Developing an Intelligent Traffic Control System for Urban Roads

M.Tech Thesis

by

Shabbir Poswal

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

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Developing an Intelligent Traffic Control System for Urban Roads

A THESIS

Submitted in partial fulfillment of the

requirements for the award of the degree

of

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by

Shabbir Poswal

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **Developing an Intelligent Traffic Control System for Urban Roads** in the partial fulfillment of the requirements for the award of the degree of **Master of Technology** and submitted in the **Department of Computer Science and Engineering, Indian Institute of Technology Indore,** is an authentic record of my own work carried out during the period from July 2023 to May 2025 under the supervision of Dr. Ayan Mondal, Indian Institute of Technology Indore, India.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

19/May/2025
Signature of the Student with Date

(Shabbir Poswal)

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

19/05/2025
Signature of Thesis Supervisor with Date

(Dr. Ayan Mondal)

Shabbir Poswal has successfully given his M.Tech. Oral Examination held on **30/April/2025**.

19/05/2025
Signature(s) of Supervisor(s) of M.Tech. thesis

Date:

Subhra Mazumdar

Signature of Chairman, PG Oral Board

Date: 20.05.2025

Signature of HoD

Date: 20-May-2025

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Lastly, I would like to express my heartfelt appreciation to my family. To my parents and loved ones, thank you for your endless support, patience, and understanding. Without your encouragement and love, this achievement would not have been possible.

Shabbir Poswal

Dedicated to My Family and Friends

Conference Presentation

I am pleased to share that a part of the work presented in this thesis has been accepted for oral presentation at the **International Conference on Computer-Aided Modeling for the Sustainable Development of Smart Cities (CAM-SMART 2024)**, held at **North Eastern Regional Institute of Science and Technology (NERIST), Nirjuli, Arunachal Pradesh, India**, from **November 27 to 30, 2024**.

The research, titled:

"Development of Real-Time Smart Traffic Management System for Urban, Rural, and Highways of Indore"

was presented as part of the conference's agenda focused on cutting-edge technologies for sustainable urban development. This recognition provided a valuable platform to showcase our work to an audience of researchers, academicians, and smart city experts from across the country.

Participating in CAM-SMART 2024 offered insightful feedback, fostered academic exchange, and encouraged collaborative dialogue around the future of smart and sustainable cities. I am honored to have contributed to this forum and grateful for the opportunity to represent my institute at this esteemed event.

ABSTRACT

With the steady rise in urban populations and the rapid increase in the number of vehicles on the road, traffic congestion has emerged as a pressing concern, particularly in densely populated metropolitan areas. This growing congestion not only causes frustrating delays for commuters but also leads to excessive fuel consumption and elevated levels of air pollution, posing a serious threat to both public health and the environment.

To address these challenges effectively, there is an urgent need for smart, real-time traffic monitoring systems that can enhance the way we manage and control traffic flow. Traditional traffic control mechanisms often rely on fixed signal timings, which fail to adapt to the dynamic nature of real-world traffic conditions. As a result, they are ill-equipped to meet the increasing demand and complexity of modern urban mobility.

Our proposed solution introduces an intelligent, real-time traffic management system that leverages live camera feeds from traffic intersections. Using cutting-edge image processing and artificial intelligence techniques, the system continuously monitors and analyzes traffic density. Based on real-time data, it dynamically adjusts traffic signal timings to better align with current traffic patterns and volumes.

This adaptive approach not only helps in reducing congestion and travel time but also contributes to lower fuel consumption and emission levels—creating a smoother, faster, and more sustainable commuting experience. By integrating advanced technology into traffic control infrastructure, we aim to transform the way cities handle traffic—making urban transportation smarter, greener, and more responsive to the needs of its citizens.

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Chapter 1

Introduction

As urbanization continues to accelerate, cities around the world are witnessing a rapid increase in both population and the number of vehicles on the road. This growth has exacerbated traffic congestion, particularly in large metropolitan areas, where traffic jams have become a daily ordeal. The consequences of traffic congestion are far-reaching, affecting not only the everyday lives of commuters but also leading to increased fuel consumption, higher levels of air pollution, and greater economic inefficiencies. According to studies, prolonged traffic congestion can contribute significantly to environmental degradation through excessive emissions of greenhouse gases, worsening air quality in urban environments.

