International Journal of Intelligent Computing Systems

Volume 1, Issue 1, June 2025

Optimized Traffic and Vehicle Tracking Solution Using YOLOv8

[1]P.J.S.Kumar, [2]V.T.Ram Pavan Kumar

[1] Dept. of CSE, Akkineni Nageswara Rao College, Gudivada, A.P., India

[2]P.G. Dept. of Computer Science Kakaraparti Bhavanarayana College Vijayawada, AP, India

[2]pjskumar@gmail.com, [3]mrpphd2018@gmail.com

Abstract - Object detection plays a crucial role in the development of intelligent and efficient traffic management systems, allowing authorities to effectively monitor, analyze, and regulate traffic flow. This paper introduces the design and implementation of a real-time object detection system powered by YOLOv8 (You Only Look Once), a cutting-edge deep learning model recognized for its high speed and accuracy in object detection tasks.

The proposed system can identify and classify various vehicle types—such as cars, trucks, buses, motorcycles, and bicycles—from live traffic surveillance footage. Experimental results indicate that YOLOv8 delivers high detection accuracy alongside real-time processing, making it highly viable for practical deployment in traffic monitoring and law enforcement applications.

By integrating object detection with speed and surveillance features, the system offers a holistic solution to modern traffic management issues. This research underscores the potential of YOLOv8-based systems in supporting automated and Intelligent Transportation Systems (ITS), contributing to safer and more efficient urban mobility.

Future enhancements may involve incorporating multi-object tracking (MOT) for persistent vehicle tracking and extending the system's functionality to operate under nighttime or low-visibility conditions.

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

I.INTRODUCTION

The swift rise in urbanization and the growing number of vehicles have created substantial challenges in effective 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 Traditional methods of vehicle counting and speed monitoring rely on manual observation or outdated sensor-based technologies, which are often inefficient, costly, and prone to errors.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 study centers on utilizing YOLOv8 for real-time vehicle detection and traffic monitoring. The model is trained on a custom dataset that includes diverse vehicle categories such as cars, trucks, buses, motorcycles, and bicycles. The developed system not only detects and classifies vehicles but also lays the groundwork for future enhancements like speed estimation and traffic violation detection.

Object detection, a vital component of computer vision, plays a key role in traffic surveillance systems by enabling the recognition and categorization of objects—particularly vehicles—in images and video feeds. Recent progress in deep learning and convolutional neural networks (CNNs) has greatly enhanced both the accuracy and processing speed of object detection models, making them highly suitable for real-time use. Among these, the YOLO (You Only Look Once) model family stands out for its ability to achieve high-speed, high-accuracy detection in a single pass through a neural network.

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. LITERATURESURVEY

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 methods such as Haar Cascades and Histogram of Oriented Gradients (HOG) had limited effectiveness in real-time traffic monitoring due to their inability to generalize well on dynamic and complex traffic data. The advent of deep learning significantly boosted detection accuracy. Models like Faster R-CNN, SSD (Single Shot Detector), and YOLO (You Only Look Once) have gained traction for real-time object detection because of their end-to-end training frameworks and fast inference speeds [6].

Among these, the YOLO model family stands out as the most suitable for real-time applications due to its unified architecture and lower computational overhead. Numerous studies have explored various YOLO versions for vehicle detection. YOLOv3 achieved widespread use thanks to its balance of speed and accuracy, though it faced challenges in detecting small objects and managing complex backgrounds [7]. YOLOv4 addressed these issues by incorporating Cross-Stage Partial Connections (CSP) and Spatial Pyramid Pooling (SPP), enhancing accuracy without significantly slowing down processing [8]. While YOLOv5 and YOLOv6 introduced further efficiency improvements, YOLOv8 has set new performance standards with its upgraded backbone and anchor-free detection approach [9]. Its excellent precision and real-time capability make it exceptionally well-suited for modern 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. RELATEDWORK

Object detection remains a crucial area of research in computer vision, especially for applications like traffic surveillance and smart city infrastructure. Over time, many algorithms have been developed to detect vehicles, pedestrians, and other road-related objects in real-time settings.

