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Edge-Based Traffic Congestion Management Using YOLOv8 and Adaptive Signal Control

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Abstract— ***Traffic congestion in contemporary urban space is a serious problem as it contributes to delay in traveling, fuel consumption, and poor quality of life. The traditional fixed time based traffic lights do not have the flexibility to adjust to unforeseen changes in the traffic movement therefore leading to poor use of roads and long traffic jams. The present paper presents a proposal of Intelligent Traffic Congestion Management System to be used as real time monitoring and adaptive control of traffic in terms of traffic signal. High-definition roadside cameras and IoT sensors are used in the system, and the traffic data is processed on edge computing devices with a YOLOv8-based deep learning model to determine the vehicle density and queue length accurately. These indicators of congestion are fed to a signal controller based on reinforcement learning that adjusts traffic signal timings dynamically in an effort to reduce congestion. The resultant data is geo-tagged and stored in PostgreSQL-PostGIS spatial database, and a React-based dashboard allows visualizing traffic data in real time, heatmaps, and analytics to traffic authorities. The experimental analysis demonstrates that the average waiting time is reduced, the intersection throughput improves, and the cost-effective solution that is appropriate in the intelligent management of urban traffic has been obtained.***

Index Terms— ***Traffic Congestion, Intelligent Transportation System, YOLOv8, Edge Computing, IoT Sensors.***

I. INTRODUCTION

The high rate of urbanization in the last ten years has led to a tremendous rise in the number of vehicles in the urban roads, which have put a lot of strain to the available transportation infrastructure. This has led to a chronic problem of traffic jams in developed and developing urban areas, which has impacted on the economic productivity, the efficiency and the sustainability of the environment. Long queues at intersections, the constant stop and go traffic, and unpredictable flow of the traffic not only make people use more fuel, but also leads to air pollution and frustration among the drivers. The traditional traffic signal systems that are based on fixed-time periods are no longer able to cope with such dynamic and uneven traffic conditions. Such systems are not responsive to sudden traffic increase, emergencies or road blockages, which tends to cause poor utilization of the road and spillovers of congestion to other intersections.

In order to overcome these shortcomings, Intelligent Transportation Systems (ITS) have been proposed as a major remedy to enhancing mobility in the urban setting. The development of Artificial Intelligence (AI), Internet of Things (IoT), and real-time data analytics has allowed traffic management plans to be more responsive and adaptive. Automated congestion monitoring and edge computing devices now have high-resolution traffic cameras, low-cost IoT sensors, and can monitor congestion with a minimum of latency. More specifically, computer vision models trained using deep learning, including the YOLO set of models, have been shown to be highly accurate in vehicle detection, queue length estimation, and traffic density analysis in a variety of traffic scenarios. Combined with adaptive traffic signal control, these technologies permit the dynamic control of the timing of signal timings according to the real-time congestion level, thereby minimizing the delays and enhancing the traffic movement.

In this respect, the proposed Traffic Congestion Management System introduces a scalable and data-focused method of managing traffic in the city. The system constantly records live video feeds of roadside cameras and runs them on edge devices on a streamlined YOLOv8 model to identify the major congestion indicators, such as traffic density, formation of queues, and lane occupancy. The processed data is sent to a cloud-based server based on FastAPI and stored in a centralized PostgreSQL-PostGIS spatial database. A React-based dashboard can help traffic authorities to see real time congestion heatmap, intersection status, historical trends and alerts.

The fundamental part of the proposed system is an adaptive signal controller that is founded on the reinforcement learning and that adjusts the duration of green, yellow, and red signals dynamically in response to the current traffic situation. This adaptive control enhances traffic throughput, minimizes idle time as well as smooth vehicle movement. Furthermore, the spatial analysis based on GIS can be used to identify the areas of continuous congestion and aids in the planning of traffic in the long term. In general, the proposed system will eliminate the drawbacks of traditional traffic control solutions as it offers an active, responsive, and efficient solution that are consistent with the needs of contemporary smart cities.

