



YoloV8 Based Traffic Violation Detection and Intelligent Signal Control using Roboflow

Dr. Lokesh M R¹, Devesh², Jyothi³, Kanvika R⁴, Nidhi J M⁵

Professor, Information Science and Engineering, AJ Institute of Engineering and Technology, Mangaluru, India¹

Student, Information Science and Engineering, AJ Institute of Engineering and Technology, Mangaluru, India^{2,3,4,5}

Abstract: In recent years, vehicle numbers have surged, but road infrastructure and traffic systems have lagged, leading to inefficient management. The rise in vehicle types, poor traffic control, and technical failures in signal systems exacerbate congestion, emissions, and noise pollution in smart cities. Conventional traffic control systems do not handle the complex traffic flow at the junctions, whereas existing traffic control systems work on fixed time-based techniques. The number of new vehicles on the road is increasing rapidly, which in turn causes highly congested roads and serving as a reason to break traffic rules by violating them. This leads to a high number of road accidents. New technologies such as computer vision (CV) and artificial intelligence (AI) are being used to solve these challenges. The proposed system integrates automated traffic signal adjustments and violation detection to address the challenges of increasing vehicular density and non-compliance with traffic rules. With its ability to enhance traffic flow efficiency and promote disciplined driving behavior, this system represents a significant step toward smarter and safer cities. The use of algorithms such as YOLO has the potential to revolutionize traffic management in urban areas, leading to a more efficient and sustainable transportation system. As a result, these technologies have established a distinct identity in the surveillance industry, particularly for continuous traffic monitoring. Traffic violation detection systems using computer vision efficiently reduce violations by tracking and penalizing offenders while alerting compliant drivers, ultimately decreasing fatal motorcycle accidents. Effectiveness is measured through key metrics such as traffic density estimation, violation detection accuracy (for red-light and helmet violations), and processing speed, ensuring real-time decision-making and optimized traffic management.

Keywords: Smart Traffic, YOLOv8, Traffic Violation, Real-Time Detection, Signal Control, AI for Safety, Smart cities.

I. INTRODUCTION

With rapid urbanization and population growth, cities face increasing challenges in managing traffic efficiently. Traffic congestion, road safety concerns, and frequent rule violations result in longer commutes, higher fuel consumption, and increased environmental pollution. Urban areas report a high number of traffic-related fatalities, often caused by reckless driving, signal violations, and limitations of traditional monitoring systems (Chaturvedi et al., 2023). The absence of adaptive control mechanisms and automated violation detection highlights the need for intelligent traffic solutions (Gulati & Srinivasan, 2019).

While sensor-based, RFID, and IoT approaches offer partial automation (Alsubai et al., 2024), they lack real-time adaptability. Recent advances in machine learning and computer vision, especially video analytics (Shao et al., 2022), have introduced smarter monitoring methods. However, issues like limited accuracy, poor scalability, and weak integration with smart city infrastructure persist (Ng & Kwok, 2020).

This study proposes an AI-powered traffic control system combining dynamic signal optimization and automated violation detection (Agarwal et al., 2024). Using real-time video feed analysis and deep learning models like YOLO, the system adjusts signal timings based on congestion levels and detects violations such as no-helmet usage, signal jumping, and wrong-way driving. This minimizes human intervention, improves traffic flow, and promotes safer driving behavior.

Expected outcomes include reduced congestion, improved compliance with traffic rules, and enhanced road safety. The system also provides authorities with actionable insights for effective regulation and long-term urban planning. By leveraging deep learning and real-time data, this solution supports scalable, smart city traffic management and encourages sustainable urban transport.

The proposed methodology details the system architecture, AI-driven violation detection, and adaptive traffic control. The Implementation and Experimental Setup covers dataset collection, model training, validation, and integration. The Results and Analysis evaluate system performance using accuracy metrics and comparisons. Finally, the Conclusion and Future Scope summarize findings and suggest improvements for urban traffic management.