The emergence of deep learning has significantly advanced object detection, with Convolutional Neural Networks (CNNs) playing a central role. Prominent models such as Faster R-CNN, SSD (Single Shot MultiBox Detector), and the YOLO (You Only Look Once) series have enhanced both the speed and accuracy of detection systems. While Faster R-CNN offers high accuracy, it is computationally demanding, which limits its use in real-time applications. In contrast, SSD and YOLO introduced single-stage detection strategies that achieve a practical balance between speed and precision.

Among these, the YOLO series has garnered substantial attention for its real-time performance and efficient end-to-end detection. From YOLOv1 to YOLOv7, each iteration has brought improvements in terms of speed, accuracy, and small object detection capabilities. YOLOv8, the most recent advancement, features an improved architecture, a more robust training pipeline, enhanced backbone networks, and anchor-free detection methods. These upgrades make YOLOv8 highly effective in complex traffic environments where objects like vehicles vary widely in size, orientation, and shape.

With ongoing advancements in deep learning and computer vision, object detection and real-time traffic analysis continue to evolve. Many modern models and frameworks now support tasks like vehicle counting, traffic flow monitoring, and violation detection (e.g., over-speeding, red light running), contributing to more efficient and intelligent transportation systems.

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) has significantly transformed object detection by providing higher accuracy and robustness. Several deep learning-based models have been utilized for traffic surveillance tasks. R-CNN and its variants, such as Fast R-CNN and Faster R-CNN, brought notable improvements in detection performance. However, their multi-stage detection pipelines made them less suitable for real-time applications due to slower processing times. To address speed limitations, models like Single Shot MultiBox Detector (SSD) and RetinaNet adopted a single-shot detection approach, offering faster performance. Nonetheless, they often encountered difficulties in detecting small objects, especially in complex and cluttered environments. The YOLO (You Only Look Once) series emerged as a powerful alternative, offering real-time object detection with impressive accuracy. Versions like YOLOv3, YOLOv4, and YOLOv5 have been widely adopted in traffic monitoring systems for their ability to detect multiple object types efficiently in dynamic traffic scenarios.

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 for deployment.

International Journal of Intelligent Computing Systems

Volume 1, Issue 1, June 2025

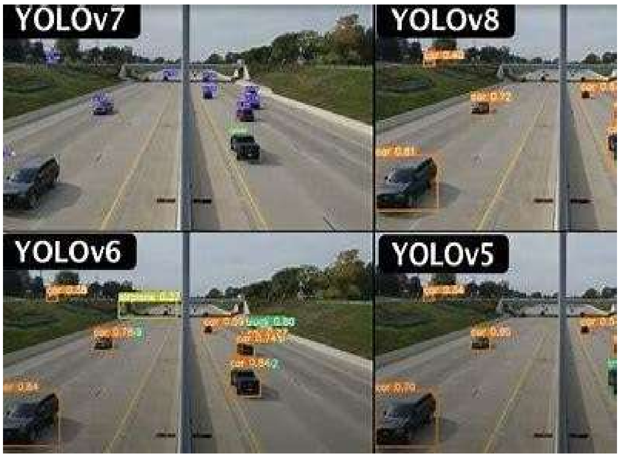


Figure1.Yoloalgorithmsandtheiraccuraciesover theyears

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:

- The input images were resized and normalized to meet the input requirements of YOLOv8.
- To improve the model's robustness and generalization, data augmentation techniques such as rotation, flipping, and brightness adjustments were applied.
- Additionally, the dataset was divided into training, validation, and test subsets to ensure proper evaluation of the model’s performance.