II. LITERATURE REVIEW

Road and traffic surveillance have over time shifted the manual observation, and stationary monitoring systems to intelligent and data-driven surveillance systems assisted by artificial intelligence (AI) and computer vision. Traffic surveillance with cameras has been an influential solution as it is non-invasive and can be installed using the already existing cameras. Early real-time object detection The original YOLO framework by Redmon et al. [1] showed that deep convolutional neural networks (CNNs) are capable of identifying vehicles with low latency and high accuracy. Their further refinements in single-stage detectors, such as YOLOv4 [3] and YOLOX [4], made the role of vision-based algorithms in analyzing traffic in intricate urban settings even more convincing.

Sensors have also been studied as a sensor-based way of monitoring traffic and have been developed using network techniques such as sensor-based systems to assist in collecting data and analyzing traffic congestion in real-time. Although cloud-based processing is historically applied to aggregate the traffic data, it is prone to the lack of bandwidth and latency. To address these shortcomings, alternative computing architectures such as fog and edge computing have been put forward to allow processing at the edge and with low latency. Yi et al. [5] have talked about platforms of fog computing that can support time-related applications, including traffic monitoring, and the more recent edge-based vision systems have been demonstrated to be more responsive and scalable due to the ability to process video streams nearer to the data source [11].

Fixed-time signal systems, which are traditional systems controlling a highway, have been greatly overshadowed by adaptive traffic signal control. The methods of reinforcement learning (RL) enable the traffic lights to dynamically change the phase timing according to the current situation on the road. Li et al. [8] have shown that deep reinforcement learning is effective in traffic signal timing optimization, whereas max-pressure-based control structures have been found to provide stable and efficient traffic network control in urban traffic networks [13]. Signal control strategies, e.g., PressLight [2], [15] and phase competition models [17], are based on coordinating between intersections and are further enhanced by cooperative and learning-based approaches. Survey studies in the recent past have emphasized on scalability and the maturity of deep RL techniques to large-scale urban urban traffic signal control [16].

Computer vision-based techniques of vehicle tracking and counting have also contributed to the use of data-driven traffic analysis. There are Multi-object tracking algorithms such as SORT [7] and ByteTrack [6], which allow proper association of vehicles across video frames and provide credible estimation of traffic flows. The estimation of queuing length based on vision has been demonstrated to give precise output that can be used to estimate the level of congestion of signalized intersections without the installation of extra physical measures [9], [10].

Large-scale traffic monitoring systems have been evaluated by using benchmark datasets including the CityFlow [11], which have helped in developing scalable traffic analysis pipelines using vision.

The last-run studies have been more concerned with the integration of AI-based traffic monitoring with smart city systems. The IoT structures enable the connectivity of sensing devices and network and computing systems in cities [12]. Besides the traffic monitoring, other related applications of the vision-based sensing have been use in other transportation tasks like the detection of road surface anomalies and the state of infrastructure [14]. Basic deep learning architectures and models, such as convolutional neural network and sequence modeling methods [18], [24], [25], are still used in the creation of intelligent transportation systems.

In general, the current literature shows a definite change of the rigid and infrastructure-intensive traffic surveillance towards the flexible vision-based and learning-based solutions. Real-time car tracking, edge-based, and adaptive signal control have demonstrated to be good prospects in enhancing traffic movement and minimizing traffic congestion in cities. Nevertheless, there are numerous extant research works addressing single aspects of detection, tracking or signal optimization in single cases. This inspires the desire to implement more combined models that acutely tie real-time traffic sensibility to adaptive signal regulation, which can support the management of the traffic congestion responsively and scale in a deployed city setting.