II. LITERATURE SURVEY

Existing AI-driven traffic management solutions have improved traffic flow using techniques like reinforcement learning, computer vision, and IoT-based optimization. However, many lack real-time violation detection, focusing primarily on adaptive signal control. While some studies have successfully implemented helmet detection, vehicle tracking, and license plate recognition, they do not integrate congestion management. Blockchain based approaches enhance violation tracking but do not optimize real-time traffic flow. To bridge these gaps, the proposed system combines AI-powered congestion control with automated violation detection, ensuring a comprehensive and efficient traffic management system

A. Traffic Control

Li et al. (2021) proposed an AI-powered adaptive traffic signal control system using reinforcement learning, achieving a 15% reduction in congestion. While aligned with our goal of optimizing traffic flow, it lacks real-time violation detection, a key feature of our system. Mehta et al. (2020) utilized YOLOv3 and Kalman filtering for vehicle detection and tracking, improving congestion management by 30%. However, their model does not include violation detection. Chen et al. (2019) developed an IoT-enabled smart traffic system with edge computing and deep learning, reducing travel time by 20%. Though effective for signal optimization, it does not address traffic rule violations. Gupta et al. (2018) introduced a hybrid control system using SVM and decision trees, focusing on predicting traffic flow and reducing wait times. However, it lacks real-time adaptability and violation detection. Wang et al. (2018) combined fuzzy logic and deep learning for adaptive signal control, reducing wait times by 35%, yet did not include enforcement mechanisms. Sharma et al. (2022) applied edge AI and YOLOv4 for dynamic signal optimization, reducing congestion by 20%, but did not cover helmet or rule violation detection. Kumar et al. (2019) proposed a blockchain-based traffic management system to secure traffic data and improve violation tracking, but lacked adaptive signal control.

B. Violation Detection

Ul Haq et al. (2022) proposed a CNN-based helmet violation detection system using 493 images, evaluating four models—GoogleNet achieved the highest accuracy of 85%. While relevant to our helmet detection module, the limited dataset may affect real-world performance. Boonsirisumpun et al. (2018) used YOLOv3 and YOLO-Dense for helmet detection, achieving mAP scores of 95% and 98%. Though effective in violation detection, their system lacks congestion control and adaptive signaling features. Siebert and Lin (2020) developed a Faster R-CNN-based model with 97% accuracy for helmet violation detection, supporting our focus on traffic rule enforcement but without addressing broader traffic management. Sridhar et al. (2022) introduced a license plate recognition system for constrained environments, useful for identifying violators but not for congestion control. Wu et al. (2019) proposed a CNN model integrating vehicle classification, helmet detection, and mask detection. Their work aligns with our road safety goals but does not include adaptive traffic signal control, a key feature of our system.

III. METHODOLOGY

The figure 1 shows the layered representation of a Smart Traffic Management System, structured into multiple layers to handle different functionalities efficiently. It begins with the Sensing Layer, which collects raw traffic data from CCTV cameras, sensors, and other monitoring devices. The Data Acquisition Layer processes this data by extracting video frames for further analysis.

