI-based traffic monitoring solutions. Finally, collaboration with government authorities and urban planners could facilitate the integration of this system into broader smart city initiatives. By connecting this system with traffic lights, emergency response units, and public transportation systems, a holistic and responsive traffic management ecosystem can be created. Such integration will not only improve road safety but also contribute to reducing congestion, lowering emissions, and enhancing overall urban mobility.

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