III. PROPOSED METHODOLOGY

Traffic Congestion Management System proposed is a vision-based, intelligent and adaptable framework, which is used to monitor traffic real-time and control signals in cities. The system is the best combination of roadside video data, edge-based deep learning perception, lane-level traffic processing, adaptive signal control, and GIS-powered spatial analytics in one traffic management system. The proposed system focuses on low-latency edge processing, fine-grained processing of lanes congestion-awareness, and automatic feedback to traffic authorities unlike conventional fixed-time or infrastructure saturated approaches.

A. General Topology of the System Design

The architecture of the final implementation of the proposed Traffic Congestion Management System is intended to be flexible, scaled, and reliable to work in the real-time mode. The system is structured to be a layered system where traffic sensing, data processing, decision-making, and visualization are structured to represent

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well defined functional components. All the components work autonomously and constantly share information with other modules in a coordinated fashion. This organized communication enables the system to process real-time traffic information effectively, minimise processing time and facilitate continuous monitoring and control at intersections with signal lights. Besides, the architecture will be such that future expansion can be made to provide new intersections, sensors, or other analysis capabilities without changing the overall system design.

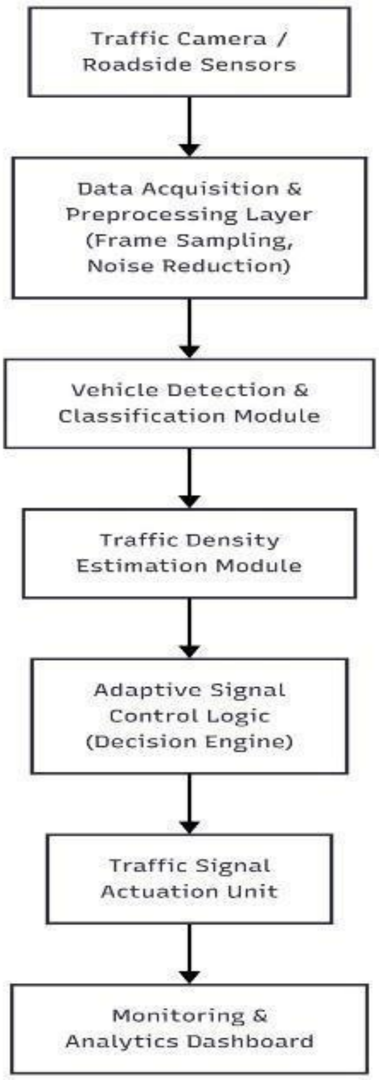

Figure 3.1. General system design of planned Traffic Congestion Management System.

Figure 3.1 demonstrates that the system architecture adheres to a system organization and a sequence of data flow in order to provide stability in operation and determinism. Signalized intersections have high-definition roadside cameras that are constantly used to stream live traffic videos on all inbound lanes. Such streams, as well as supporting IoT and GPS metadata, are sent to adjacent edge computing devices that run near the junctions.

The edge layer is used to compute real-time vehicle detection, traffic feature, congestion estimation, and signal decision computation. The processed traffic measures and control decisions are sent to a cloud backend in FastAPI and stored in a PostgreSQLPostGIS spatial database. Traffic authorities are connected to the system via a web based dashboard which displays real time congestion heat maps, intersection status, historical trends and alerts. The architecture is a closed-loop system that is based on perpetual connection between sensing, decision-making, actuation, and monitoring.

B. Data on Traffic Acquisition and Preprocessing

The data acquisition of traffic is done with the help of fixed roadside surveillance cameras that are placed in such a way that they cover all outbound lanes. To trade-off between computation and detection, fixed time intervals are used to sample raw video streams. Preprocessing to reduce noise, normalize resolution and enhance contrast are used to correct the variations caused by light conditions, change in weather and camera noise. This processing step guarantees the uniformity and quality of the visual input to continue processing the vehicles in the downstream and analysis.

