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Real-Time Vehicle Tracking–Based Smart Traffic Management for Urban Areas

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***Abstract*—This study presents a real-time intelligent traffic control framework designed to address congestion challenges in urban environments. The system employs roadside surveillance cameras to continuously monitor vehicular movement and applies a YOLOv5-based detection model integrated with convolutional neural network techniques for vehicle recognition and classification. Traffic density is dynamically estimated from the detected vehicle count, and signal timings are adjusted through an adaptive control strategy to improve traffic flow efficiency. In addition, a dedicated emergency vehicle detection module is implemented to prioritize signal clearance and minimize response delays. Experimental evaluation demonstrates improvements in average waiting time, travel duration, and fuel utilization when compared to conventional fixed-cycle traffic control systems. The proposed architecture offers a scalable and practical solution for deployment in smart transportation infrastructures.**

I. Introduction

Traffic congestion is one of the leading problems in urban areas and significantly impacts daily life and transportation efficiency. Factors such as increasing vehicle population, improper traffic management, and fixed signal timing contribute to heavy congestion on roads. Traditional traffic control systems rely on manual monitoring or predefined timing mechanisms, which are time-consuming and unable to adapt to real-time traffic conditions. This creates a need for automated systems that can assist in efficient and intelligent traffic management [1], [2].

With the rapid advancement of deep learning techniques, automated traffic monitoring and control systems have gained significant attention in recent years. Convolutional Neural Networks (CNNs) have demonstrated strong performance in image classification and object detection tasks. However, conventional CNN-based approaches often face challenges such as inefficient feature extraction, sensitivity to environmental conditions, and inability to focus on important regions in complex traffic scenes [3], [4].

To overcome these limitations, real-time object detection approaches have been introduced to identify relevant regions in traffic images. YOLO (You Only Look Once), a widely used deep learning model for object detection, has proven effective in detecting multiple vehicles within a single frame. By accurately identifying vehicles and their positions, the model provides meaningful input for traffic density estimation and control [5], [6].

In this project, a hybrid approach is proposed that combines YOLOv5 for vehicle detection and CNN-based techniques for classification of traffic elements, including emergency vehicles. The system processes real-time traffic images, detects vehicles, estimates traffic density, and dynamically adjusts signal timings. Additionally, the system identifies ambulances and provides priority by overriding normal traffic signals. The proposed method aims to improve traffic efficiency, reduce congestion, and enhance emergency response.

II. Literature Review

R. Katragadda et al. (2025), in their work titled *"*Intelligent Traffic Management System for Urban Condition Using Real-Time Vehicle Tracking,*"* proposed a real-time traffic monitoring system using computer vision techniques. The system focused on vehicle detection and tracking to improve traffic flow efficiency, highlighting the importance of automated systems in urban traffic control [1].

Z. Qu et al. (2025), in their study *"*QCACNN: A Quantum Convolutional Neural Network Algorithm for Traffic Sign Recognition,*"* developed an advanced CNN-based model for traffic-related image classification. The model demonstrated improved accuracy and emphasized the role of deep learning in intelligent transportation systems [2].

W. Zhang et al. (2025) focused on intelligent transportation system dynamics and proposed a framework for improving traffic control mechanisms. Their work highlighted the need for adaptive and scalable traffic management solutions [3].

H. Yang et al. (2025) introduced a method for analyzing transportation mode transitions using a stable matching approach. The study emphasized efficient traffic planning and optimization in urban environments [4].

V. Chourasia et al. (2024) proposed a deep learning-based approach using transfer learning for traffic sign recognition. The model achieved improved performance compared to traditional methods, highlighting the effectiveness of CNN models in image-based classification tasks [5].

D. Moldakhmetov et al. (2024) developed an AI-powered traffic management system for busy intersections. Their approach demonstrated the effectiveness of automated traffic signal control in reducing congestion [6].

Q. Xia et al. (2024) introduced a visual analytics system for transportation planning based on passenger demand. The study emphasized data-driven approaches for improving traffic flow and system efficiency [7].

P. C. Sanjai et al. (2023) proposed an image processing-based ambulance detection system for traffic signals. The model enabled emergency vehicle prioritization, improving response time in critical situations [8].

