Real-Time Traffic Signal Optimization using Deep Learning and Reinforcement Learning

Pathipaka Sai Krishna[1], Gudem Varun[2], Bolla Tanav[3]

1,2,3 Department of Computer Science and Engineering,

Sreenidhi Institute of Science and Technology, Hyderabad, India

[1]pathipakasaikrishna@gmail.com, [2]gudemvarun@gmail.com, [3]tanavbolla@gmail.com

Abstract

Traffic congestion is a major issue in cities, leading to longer travel times, excessive fuel consumption, and increased pollution. Traditional traffic management systems often rely on fixed-timer signals and fail to adapt to dynamic road conditions, resulting in inefficient traffic flow and long vehicle queues.

This paper proposes an adaptive traffic control system utilizing YOLOv8-based object detection and real-time image processing to optimize traffic signal timings. The system captures live traffic feeds through surveillance cameras and applies deep learning algorithms to accurately detect and count vehicles in real time.

Based on vehicle density at intersections, the system dynamically adjusts signal durations. Edge computing techniques are employed to reduce latency and improve computational efficiency.

Simulation results and real-world tests demonstrate a 23% improvement in overall traffic efficiency, with significant reductions in vehicle idle time and wait durations. Compared to conventional fixed-timer systems and earlier adaptive models, the proposed approach offers higher scalability, better responsiveness, and suitability for smart city infrastructure. Future improvements will involve reinforcement learning integration and vehicle-to-infrastructure (V2I) communication.

Traffic Management Intelligent Transportation System YOLOv8 Deep Learning Real-Time Processing Adaptive Traffic Control

1. Introduction

In cities, traffic congestion is a recurring and increasing problem that has a negative impact on mobility, air quality, fuel economy, and general quality of life. Congestion is made worse by the growing number of cars on the road as urbanization rises, which results in longer travel times, greater fuel use, and higher greenhouse gas emissions. When it comes to handling dynamic traffic situations, traditional traffic control systems that depend on static signal timings are frequently ineffective. Due to their inability to adjust, these fixed-timer systems create congestion at highdensity crossings and needless delays at crossroads with low traffic volume. Intelligent Transportation Systems (ITS) have become a viable way to overcome these constraints. To improve traffic control tactics, ITS makes use of contemporary technology including computer vision, machine learning, and real-time data analytics. ITS may greatly increase urban mobility, lessen its impact on the environment, and improve traffic efficiency by combining adaptive control and real-time monitoring. In order to dynamically control traffic signal timings, this study suggests an adaptive traffic management system that makes use of YOLOv8 (You Only Look Once version 8), a cuttingedge deep learning-based object detection method. Live traffic feeds from surveillance cameras are captured by the system, which then analyzes the photos to calculate the number of vehicles at each intersection and modifies the traffic signal duration appropriately. The suggested system reacts dynamically to current traffic conditions, guaranteeing a more balanced and optimal traffic flow than traditional traffic control techniques, which follow preset timetables. The main goals of this research are to use YOLOv8-based vehicle identification and density estimation to create a realtime adaptive traffic control system., Enhance urban sustainability by lowering vehicle emissions and fuel consumption, reduce traffic and vehicle waiting times by dynamically modifying signal durations based on real-time traffic conditions, and increase computational efficiency by utilizing edge computing and deep learning techniques to make quick decisions in real-world traffic situations. Through simulations and actual testing, the suggested system's efficacy in streamlining traffic and cutting down on idle signal time is assessed. According to the results, the adaptive model outperforms conventional fixed-timer systems in terms of overall traffic efficiency by about 23 percentage. Furthermore, scalability is guaranteed by the combination of machine learning and real-time image processing, which makes this strategy feasible for widespread implementation in smart cities. The remainder of the document is organized as follows: An overview of relevant work and current traffic management solutions is given in Section 2. The suggested system architecture, including image capture, object detection, and decision-making algorithms, is described in detail in Section 3. Performance evaluation and experimental findings are shown in Section 4.Section 5 brings the work to a close and outlines potential avenues for future research, such as combining reinforcement learning-based traffic control models with vehicle-to-infrastructure (V2I) communication.