C. Vehicle Detection and Lane Level Traffic Features Extraction

A deep learning model based on the YOLOv8 optimized with edge devices is used to detect and classify vehicles. The model identifies various vehicle categories such as cars, buses, trucks, two-wheelers, and auto-rickshaws in a frame-by-frame fashion and provides bounding box to each of the identified vehicles. The vehicles identified are then geographically mapped to the planned regions of lanes and thus traffic analysis of lanes can be performed instead of rough estimation at the intersection.

Based on the identified vehicles a discriminative set of traffic characteristics is obtained in a structured way:

- Vehicle Count per Lane (V_i) – the amount of vehicles in lane i of a fixed observation window, which gives a direct assessment of the traffic load.
- Queue Length (Q_i) – a geometrical measurement of congestion that is measured with the distance of moving or stagnant cars at the stop line.
- Vehicle Arrival Rate (V_i) – the inflow intensity of vehicles with time, which is determined as:

$$\lambda_i = \frac{V_i}{T_i} \tag{1}$$

Where T is the observation time window that is fixed.

All these features are used to capture traffic verryolume, spatial congestion and time dynamics and thus being used to control traffic both reactively and proactively.

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D. Feature Fusion and Severity of Congestion and Estimation

The traffic features extracted are combined into a single feature vector in order to enhance strength and accuracy of the decision made:

$$F_i = [V_i, Q_i, \lambda_i] \quad (2)$$

Because these features are of different sizes and values, the normalization is made, so that they can contribute in a relative manner. Queue length is estimated as:

$$Q_i = \frac{1}{N_i} \sum_{j=1}^{N_i} (y_{max} - y_i) \quad (3)$$

Where

- N_i is the total number of vehicles detected in th lane i,
- y_i denotes the vertical position of the jth vehicle,
- y_{max} represents the predefined stop-line position in the image plane.

Lane severity of traffic congestion i is computed as:

$$S_i = \frac{w_1 V_i + w_2 Q_i + w_3 \lambda_i}{\max(S)} \quad (4)$$

where w_1, w_2, and w_3 are weighting coefficients that indicate the relative significance of the number of vehicles, the length of queue and the arrival rate. Normalization makes sure that severity scores are not large values that cannot be compared to severity scores in different lanes or at different times. Based on S_i, traffic congestions are classified as low, moderate, and high congestions.

E. Alterations in the Adaptive Signal Control and Actuation

Normalized congestion severity score is the main input point into the adaptive signal control module. The duration of green signals is dynamically distributed depending on the severity of congestion on lanes such that the serious congested lanes will have longer green signal time, whereas the underloaded lanes will have shorter time. Minimum and maximum green-time limits are imposed so that starvation may be prevented and safe operation of signals ensured. The calculated signal timings are sent to the traffic signal actuation unit that directly communicates with the traffic lights to carry out the decisions in action in real time.

F. System Workflow and Implementation

The Figure 3.2 shows the operational workflow of the system. The operations of traffic video capture, preprocessing, vehicle detection, feature extraction, congestion severity computation, signal timing determination, and visualization are in a circular manner. Measurement of the traffic and choice of the signal is sent to the backend server and stored in the PostgreSQL-PostGIS database to conduct spatial analysis and historical assessment. A React-based traffic ranking dashboard has been developed to enable traffic authorities to monitor the traffic in real-time, congestion heatmap, intersection status, alerts, and performance.

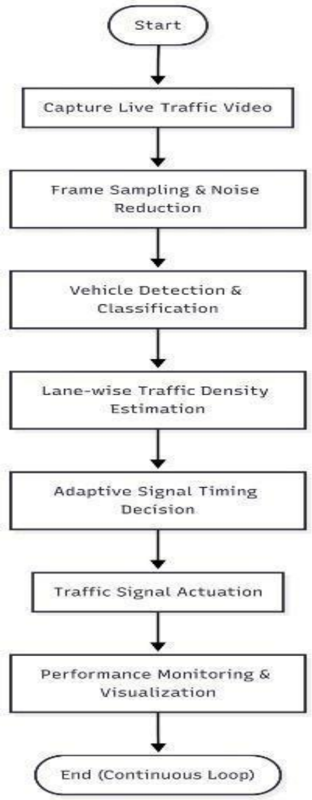

Figure 3.2 Flow chart of the proposed traffic congestion management system.