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 CSPDarknet as backbone.
• Neck and head networks for multi-scale feature fusion.
• Output layers generating bounding box coordinates, objectness 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

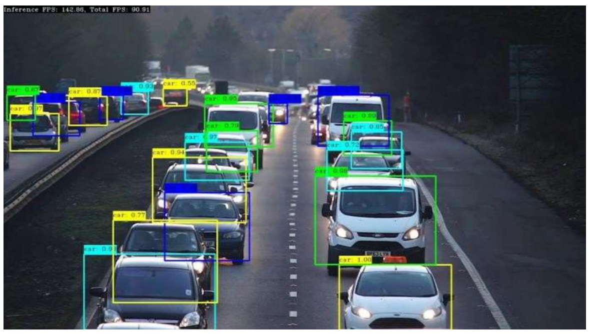
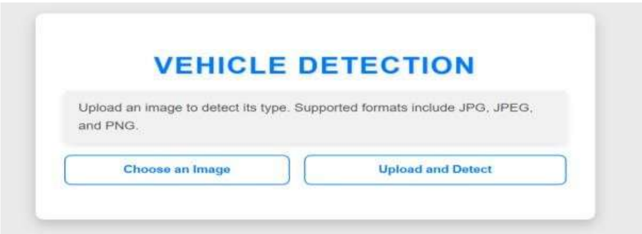


Figure2.Sample Annotated Dataset Images for

International Journal of Intelligent Computing Systems

Volume 1, Issue 1, June 2025



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

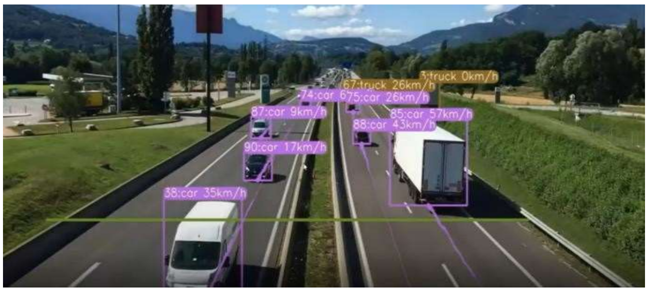


Figure3.Object Classification Along with Speed Estimation

B. SystemWorkFlow

The complete workflow of the proposed methodology is as follows:

Figure 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.

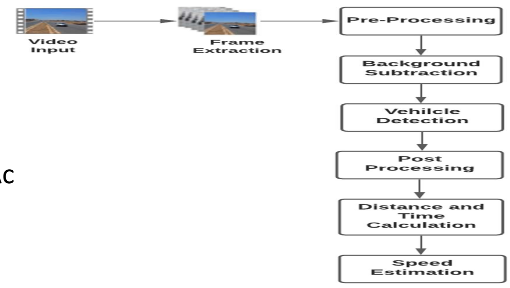
Figure 5: Interface to upload Vehicle Images

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, themodel accurately identifies vehicles by enclosing them in bounding boxes with their respective class labels and confidence scores.

Figure6: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



International Journal of Intelligent Computing Systems

Volume 1, Issue 1, June 2025

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.

Figure 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.

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

Table1:Vehicle Detection Performance

B. 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.

Metric	YOLO v8	YOLOv 5	YOLOv4
Vehicles Detected	38	24	36
Vehicles Tracked	37	22	32
Accuracy	97%	91.3%	88.5
Average FPR	24FPS	24FPS	24FPS