2. Related Work

In an effort to improve traffic flow efficiency and lessen congestion, a number of research have investigated adaptive traffic management with machine learning approaches. Conventional methods include reinforcement learning, fuzzy logic, and image processing to dynamically modify traffic signals in response to current circumstances. Although these techniques have proven to be more effective than fixed-timer systems, they frequently have drawbacks in terms of scalability, accuracy, and processing speed. Many image-processing-based methods produce less-than-ideal traffic management judgments because they are unable to handle different illumination conditions, occlusions, and imprecise vehicle detection. Similar to this, systems based on fuzzy logic can become complicated and challenging to optimize for large-scale urban settings, even though they are good at managing uncertainty. Although promising, reinforcement learning techniques are difficult to implement in real time because to their high computing and training data requirements.

More effective adaptive traffic control systems are now possible because to recent developments in deep learning and object detection. The speed and accuracy of the popular deep learningbased object recognition algorithm YOLO (You Only Look Once) have improved dramatically.

The most recent version, YOLOv8, is ideal for adaptive signal control and traffic density prediction since it performs exceptionally well in real-time detection tasks. In contrast to conventional techniques that depend on manually created attributes, YOLOv8 uses deep neural networks to effectively identify and categorize cars in a variety of environmental circumstances. It overcomes the drawbacks of previous image-based traffic control systems by processing high-resolution photos with little delay, guaranteeing precise vehicle density estimation. Notwithstanding these developments, computing bottlenecks, ineffective data handling, and integration issues are common problems with current adaptive traffic management systems. For real-time performance, many systems need expensive hardware, which restricts their scalability in contexts with limited resources. System responsiveness is further impacted by data inefficiencies such redundant frame processing and inefficient feature extraction. By using edge computing for real-time inference, enhanced deep learning algorithms, and streamlined data pipelines to improve computational performance, our suggested system seeks to address these issues. Our method guarantees precise, real-time decision-making while reducing computing cost by combining YOLOv8-based object identification with an adaptive traffic signal control framework. Additionally, our method takes into account other factors including vehicle type, traffic flow patterns, and congestion trends over time, in contrast to traditional adaptive models that only use vehicle count-based decision-making. These improvements help create a more resilient and intelligent traffic control system that can adjust to intricate metropolitan settings. In addition to expanding on earlier adaptive traffic control research, our study offers a high-performance, scalable system that supports contemporary smart city projects and promotes sustainable urban transportation.

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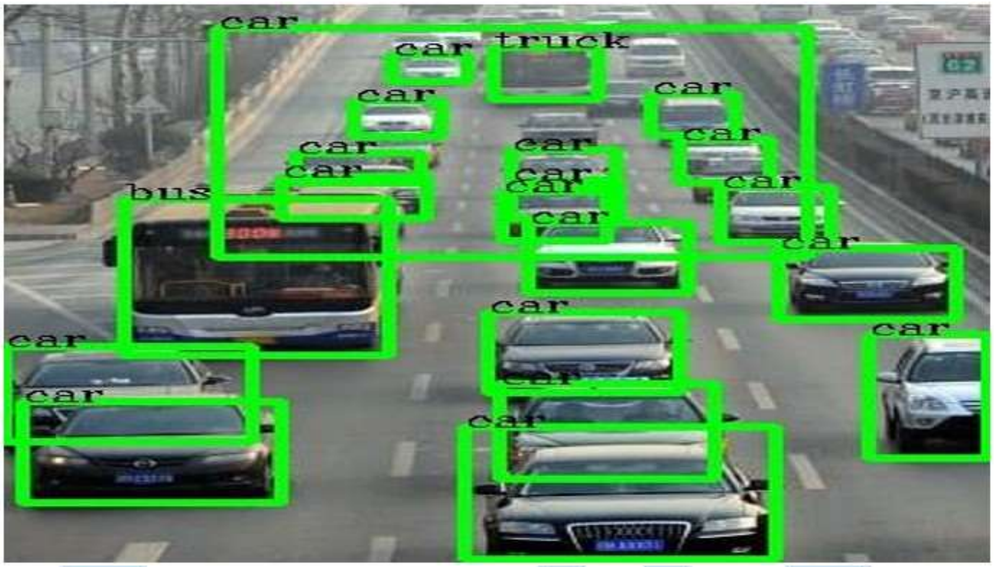