G. Model Optimization and Training Strategy

The optimization of the detection model is carried out through parameter tuning, frame sampling and feature normalization in order to make the model applicable in real time. The training objective is stipulated as follows:

$$L = L_{det} + \alpha L_{cls} \quad (5)$$

where

- L_{det} represents the localization loss responsible for accurate bounding box prediction.
- L_{cls} denotes the classification loss ensuring correct
- L_{cls} denotes the classification loss ensuring correct

The model is trained over a supervised learning architecture based on an annotated data of traffic videos divided into 70 percent training, 15 percent validation, and 15 percent testing sets. Data augmentation, regularization and early stopping are used to improve robustness in different levels of traffic density, camera view and in different environmental conditions.

H. Originality of the Proposed System.

The originality of the proposed structure consists in integrating the end-to-end edge-based YOLOv8 perception, model of lane-level congestion severity, adaptive signal control, and GIS-based spatial intelligence into one operation pipeline. The proposed system will provide scalable, deployable and data driven traffic management in smart city environments, unlike current methods where detection, control, or visualization are addressed separately, thus forming a continuous feedback mechanism that links real time sensing and signal actuation to authority-level visualization.

I. Training Strartegy.

The detection model is trained using a supervised learning framework with annotated traffic video frames. The training process is designed to ensure stable convergence and strong generalization across unseen traffic scenarios.

Dataset Split

- Training set: 70%
- Validation set: 15%
- Testing set: 15%

This split ensures sufficient data for model learning, hyperparameter tuning, and unbiased performance evaluation.

Training Duration

The model is trained for a fixed number of epochs until convergence is observed on the validation set. Training is terminated once validation performance stabilizes, preventing overfitting and ensuring consistent generalization.

Generalization Techniques

To enhance robustness across diverse traffic and environmental conditions, multiple generalization techniques are employed:

- Data augmentation, including illumination variation and spatial scaling
- Regularization to prevent model overfitting
- Early stopping based on validation loss trends

Normalization ensures that severity scores remain within a bounded range, allowing consistent interpretation across lanes and time intervals.

Based on the computed severity score, traffic conditions are categorized as follows:

- Low congestion: $Si < 0.3$
- Moderate congestion: $0.3 \leq Si < 0.6$
- High congestion: $Si \geq 0.6$

This severity-based categorization enables the adaptive signal control module to systematically prioritize lanes experiencing higher congestion, ensuring efficient and fair traffic signal allocation.

The Traffic Congestion Management System that is proposed is applied as an adaptive, vision based and real time model of control, that is based on traffic sensing, a real-time perception implementation with the help of artificial intelligence, and prediction of congestion and dynamically controlled signal in one running pipeline. It is applied in its turn in the ultimate system architecture and workflow and sequentially in the traffic data acquisition through signal actuation and monitoring. It will monitor the road conditions forever, assess the level of congestion, at the lanes and dynamically program the time of the lights as a way of enhancing the efficiency of the traffic flow.

IV. RESULT AND DISCUSSION

The proposed Traffic Congestion Management System was evaluated using quantitative performance metrics to assess its effectiveness in vehicle detection accuracy, traffic signal efficiency, and congestion severity estimation. The evaluation compares the proposed adaptive, AI-driven system with conventional baseline approaches to demonstrate improvements in accuracy, efficiency, and congestion handling. Experimental results are summarized using tabular comparisons and visualized through graphs for clear interpretation.