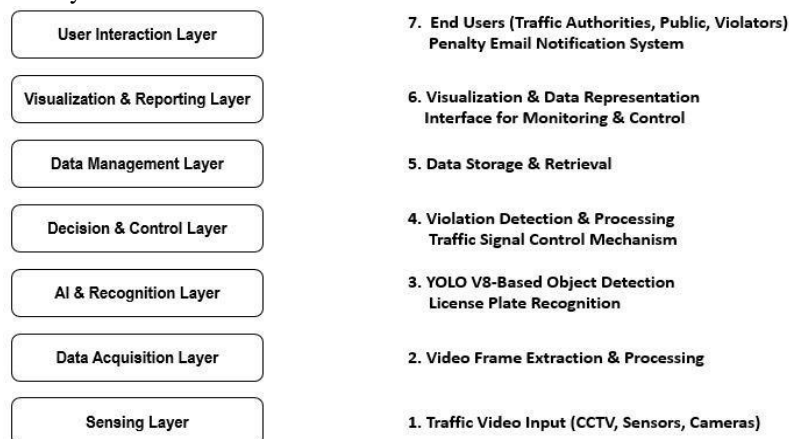


Figure 1 Multilayered system framework



The AI & Recognition Layer utilizes YOLO V8-based object detection and license plate recognition to identify vehicles and detect traffic violations. The Decision & Control Layer plays a crucial role in processing detected violations and implementing traffic signal control mechanisms based on real-time traffic conditions. The Data Management Layer ensures efficient data storage and retrieval for analysis and reporting. The Visualization & Reporting Layer provides an interface for monitoring and controlling traffic conditions through graphical data representation. Finally, the User Interaction Layer delivers processed information to relevant stakeholders, including traffic authorities, the public, and violators, integrating a penalty email notification system for traffic rule enforcement. This layered approach enhances traffic management by combining AI-driven detection, automated decision-making, and real-time monitoring for improved efficiency and road safety.

A. YOLOv8 Model

YOLO (You Only Look Once) is a popular object detection algorithm that can detect objects in real-time from images or videos. There have been eight different versions of YOLO developed so far, each with its own improvements and enhancements. YOLOV8 is a variant of the YOLO model family that uses a novel backbone architecture based on EfficientNet, a family of convolutional neural networks that are designed to achieve high accuracy while using fewer parameters than traditional models. This makes YOLOV8 more efficient and faster than some other object detection models, while still maintaining high accuracy.

B. Proposed Method

The figure 2 shows the system architecture of the Smart traffic control and violation detection system. The Proposed System consists of 6 main modules as follows: The Input Layer captures live traffic video, converting it into frames for analysis. The Processing Layer employs YOLO v8 for real-time object detection, recognizing vehicles, violations, and congestion patterns. The Processed Data Layer stores and analyzes traffic data for insights and long-term planning. Finally, the Management Layer takes action based on detected violations and congestion levels, dynamically controlling signals and notifying violators through automated penalties. This structured workflow ensures an efficient, adaptive, and data-driven traffic management system, reducing congestion and improving road safety.