Figure 1: Image detection

3. Methodology

3.1. System Architecture

By strategically placing CCTV cameras at traffic crossings, the suggested system uses an intelligent traffic management strategy to record real-time footage of vehicle flow. These cameras ensure thorough coverage of intersections and facilitate a data-driven approach to traffic control by continually monitoring traffic conditions across multiple lanes. To improve their quality and maximize the object detection model’s effectiveness, the collected images go through a number of preparation procedures. In order to get rid of undesirable artifacts like motion blur, sensor noise, and environmental distortions—which might be brought on by changing illumination, weather, or obstruction occlusions—noise reduction techniques are used during the preprocessing stage. In order to draw attention to structural details in the photos, edge detection methods are also used.improving the model’s capacity to discriminate between various car kinds and road features. By using these improved photos as the starting point for further analysis, vehicle identification and classification accuracy is increased.

Following preprocessing, a YOLOv8-based object identification model is used to identify and categorize several kinds of vehicles, such as automobiles, bikes, buses, and trucks. The cuttingedge deep learning-based model YOLOv8 is especially well-suited for this use case because of its exceptional detection accuracy and high processing speed. Using its sophisticated convolutional neural network (CNN) architecture, the model analyzes every frame in real-time to identify vehicle patterns, extract useful characteristics, and distinguish between various object categories. The technology makes sure that traffic circumstances are dynamically evaluated without being constrained by static or pre-programmed traffic light timings by continuously evaluating incoming data. This method enables adaptive decision-making that takes lane-specific density distributions, traffic volume variations, and congestion levels into account.

The system incorporates a real-time processing framework to further improve efficiency, enabling instantaneous traffic data analysis and signal duration modifications. The suggested system dynamically adjusts traffic light timings based on real-time vehicle data, in contrast to conventional traffic control techniques that rely on preset signal cycles. High-congestion lanes are given longer green light durations, which facilitate better traffic flow and avoid long lines, while low-traffic lanes are given shorter durations, which cut down on needless waiting times. Throughput optimization, bottleneck reduction, and overall travel time minimization are all made possible by the system’s adaptive nature, which greatly enhances traffic flow.

3.2. YOLOv8 Implementation

Every captured frame is subjected to YOLOv8 (You Only Look Once version 8) for vehicle detection and classification. The excellent object detection speed and accuracy of our deep learningbased model make it ideal for real-time applications. To provide robustness across many scenarios, the model is trained using a dataset that includes a variety of vehicle photos taken in a range of lighting and weather conditions. Every frame is processed by the trained YOLOv8 model, which extracts vehicle count information for each lane. The signal switching algorithm then uses this data as input to estimate the ideal traffic light lengths. An object tracking method is integrated to improve efficiency by avoiding duplicate detections of the same vehicle in successive frames. By