Table 2: Model Comparison for Vehicle Detection

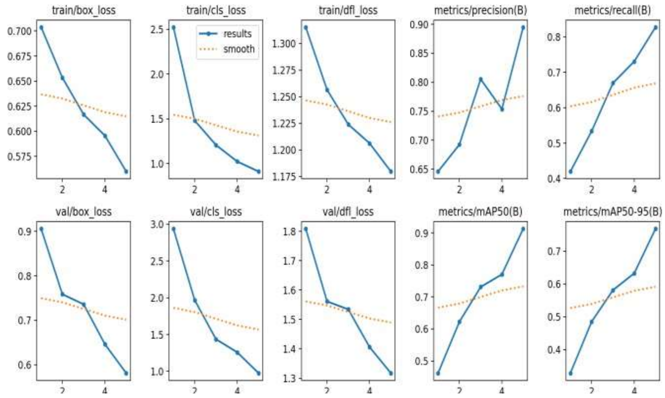
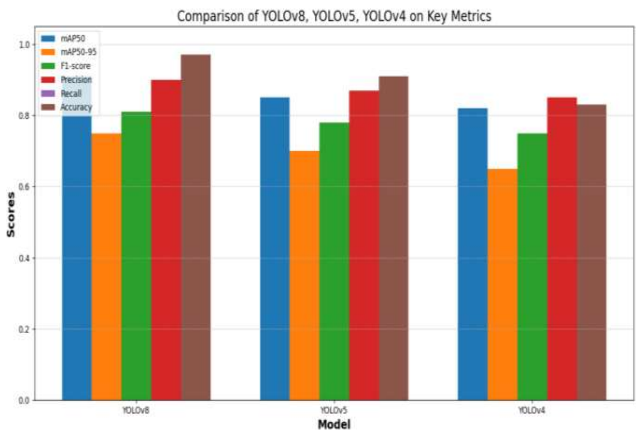


Figure 8: Results Graph of Proposed System



International Journal of Intelligent Computing Systems

Volume 1, Issue 1, June 2025

Figure 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.

VII. REFERENCES

[1] Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). "You Only Look Once: Unified, Real-Time Object Detection." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[2] Bochkovskiy, A., Wang, C., & Liao, H. (2020). *YOLOv4: Optimal Speed and Accuracy of Object Detection.* arXiv preprint arXiv:2004.10934.

[3] Jocher, G. et al. (2023). *YOLOv8: Ultralytics' Implementation of YOLO for Real-Time Object Detection.* Ultralytics Documentation.

[4] Lin, T. Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., & Zitnick, C. L. (2014). "Microsoft COCO: Common Objects in Context." *European Conference on Computer Vision (ECCV)*.

[5] Ge, Z., Liu, S., Wang, F., Li, Z., & Sun, J. (2021). *YOLOX: Exceeding YOLO Series in 2021.* arXiv preprint arXiv:2107.08430.

[6] Ren, S., He, K., Girshick, R., & Sun, J. (2015). "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks." *Advances in Neural Information Processing Systems (NeurIPS)*.

[7] Ultralytics. (2023). *YOLOv8: Next-Generation Object Detection Model.* Retrieved from https://github.com/ultralytics/ultralytics

[8] Zhou, J., Jiang, J., Tang, H., & Zhao, H. (2018). "Real-Time Vehicle Detection and Classification in Highway Scenes Using Deep Learning." *IEEE Transactions on Intelligent Transportation Systems.*

[9] Deng, J., Dong, W., Socher, R., Li, L. J., Li, K., & Fei-Fei, L. (2009). "ImageNet: A Large-Scale Hierarchical Image Database." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).*

[10] Huang, C., Liu, Y., & Qian, L. (2020). "YOLO-Based Traffic Sign Detection Algorithm for Intelligent Transportation Systems." *IEEE Access.*

[11] Zhang, Y., Yang, L., Jiang, L., & Song, Z. (2022). "A Review of Object Detection Methods Based on Deep Learning Networks." *Journal of Big Data.*

[12] Sivaraman, S., & Trivedi, M. M. (2013). "Looking at Vehicles on the Road: A Survey of Vision-Based Vehicle Detection, Tracking, and Behavior Analysis." *IEEE Transactions on Intelligent Transportation Systems*, 14(4), 1773–1795.

[13] Kaur, H., Sharma, S., & Kumar, R. (2021). "Real-Time Vehicle Detection and Speed Estimation Using YOLOv4 and SORT." *International Journal of Advanced Research in Computer Science*, 12(2), 45–52.

[14] Jadon, S. (2020). "A Survey of Object Detection Models Based on Convolutional Neural Networks." *arXiv preprint*, arXiv:2009.06382.

[15] Khandelwal, S., Tiwari, R., & Singh, P. (2022). "Real-Time Vehicle Detection and Tracking Using YOLOv5 and DeepSORT for Intelligent Transportation Systems." *2022 IEEE Conference on Smart Technologies (ICST).*