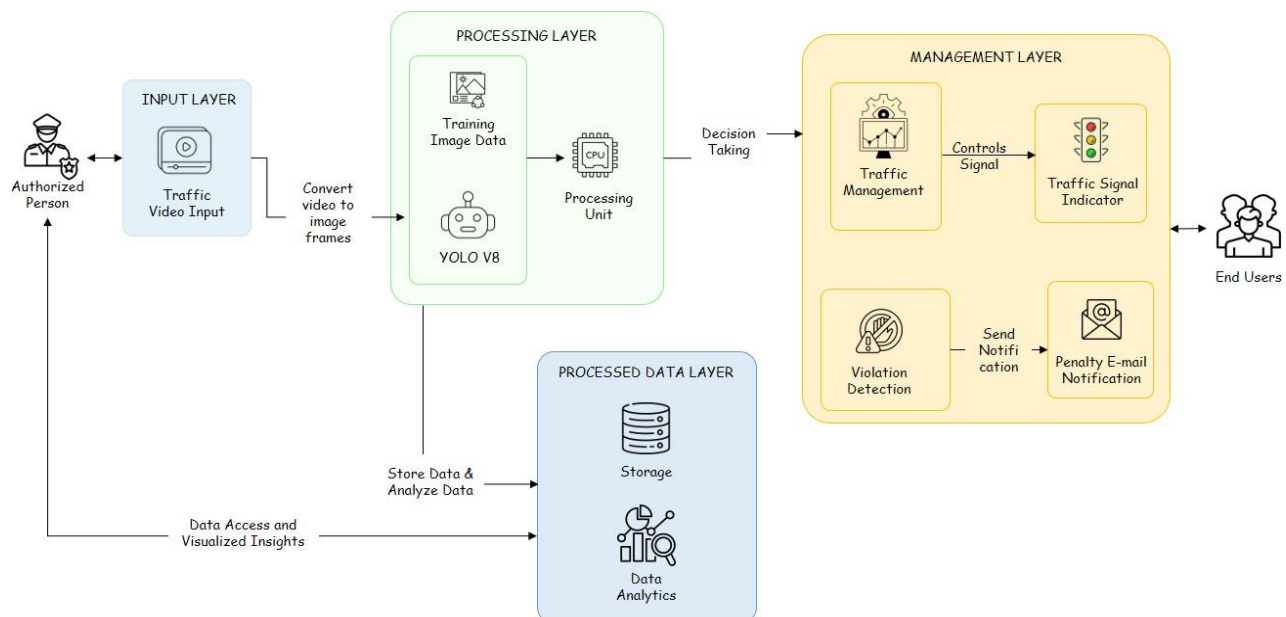


Figure 2 Smart traffic control and violation detection architecture

The Input Layer is responsible for collecting real-time traffic video feeds from surveillance cameras placed at intersections or roadways. An authorized person, such as a traffic officer, may access and monitor these video feeds for enforcement and management purposes. The captured video is converted into individual image frames to facilitate further processing by the system. This conversion allows for object detection, such as identifying vehicles, traffic signals, and potential violations. The Input Layer serves as the primary source of raw data for the entire system, ensuring that real-time traffic conditions are captured accurately. The Processing Layer is the core computational module where traffic analysis takes place using artificial intelligence. The image frames received from the Input Layer are processed by the YOLO V8 deep learning model, which is trained to detect vehicles, pedestrians, traffic lights, and rule violations. A dedicated processing unit, such as a high-performance CPU or GPU, handles complex computations



to ensure efficient and real-time detection. Once the system identifies relevant objects and events, it makes intelligent decisions, such as detecting a traffic violation. This processed information is then sent to the Management Layer for enforcement and response actions

The Processed Data Layer is responsible for data storage and analytics, ensuring that historical traffic information is preserved for future reference. This module also incorporates data analytics tools that allow traffic authorities to visualize insights, track patterns, and optimize traffic control strategies. By analyzing stored data, authorities can make data-driven decisions to improve road safety and efficiency. Additionally, this layer enables system users to retrieve past violation records and traffic trends for enforcement and planning purposes.

It includes multiple submodules, such as Traffic Management and Violation Detection. Traffic Management ensures smooth traffic flow by controlling signal changes dynamically based on real-time conditions. The Violation Detection system identifies traffic infractions, such as running red lights or speeding, and triggers automated penalty email notifications to the offenders. The final output of this layer is directed towards end users, including traffic authorities and rule violators, ensuring effective enforcement and public compliance with traffic laws.

C. Modeling

The Smart Traffic Control and Violation Detection System relies on a mathematical framework to process traffic video input, detect objects and violations using YOLOv8, and make automated decisions for traffic signal control and penalty notification.

1) Video Frame Extraction:

Traffic video input, represented as a continuous time-dependent signal $V(t)$, undergoes frame extraction to convert it into discrete image frames. The system extracts frames at a fixed frame rate F_r (frames per second) over a video duration T , resulting in a total number of frames N . Each extracted frame, denoted as I_n , is obtained through the frame extraction function $f(V(t))$, ensuring structured processing for further analysis.

$$I_n = f(V(t))$$

$$N = F_r \cdot T$$

2) Object Detection using YOLOv8:

YOLOv8 processes each image frame I_n and detects objects, represented as a set D_k . Each detected object d in D_k is defined by its bounding box center coordinates $(x,y)(x, y)(x,y)$, width and height $(w,h)(w, h)(w,h)$, class label c (e.g., vehicle, pedestrian, traffic light), and confidence score s , which indicates the reliability of detection.

$$D_k = \text{YOLO}(I_n)$$

$$d = (x, y, w, h, c, s)$$

3) Traffic Density Estimation:

The system calculates vehicle density within a monitored observation area A , determining the level of congestion based on the number of detected vehicles N_v . This information is crucial for adaptive traffic control, ensuring efficient traffic flow management.

$$\rho = \frac{N_v}{A}$$

The traffic signal state S is determined based on congestion levels,

$$\text{Green}, \rho < \rho_{low}$$

Where ρ_{low} are ρ_{high} predefined thresholds. $S = \{ \text{ellow}, \rho_{low} \leq \rho \leq \rho_{high} \}$

$$\text{Red}, \rho > \rho_{high}$$

4) Violation Detection and Penalty Notification:

Traffic violations are identified using a function that detects violations in each video frame I_n , producing a set of violations V_j . The system analyzes each detected violation to extract relevant details for further action.

$$V_j = v(I_n)$$

For each detected violation, the system first extracts the vehicle's number plate using Optical Character Recognition (OCR). The extracted number plate information is then used to retrieve the registered email address of the vehicle owner from the database.

$$P = \text{OCR}(d)$$



An automated email notification is sent to the vehicle owner, where E represents the email address associated with the detected number plate P, and V_j contains the violation details

$$E = \text{lookup}(P) \\ \text{email}(E, V_j)$$

This mathematical model provides a structured approach for real-time smart traffic management by integrating video processing, object detection, decision-making, and violation detection. These formulations ensure efficient traffic control and automated penalty enforcement, enhancing road safety and compliance with traffic regulations.

IV. RESULT AND DISCUSSION

A. Dataset and Preprocessing

The COCO dataset can be used in huge volumes of datasets for object detection and instance segmentation with more than 85 classes like car, person, and bicycle, etc., It includes all images with more than 85 objects. Initially were applied the pre-train process to extract features in the COCO dataset with all categories. Objects are labeled (Car) and instance segmentation has been done.

B. Validation of Results

The comparison of object detection models in this study is informed by Table 1 in [40], which highlights the superior performance of YOLOv8 models in terms of both accuracy and real-time processing capabilities. Specifically, YOLOv8 achieved 100% accuracy while maintaining an impressive 1100 FPS, making it the ideal choice for traffic monitoring and violation detection.

TABLE I: COMPARISON TABLE FOR DIFFERENT OBJECT DETECTION MODELS

| Method | Backbone | Model Size | Accuracy for mAP 0.5 | FPS | Average Inference Time | Batch Size | Input Reso- lution |
|--------------|-----------------------|------------|-------------------------|------|---------------------------|---------------|-----------------------|
| Faster R-CNN | ResNet101 | 72.8 MB | 100% | 19 | 0.0528 seconds | 8 | 600x600 |
| SSD | Mobilenet-v2 | 9.2 MB | 86% | 433 | 0.00023 seconds | 8 | 320x320 |
| YOLOv4 | CSPDarknet53 | 162.2 MB | 96% | 1083 | 0.0009 seconds | 64 | 416x416 |
| YOLOv4-Tiny | CSPDarknet53- Tiny | 22.5 MB | 97% | 1015 | 0.0009 seconds | 64 | 416x416 |
| YOLOv5 small | Yolov5s | 14.1 MB | 99% | 1002 | 0.001 seconds | 16 | 416x416 |
| YOLOv8 nano | EfficientNet | 6.2 MB | 100% | 1100 | 0.0009 seconds | 16 | 640x640 |

In contrast, models such as Faster R-CNN and SSD, while accurate, exhibited trade-offs in processing speed, making them less suitable for real-time traffic systems.