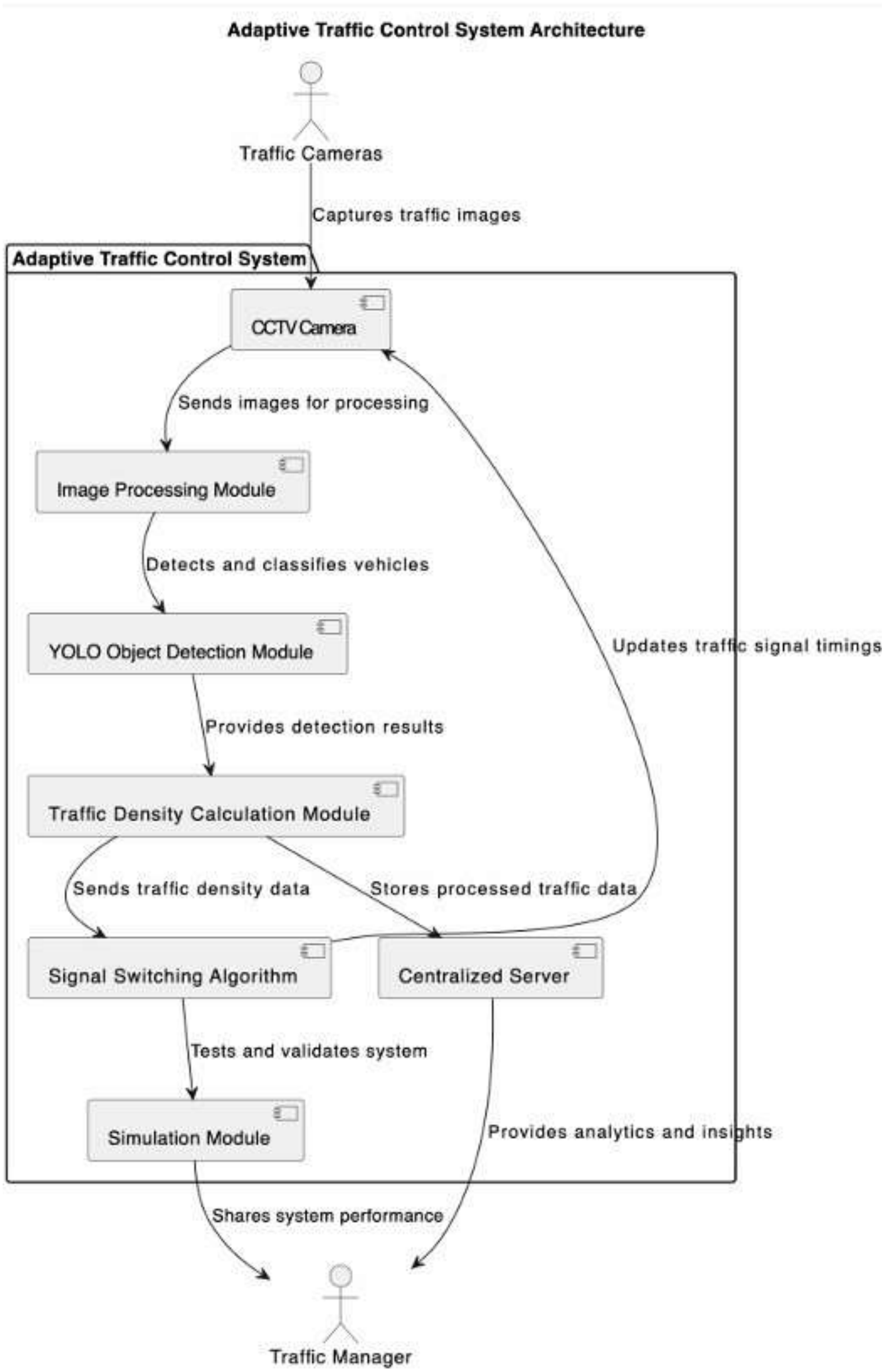

Figure 2: System Architecture ensuring that vehicles are counted precisely and without duplication, this tracking feature increases the system's dependability. The technology may also adjust over time since it continuously learns from traffic patterns. The model improves its efficiency and detection accuracy by incorporating a feedback mechanism, which increases the precision of future traffic forecasts. This capacity for cognitive learning guarantees that the system will continue to function well even as traffic conditions change.