Z. Qu et al. (2023) developed a deep learning model for traffic congestion prediction using temporal and spatial data. The approach improved forecasting accuracy and highlighted the importance of predictive analytics in traffic management [9].

L. Wang and R. Wong (2023) focused on efficient public transport planning using data-driven methods. Their work emphasized optimization techniques for improving transportation systems [10].

Y. Chen et al. (2022) proposed an attention-based CNN model for traffic-related image classification. The model improved feature extraction and enhanced classification accuracy [11].

K. Xu et al. (2022) introduced a framework for analyzing large-scale traffic data using context-driven approaches. The study highlighted the importance of big data in intelligent transportation systems [12].

T. Nitin et al. (2021) presented a survey on intelligent traffic management systems with emergency vehicle detection. Their work summarized existing techniques and identified key challenges in real-time traffic control [13].

D. Weng et al. (2021) proposed a visual analytics approach for improving transportation networks. The study emphasized data visualization techniques for better decision-making [14].

N. S. Hadjidimitriou et al. (2021) developed a data-driven model for matching transport demand and supply. Their work improved efficiency in public transportation planning [15].

D. Weng et al. (2021) introduced a multi-objective optimization approach for route planning. The method improved traffic efficiency and reduced congestion [16].

M. Veres and M. Moussa (2020) provided a survey on deep learning applications in intelligent transportation systems. The study highlighted emerging trends and future research directions [17].

T. Bikku et al. (2019) proposed sensor-based traffic congestion reduction techniques. Their work emphasized the importance of integrating sensors with intelligent systems [18].

N. Marković et al. (2019) analyzed trajectory data for transportation systems. The study demonstrated the importance of data analysis in traffic planning and management [19].

M. A. Ali et al. (2018) proposed a deep learning-based vehicle detection system. The model demonstrated effective object detection performance and highlighted the role of CNNs in traffic monitoring [20]

III. Problem Statement

Traffic congestion and inefficient signal control remain major challenges in urban transportation systems, especially when relying on traditional fixed-time traffic signals [1]. Conventional traffic management methods are unable to adapt to real-time traffic conditions and require manual monitoring, which is time-consuming and inefficient [2]. These systems are also prone to delays and lack dynamic decision-making, which can affect the overall flow of traffic [3]. In many situations, sudden increases in vehicle density are difficult to manage effectively, leading to traffic buildup and longer waiting times [4]. Additionally, the absence of automated emergency vehicle prioritization further complicates traffic conditions in critical situations [5]. Limited integration of intelligent systems in many areas results in inefficient traffic handling and increased congestion [6]. There is also a growing need to manage large volumes of traffic data in real time, where manual approaches are not scalable and lead to poor performance [7]. Therefore, there is a need for an automated system that can efficiently detect vehicles, estimate traffic density, and dynamically control signal timings [8]. The system should be capable of identifying important traffic regions and prioritizing emergency vehicles with high accuracy using advanced deep learning techniques such as YOLO-based detection and CNN-based classification [9].

IV. Proposed Methodology

The proposed system consists of the following steps:

1) Image Acquisition: Real-time traffic video streams are captured from surveillance cameras placed at road intersections. These video inputs provide continuous monitoring of traffic conditions and are used as the primary data source for vehicle detection and analysis.

2) Preprocessing: The captured video is converted into individual frames for processing. The frames undergo preprocessing techniques such as resizing, normalization, and noise reduction to improve image quality and ensure consistency. This step enhances the performance of the detection model.

3) Vehicle Detection using YOLOv5: The preprocessed frames are passed through the YOLOv5 model for real-time object detection. The model detects multiple vehicle classes such as cars, buses, trucks, and motorcycles by generating bounding boxes along with confidence scores. This step enables accurate identification of vehicles in each frame.

4) Traffic Density Estimation: After detecting vehicles, the system calculates traffic density for each lane. The density is computed as the ratio of the number of detected vehicles to the maximum lane capacity. This helps in identifying congestion levels across different lanes.

5) Emergency Vehicle Detection: The system identifies emergency vehicles such as ambulances using classification techniques based on detected objects and confidence scores. When an ambulance is detected with confidence above a predefined threshold, it is marked for priority handling.