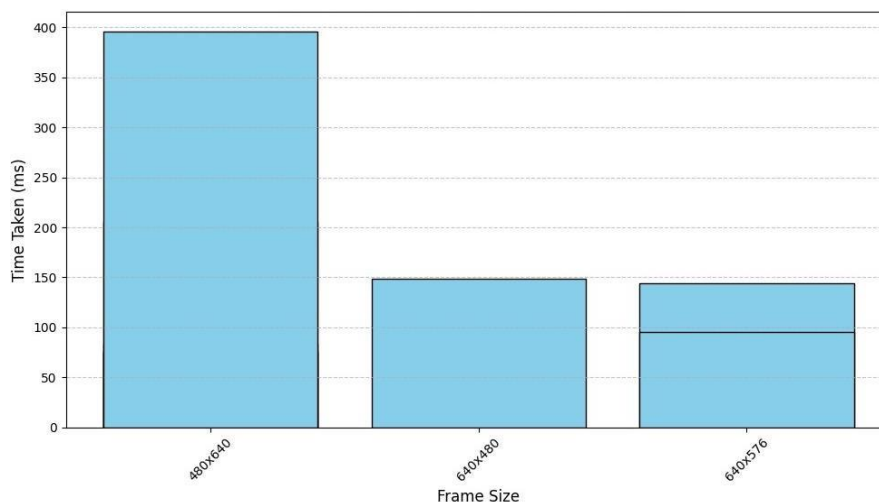


Figure 3 Time taken for vehicle recognition per frame



The bar chart in the figure 3 illustrates the variation in processing time for vehicle recognition across different frame sizes. The results indicate that smaller frame sizes require significantly more processing time, whereas larger frames tend to reduce the computational load. This suggests that optimizing the resolution of input frames can lead to more efficient detection while maintaining accuracy, making it crucial for real-time applications.

The figure 4 visually validates this approach, accurately depicting the number of vehicles in each lane as detected by the system, reinforcing the reliability of the model in real-world scenarios

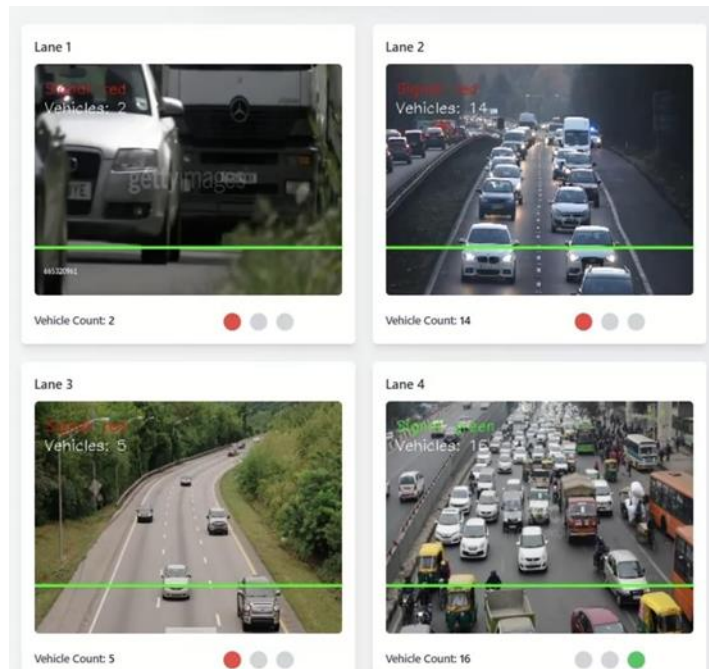


Figure 4 Real-Time Traffic Density Detection

The bar chart in the figure 5 illustrates the signal allocation process based on vehicle density across multiple lanes. The system dynamically analyzes traffic conditions and assigns the green signal to the lane with the highest vehicle count, ensuring efficient traffic flow. Lanes with lower densities remain on red to minimize congestion and optimize road usage. This adaptive approach helps prevent unnecessary delays and enhances overall traffic management.