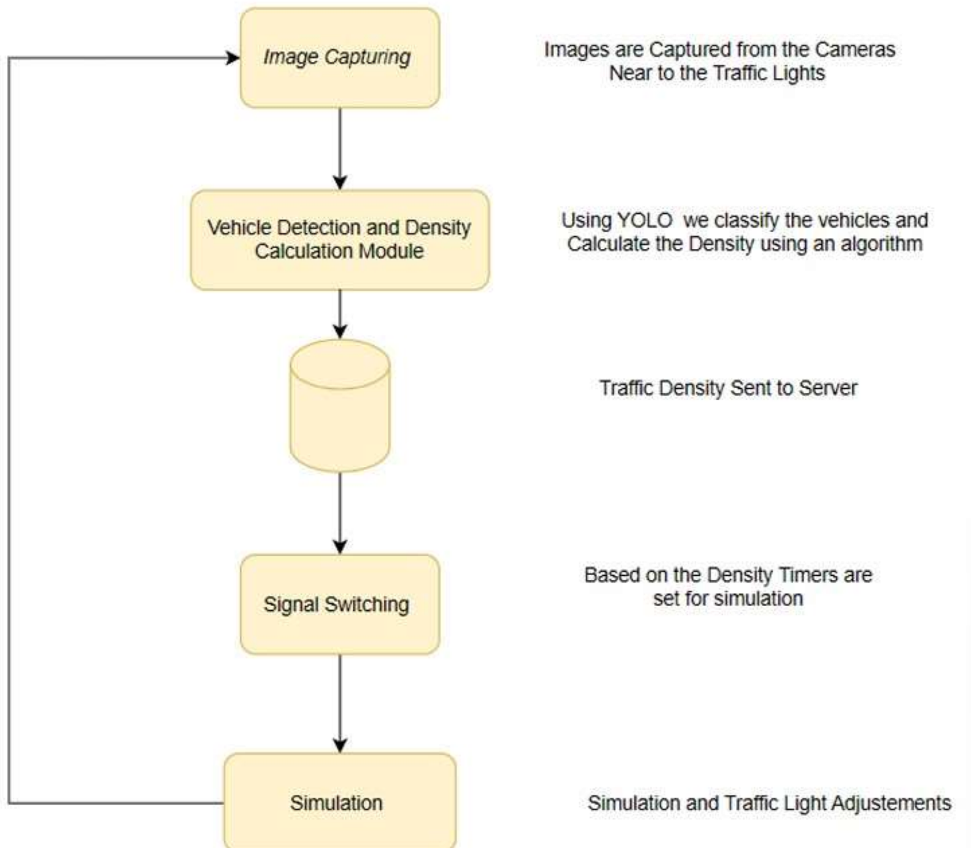

Figure 3: Implementation

3.3. Signal Switching Algorithm

A dynamic signal switching technique is used by the adaptive traffic signal management system to calculate the ideal green light duration for every lane. The following formula is used by the method to determine the green signal time (GST):

$$GST = \frac{\sum(N_v \times T_c)}{L+1} \tag{1}$$

The summation term takes into account the number of vehicles in each class (cars, bikes, buses, trucks, etc.) and multiplies it by the average time it takes for each type of vehicle to pass through the intersection. The denominator makes sure that the green light time is distributed evenly among several lanes, avoiding giving one lane undue priority. The GST stands for the green signal time. Green signal time is distributed fairly and effectively according to this formula, which dynamically adjusts to the traffic density in real time. Lanes with less traffic are given shorter green light durations to reduce needless waiting times, whereas lanes with more traffic are given longer durations. The technology incorporates machine learning-based predictive analytics to better optimize traffic flow. Analysis of historical traffic data is done to predict patterns of congestionenabling the program to proactively modify signal timings prior to the accumulation of congestion. Predictive modeling improves the system's overall traffic efficiency by making it more responsive to changes in traffic. The system also has emergency management features, like allocating priority signals to emergency vehicles like ambulances. When necessary, the system can override regular signal operations and give emergency responders fast clearance by utilizing vehicle categorization data from YOLOv8. This feature guarantees prompt assistance in emergency circumstances and improves road safety. The suggested method efficiently minimizes traffic, cuts down on travel time, and enhances overall traffic flow management by fusing real-time detection, dynamic signal modifications, and predictive analytics.