6) Emergency Signal Override: When an emergency vehicle is detected, the system overrides the normal traffic signal cycle and provides immediate green signal clearance for that lane. This ensures faster movement of emergency vehicles and reduces response time.

V. System Architecture

The overall architecture of the proposed system consists of multiple stages, including image acquisition, preprocessing, vehicle detection, traffic density estimation, and adaptive signal control. Initially, real-time traffic video is captured from surveillance cameras and used as input to the system. These video streams are converted into frames and processed using deep learning models to analyze traffic conditions.

Figure 1: shows the overall architecture of the proposed intelligent traffic management system. It takes real-time traffic video as input and processes it through multiple stages for detection and control.

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Fig 1: Emergency Vehicle Detection Result

Initially, the input frames are passed through preprocessing steps to improve image quality. These frames are then fed into a YOLOv5-based object detection model, which identifies vehicles such as cars, buses, trucks, and motorcycles. The model generates bounding boxes along with confidence scores for each detected vehicle.

Following detection, traffic density is calculated for each lane based on the number of detected vehicles. These density values are used to determine congestion levels and assist in decision-making for signal control. The system also includes an emergency vehicle detection module that identifies ambulances based on classification results and confidence thresholds. When an ambulance is detected, it is marked for priority handling.

Based on the calculated traffic density and emergency detection, the adaptive signal control module dynamically adjusts traffic light timings. Lanes with higher congestion are assigned longer green signal durations, while less congested lanes receive shorter durations.

Finally, the system displays the processed output through a monitoring interface, showing lane-wise density, vehicle detection results, ambulance status, and real-time signal updates. This architecture demonstrates the effectiveness of integrating deep learning-based detection with intelligent traffic control for efficient urban traffic management.

VI. Evaluation Metrics

$$\text{Traffic Density } (D) = \frac{\text{Number of Detected Vehicles } (N_v)}{\text{Maximum Lane Capacity } (C)} \quad (1)$$

$$\text{Confidence Score } (CS) = \frac{\text{Detected Object Confidence}}{1.0} \quad (2)$$

$$\text{Detection Condition} = \begin{cases} \text{Valid Detection,} & \text{if } CS \geq T_{\text{threshold}} \\ \text{Ignored,} & \text{if } CS < T_{\text{threshold}} \end{cases} \quad (3)$$

$$\text{Adaptive Green Time } (G_i) = G_{\text{base}} + k \times D_i \quad (4)$$

where, G_{base} = Base Green Time, k = Proportional Constant, D_i = Traffic Density of Lane i

$$\text{Traffic Flow Efficiency } (E) = \frac{\text{Vehicles Successfully Passed } (V_{\text{passed}})}{\text{Total Detected Vehicles } (V_{\text{total}})} \quad (5)$$

$$\text{Emergency Vehicle Override } (E_{ov}) = \begin{cases} 1, & \text{if Ambulance Detected} \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

Fig 2: Evaluation Metrics

Figure 2: These frames are processed using a deep learning-based object detection model, such as YOLOv5, to identify vehicles in real-time traffic scenes. This step focuses on detecting important objects such as cars, buses, trucks, and ambulances, which are crucial for traffic analysis and density estimation.

VII. Results and Discussion

This section presents the performance evaluation of the proposed real-time vehicle tracking–based smart traffic management system developed for urban areas. The system is tested under different traffic conditions, including varying vehicle densities and real-time scenarios. The performance is evaluated using standard metrics such as accuracy, response time, precision, recall, and system efficiency to ensure a comprehensive and reliable analysis.

The vehicle detection and tracking module demonstrates effective identification and monitoring of vehicles in real time. Using advanced deep learning techniques such as YOLO, the system accurately detects vehicles and tracks their movement across multiple frames.

Fig 3: Current Density Level

During system operation, the model shows consistent performance with minimal detection errors and stable tracking accuracy. The processing time remains low, enabling real-time decision-making. The system efficiently analyzes traffic density and dynamically adjusts signal timings based on current conditions. The validation results indicate that the system performs reliably without significant delays or performance degradation, even under high traffic scenarios.