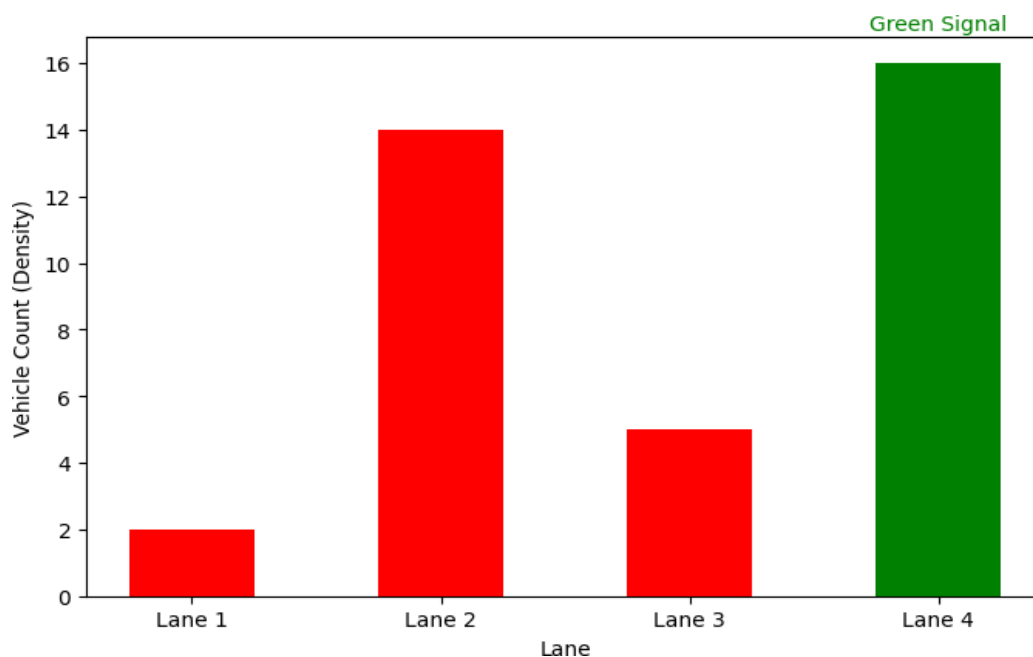


Figure 5 Signal allocation based on vehicle density



By prioritizing lanes with higher vehicle density, the system improves real-time signal control, reducing waiting times and improving road efficiency. The automated signal adjustment enhances urban mobility by preventing bottle-necks and ensuring smooth vehicle movement, demonstrating the effectiveness of AI-driven traffic management solutions. The graph in the figure 6 showcases the variations in time taken for license plate recognition across different frames in the Smart Traffic Control and Violation Detection System. Fluctuations in processing time indicate that the system dynamically adapts to varying complexities in each frame, such as multiple vehicles, lighting conditions, and occlusions.

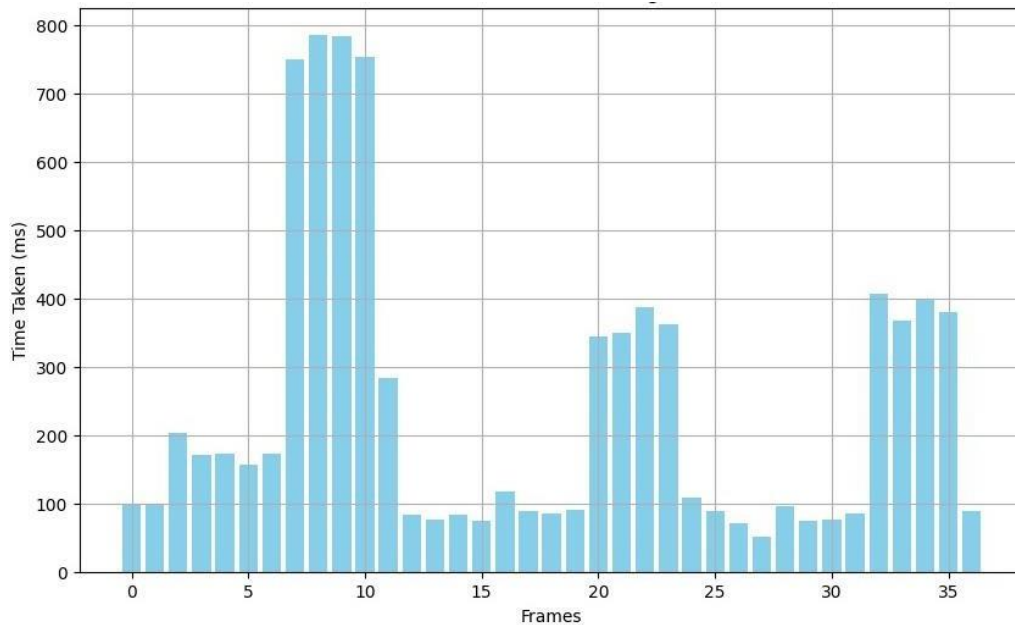


Figure 6 Time taken for number plate recognition

These variations provide valuable insights into system performance, emphasizing the need for consistent efficiency in real-time applications. Occasional increases in processing time may highlight areas for optimization, such as enhancing algorithm efficiency, utilizing hardware acceleration, or improving image pre-processing techniques.