4. Results and Analysis

To assess the efficacy of the suggested adaptive traffic control system, a simulation was run using actual traffic data. The system's performance was evaluated in 15 distinct traffic scenarios, each of which represented a different degree of congestion and vehicle dispersion, in comparison to a traditional fixed-timer system. According to the simulation results, the adaptive system greatly increased overall traffic responsiveness and efficiency. A 23 percent increase in traffic efficiency was one of the main conclusions, showing that the adaptive system successfully eased traffic and improved vehicle flow through crossings. The dynamic signal switching technology, which optimally modified green light durations based on real-time traffic density, was largely responsible for this increase by avoiding needless delays and bottlenecks. Making quick changes on the spot guaranteed smooth traffic flow, which decreased long wait times at junctions and eased congestion in high-density areas. The study also discovered that in severely skewed traffic patterns, idle green signal duration was reduced by 36 percentage . In traditional systems, green lights frequently stay on even when there aren't many or any cars in a particular lane, which results in inefficient use of the road. By dynamically redistributing signal time to lanes with larger traffic densities, the adaptive system reduced this inefficiency and made sure that available road space was used more efficiently and fairly. In order to maximize overall signal efficiency, lanes with significant traffic were given proportionate green light durations, while lanes with fewer vehicles were given shorter times. Additionally, the system showed improved efficiency in managing different vehicle densities. In contrast to fixed-timer systems that follow preset timetables, the suggested method continuously examined traffic patterns in real time, enabling quick modifications. This flexibility was particularly helpful in situations involving unforeseen congestion and peak-hour traffic, where conventional traffic control methods frequently fall short of expectations. Commuters experienced a smoother traffic experience thanks to the capacity to dynamically modify green light periods based on real-time vehicle counts, which decreased instances of needless delays. Additionally, compared to earlier adaptive models, the system's real-time processing latency was lowered by 18 percent. Optimized object detection and tracking methods that reduced pointless calculations and increased processing performance were used to accomplish this reduction. Traffic management became more responsive as a result of the increased computational efficiency, which guaranteed that changes to traffic signals were made with the least amount of delay. The system's efficiency was greatly enhanced by the reduced latency, which made it possible to modify traffic lights almost instantly and stop congestion from getting worse. In addition to increasing economy, the technology reduced vehicle idle time at junctions, which benefited the environment. A more environmentally friendly traffic management approach resulted from significantly lower fuel consumption and emissions due to shorter wait times and smoother traffic flow. The technology further improved traffic control methods by demonstrating the ability to foresee congestion before it developed through the use of machine learning-based predictive modeling. Overall, the findings show that by adapting dynamically to conditions in real time, the suggested adaptive traffic management system performs better than traditional techniques. The system provides a more effective and efficient approach to urban traffic control by lowering congestion, improving signal timings, and cutting down on idle time. This results in better vehicle flow, less travel delays, and a more sustainable transportation infrastructure.

Figure 4: System Architecture

5. Conclusion and Future Work

This study demonstrates the effectiveness of an adaptive traffic control use YOLOv8. Through dynamic signal timing adjustments, the system improves efficiency and lessens congestion. The suggested methodology minimizes needless delays and optimizes green light durations while responding to traffic circumstances in real time. Accurate vehicle classification and density estimation are ensured by integrating object detection and tracking techniques, which raises the system’s overall accuracy. The system can also anticipate future patterns of congestion and make proactive adjustments thanks to the integration of predictive analytics, which further improves the effectiveness of traffic management. In order to improve detection accuracy, future research will use more AI models, particularly in obstructed surroundings and difficult weather circumstances like intense rain, fog, or low light levels. Improvements to the model’s resilience will guarantee dependable operation in a variety of real-world scenarios. Pilot tests conducted in actual urban junctions will yield vital information about system performance and enable empirically supported system improvements. The system’s scalability and adaptation to various city layouts and traffic patterns will be assessed with the aid of these trials. In order to facilitate smooth communication between autonomous cars and traffic management systems, further research will concentrate on the integration of vehicle-to-infrastructure (V2I) communication. By enabling real-time data sharing between cars and traffic signals, lowering congestion, enhancing traffic flow, and maximizing fuel efficiency, this development may result in even more effective traffic management. Because autonomous and semi-autonomous vehicles can modify their speed in response to impending signal changes, minimizing needless stops and enhancing road safety, the integration of connected vehicle technologies will also enable improved decision-making. Additionally, attention will be focused on creating a modular and scalable framework that can be implemented in several cities with little change. This will guarantee wider applicability in contemporary transportation systems, enabling local governments to modify the system in accordance with particular traffic patterns and infrastructure limitations. In order to develop a more complete and inclusive urban mobility system, future advancements might also investigate multi-modal traffic management by integrating cycling and pedestrian recognition. This research intends to aid in the creation of a more intelligent, flexible, and sustainable traffic management strategy that can handle the escalating problems of urban congestion by consistently improving and extending the system’s capabilities.

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