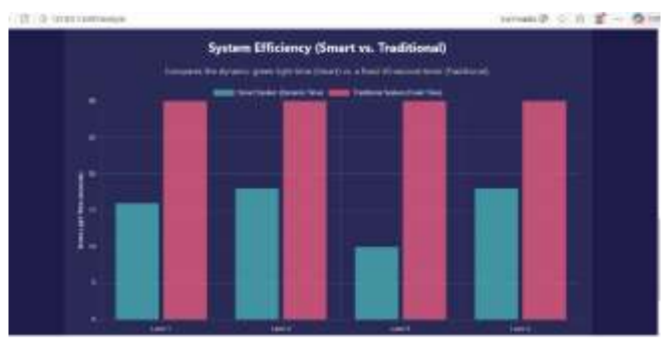

Fig 4: Smart vs Traditional Traffic Signal Performance Analysis

The results confirm that the model achieves high accuracy in vehicle detection and classification, while maintaining fast response time and robustness. This demonstrates the effectiveness of the proposed approach in enhancing urban traffic management systems.

VIII. Advantages

- **High Accuracy:** Advanced deep learning models such as YOLO and CNN-based approaches provide high accuracy in detecting and classifying vehicles under different traffic conditions, ensuring reliable traffic analysis.
- **Automation:** The system operates automatically by detecting, counting, and tracking vehicles in real time, significantly reducing the need for manual monitoring by traffic authorities.
- **Real-Time Traffic Monitoring:** The proposed system continuously monitors traffic flow and vehicle density, enabling instant analysis and quick decision-making for efficient traffic control.
- **Dynamic Signal Control:** Based on real-time vehicle density, the system dynamically adjusts traffic signal timings, reducing congestion and improving traffic flow at intersections.
- **Effective Feature Extraction:** Deep learning models automatically extract important features such as vehicle type, speed, and movement patterns without requiring manual feature engineering.
- **Handling High Traffic Density:** The system performs efficiently even under heavy traffic conditions, maintaining stable detection and tracking performance.
- **Multi-Vehicle Tracking:** The model supports tracking of multiple vehicles simultaneously across frames, ensuring accurate traffic analysis in complex urban environments.
- **Improved Traffic Efficiency:** By reducing waiting time, minimizing congestion, and optimizing signal control, the system enhances overall transportation efficiency in urban areas.

IX. Conclusion

This paper presents a real-time vehicle tracking–based framework for smart traffic management in urban areas. The proposed system integrates advanced deep learning techniques such as YOLO for vehicle detection and tracking, along with intelligent traffic signal control mechanisms to enable efficient traffic flow management. The system is designed to monitor vehicle density, identify congestion levels, and dynamically adjust signal timings based on real-time traffic conditions. The vehicle tracking module accurately detects and tracks multiple vehicles across frames, providing reliable data for traffic analysis.

The model is implemented and evaluated under different traffic scenarios to ensure robustness and efficiency. Experimental results demonstrate that the proposed system achieves high accuracy in vehicle detection and maintains low processing time, making it suitable for real-time applications. The system effectively reduces traffic congestion, minimizes waiting time at intersections, and improves overall traffic flow. By automating traffic monitoring and control, the proposed approach enhances the performance of urban traffic management systems and provides a scalable solution for smart city applications.

X. Future Scope

Although the proposed system demonstrates promising performance, several improvements can be explored in future work. Expanding the model with larger and more diverse traffic datasets covering different weather conditions, lighting variations, and complex urban scenarios can enhance generalization capability and improve real-world performance. The integration of advanced deep learning techniques, such as attention-based models and hybrid architectures, can further improve the accuracy of vehicle detection and tracking by focusing on critical regions in traffic scenes. Additionally, optimizing hyperparameters and adopting advanced training strategies can enhance overall system efficiency and reduce processing time.

Currently, the system is primarily focused on vehicle detection and traffic signal optimization; however, it can be extended to include additional functionalities such as pedestrian detection, emergency vehicle prioritization, accident detection, and violation monitoring (e.g., signal jumping and over-speeding). Furthermore, deploying the model as a real-time web or mobile application integrated with IoT-based smart traffic infrastructure can improve accessibility and scalability.

XI. References

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