V. COMPARISION

The Table 2 provides a comparative analysis of the proposed Smart Traffic Control and Violation Detection System against existing traffic management and violation detection systems based on an in-depth analysis of relevant literature. Existing system performance has been evaluated by reviewing multiple sources in the bibliography, ensuring a legitimate and well-supported comparison.

TABLE 2 COMPARISON OF THE PROPOSED SYSTEM WITH EXISTING SYSTEMS

| Feature | Proposed System (YOLOv8-based) | Existing Systems |
|------------------------|--------------------------------|--|
| Object Detection Model | YOLOv8 (Nano) | CNN-based methods, Faster R-CNN, SSD, YOLOv4, YOLOv5 |
| Accuracy | High | Moderate to high |
| Processing Speed (FPS) | 1100 FPS | Generally lower, ranging from 19-900 FPS depending on model complexity |



| | | |
|---|--|---|
| Traffic Density Estimation | Real-time, dynamic frame adjustment | Reinforcement learning-based and predefined algorithm approaches |
| Violation Detection | Red-light & helmet violations using AI | Some focus only on red-light violations, while helmet detection is less commonly integrated |
| Signal Optimization | Dynamic signal allocation based on vehicle density | Genetic algorithms, reinforcement learning, and rule-based models |
| License Plate Recognition | Efficient and adaptive license plate recognition | Slower or less reliable license plate recognition |
| Scalability | Highly scalable (adaptive to frame size, real-time alerts) | Some models are limited in scalability and require high computational resources |
| Computational Efficiency | Optimized YOLOv8-based model, low inference time | Some models require high computational resources |
| Integration with Law Enforcement | Automated penalty notifications | Some systems require manual verification or semi-automated processes |
| Deployment Feasibility | Suitable for smart city infrastructure | Some methods require high-end hardware |

The findings highlight that the proposed system provides a more efficient and scalable approach for traffic management and violation detection compared to existing systems. A thorough analysis of existing literature confirms that while some prior models achieve high accuracy, their effectiveness varies based on dataset conditions, computational efficiency, and real-time adaptability. The proposed system, supported by experimental validation and performance benchmarks, demonstrates high accuracy and robust real-time capabilities, making it a more practical and deployable solution for modern traffic management.

VI. CONCLUSION

Experiments with real-world traffic and simulation data confirm the feasibility of the Smart Traffic Control and Violation Detection System. The system adapts signal timings dynamically based on vehicle density and provides real-time feedback for effective rule enforcement. Its modular, adaptable design allows for easy customization and extension, making it suitable for deployment by municipal authorities. Potential future features include emergency vehicle prioritization and detailed violation reports, enhancing urban traffic efficiency, safety, and environmental sustainability. Future enhancements aim to broaden the system's capabilities. Integrating advanced algorithms and additional sensors can help prioritize emergency vehicles, ensuring their timely movement. The use of IoT devices and AI would enable the system to better process real-time data from sensors and cameras for smarter traffic decisions. Machine learning models like SVM and K-Means clustering could further improve vehicle density estimation and signal adjustment accuracy. Additionally, incorporating Automatic Number Plate Recognition would allow for precise



offender identification and violation reporting. Integration with public transportation systems could prioritize buses and trains at intersections, while monitoring pedestrian crossings, bike lanes, and specific traffic lanes would make the system a comprehensive traffic management solution. Future versions of the system could also integrate with public transportation networks to prioritize buses and trains at intersections, ensuring smoother operation of urban transport. These upgrades aim to build a safer, more efficient, and sustainable urban traffic ecosystem.

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BIOGRAPHY



Dr. Lokesh M R

Department of ISE
A J Institute of Engineering and Technology
Mangaluru



Devesh

Department of ISE
A J Institute of Engineering and Technology
Mangaluru



Jyothi

Department of ISE
A J Institute of Engineering and Technology
Mangaluru



Kanvika R

Department of ISE
A J Institute of Engineering and Technology
Mangaluru



Nidhi J M

Department of ISE
A J Institute of Engineering and Technology
Mangaluru