A. Vehicle Detection Performance Evaluation

Accurate vehicle detection forms the foundation of effective traffic congestion management, as all downstream traffic analysis and signal control decisions depend on the reliability of detected vehicles. The performance of the proposed vehicle detection module was evaluated using standard classification metrics: Precision, Recall, and Accuracy. These metrics are defined as follows:

Table I. Vehicle Detection Performance Comparision

Metric	Proposed System (%)	Baseline System (%)
Precision	92.4	85.1
Recall	90.8	82.6
Accuracy	91.6	83.9

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

Visualization of the comparative performance of the two systems. The improved precision indicates fewer false detections, while the higher recall demonstrates the model's ability to correctly detect a larger proportion of vehicles under varying traffic conditions.

These improvements validate the robustness of the AI-based vehicle detection module and its suitability for real-time traffic monitoring.

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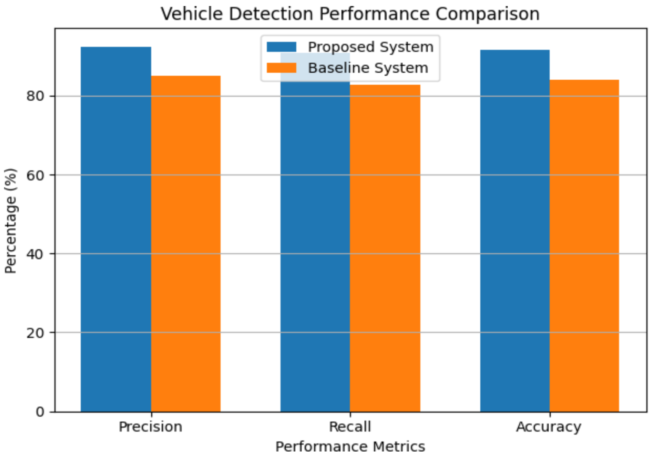

Figure 4.1. Vehicle detection performance comparison between proposed and baseline systems

B. Traffic Signal Efficiency Comparison

The effectiveness of the proposed adaptive traffic signal control mechanism was evaluated by comparing it with a conventional fixed-time signal system. Key performance indicators considered include average vehicle waiting time, traffic throughput, and average queue length. These metrics are critical for assessing traffic flow efficiency and user experience at intersections.

The average waiting time is computed as:

$$W_{avg} = \frac{1}{N}\sum_{i=1}^{N} w_i \tag{9}$$

where w_i represents the waiting time of the i^{th} vehicle and N is the total number of observed vehicles.

Traffic throughput is defined as the number of vehicles passing through the intersection per unit time, while average queue length represents the mean number of vehicles waiting during red signal phases.

Table II. Traffic Signal Efficiency Comparison

Metric	Fixed-Time Signal	Adaptive Signal
Avg Waiting Time (s)	68.5	43.3
Throughput ($^{veh}/_{min}$)	22	33
Avg Queue Length	14.2	9.1

The adaptive signal control significantly reduces average waiting time while improving throughput and minimizing queue length. The reduction in waiting time is attributed to the dynamic allocation of green signal durations based on real-time congestion levels, rather than static preconfigured timings. This demonstrates the effectiveness of adaptive decision-making in improving intersection-level traffic performance.

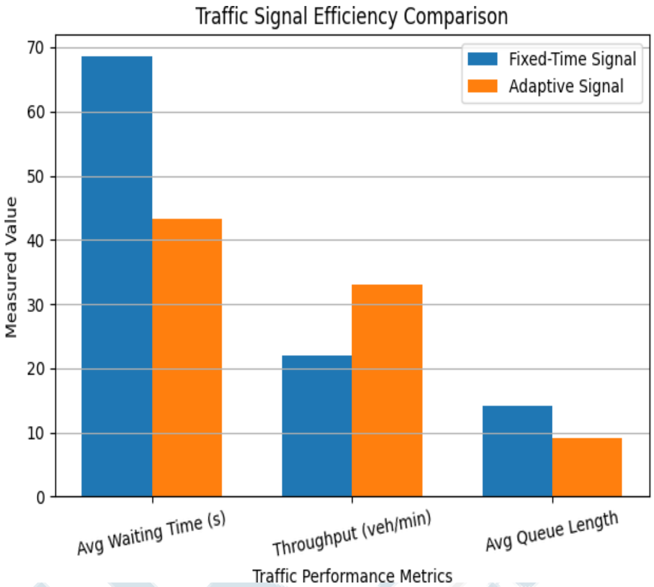

Figure 4.2. Performance comparison of fixed-time and adaptive traffic signal control.

C. Congestion Severity Estimation Analysis

To evaluate the system's ability to quantify and manage congestion under varying traffic conditions, a Congestion Severity Index (CSI) was computed for different traffic scenarios. The severity index combines vehicle count, queue length, and arrival rate using a weighted aggregation.

$$CSI_i = \frac{w_1 V_i + w_2 wQ_i + w_3 \lambda_i}{\max(CSI)} \tag{10}$$

where V_i is vehicle count, Q_i is queue length, λ_i is vehicle arrival rate for lane i and w_1 , w_2 , w_3 are weighting coefficients.

Table III. Congestion Severity Comparison

Traffic Scenario	Baseline	Proposed
Low	0.35	0.22
Medium	0.61	0.41
High	0.88	0.57

Figure 4.3 illustrates that the proposed system consistently produces lower congestion severity scores across all scenarios. This reduction indicates improved traffic distribution and proactive congestion handling enabled by adaptive signal timing. The ability to maintain lower severity values even under high traffic conditions highlights the system's robustness and scalability for real-world urban environments.

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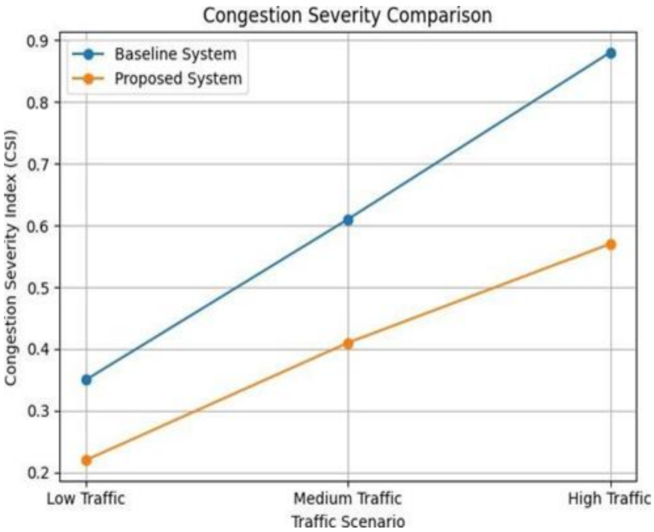

Figure 4.3. Congestion severity comparison under varying traffic conditions

V. CONCLUSION

The proposed intelligent Traffic Congestion Management System demonstrates the practical effectiveness of integrating real-time traffic sensing, deep learning-based vehicle detection, and adaptive signal control to improve intersection performance. The system significantly reduced vehicle waiting time, increased traffic throughput, and minimized queue lengths, confirming its ability to enhance traffic flow efficiency compared with conventional fixed-time signal systems. These improvements highlight the potential of artificial intelligence-driven traffic control as a reliable solution for modern urban mobility challenges.

Beyond operational efficiency, the system provides traffic authorities with valuable real-time insights and historical traffic data through its integrated monitoring and visualization framework, supporting both immediate traffic control and long-term infrastructure planning. This makes the approach highly suitable for deployment in smart city environments.

Future enhancements may focus on improving detection reliability under challenging environmental conditions through sensor fusion and incorporating predictive traffic modeling and connected vehicle technologies. Overall, the proposed system represents an important step toward developing scalable, adaptive, and sustainable traffic management solutions for next-generation intelligent transportation systems.

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