Traditional traffic light management systems operate on pre-set timing cycles that do not account for real-time traffic conditions. These systems are typically programmed to change signals based on a fixed sequence and duration, regardless of current vehicle flow, density, or pedestrian movement. While this approach is relatively simple to implement and requires minimal technology, it often leads to inefficiencies, especially during peak traffic hours or in highly variable traffic conditions. In such systems, vehicles may experience unnecessary delays at red lights, even when there is little to no opposing traffic, resulting in increased congestion, longer commute times, and higher emissions due to idling.

Advancements in artificial intelligence and computer vision offer promising solutions to address these challenges. By utilizing real-time video feeds and leveraging AI-based object detection algorithms, such as You Only Look Once (YOLO) [10], traffic density at intersections can be accurately analyzed. Specifically, the latest iteration of YOLO, YOLOv8, demonstrates significant improvements in speed and accuracy for vehicle detection, making it a powerful tool for traffic management applications.

This project proposes the development of an automated traffic control system that integrates YOLOv8 for real-time vehicle detection and counting. Additionally, the system aims to optimize traffic light timings using the Webster method [12], a well-established traffic signal design approach. By combining real-time object detection with dynamic traffic light adjustment, the system seeks to improve traffic flow efficiency, reduce congestion, and minimize delays at key intersections.

In this report, we will explore the system's architecture, including the integration of YOLOv8 for traffic analysis and the application of the Webster method for signal timing optimization. We will also evaluate the system's potential impact on urban traffic management and its broader implications for sustainable urban mobility.

1.1 Motivation

In recent years, the dramatic growth in urbanization and vehicle ownership has led to increasingly congested roads, especially in rapidly developing cities like Indore. Daily commuters, emergency services, and public transport systems are all affected by inefficient traffic management, leading to delays, elevated stress levels, increased fuel consumption, and rising air pollution. Despite advancements in infrastructure, conventional traffic control systems in many regions still rely on static signal timings, failing to adapt to real-time traffic conditions. This gap between growing mobility demands and outdated traffic solutions became the initial trigger for this research.

Having personally experienced the daily challenges posed by urban congestion, particularly in Indore—a city actively undergoing smart city transformation—I was inspired to explore how modern technologies could offer intelligent, responsive alternatives. The vision of combining artificial intelligence and image processing to monitor and manage traffic in real time resonated strongly with my interest in creating impactful, tech-driven solutions for societal problems. This project presented an opportunity to move beyond theoretical study and work on something practical that could contribute meaningfully to the community.

Moreover, Indore's inclusion in the Smart Cities Mission offered a unique and timely context for this research. The availability of support from institutions like IIT Indore and the Indore Smart City Organization not only provided access to real-world data and infrastructure but also reaffirmed the importance and relevance of this work. The motivation grew further from the realization that this project could serve not just urban intersections, but also rural roads and highway corridors where efficient traffic management is equally critical but often overlooked.

Beyond the local impact, the broader motivation lies in contributing to global sustainability goals. Traffic congestion is not just a transportation issue—it's a public health, environmental, and economic concern. By reducing idle times and improving traffic flow, intelligent traffic systems can lower carbon emissions and fuel consumption, directly supporting green mobility initiatives. This aligns with the global push toward smart cities that leverage data and technology to improve quality of life.

In essence, this project is driven by a passion to solve real-world problems through innovative technology. It is motivated by the belief that integrating artificial intelligence into traditional infrastructure can lead to smarter, safer, and more sustainable cities—not just for today, but for the future. The prospect of making even a small contribution to this transformation is what fuels this research.

1.2 Objective

The primary objective of this research project is to develop a real-time, intelligent traffic management system that can dynamically respond to fluctuating traffic conditions in urban, rural, and highway environments using live video surveillance and artificial intelligence (AI)-based image processing. As cities continue to expand and vehicle usage increases exponentially, traffic congestion has become a significant issue impacting not only the efficiency of transportation but also environmental and economic sustainability. Traditional traffic signal systems, which rely on pre-set timers, are unable to adapt to the varying and unpredictable nature of modern traffic, resulting in prolonged delays, increased fuel consumption, and heightened pollution levels.

To address these challenges, our project focuses on the design and deployment of an AI-powered traffic control framework that can analyze real-time video feeds captured from traffic intersections to determine vehicle density and flow patterns. By applying advanced image processing techniques, the system identifies and counts vehicles, categorizes them by type if necessary, and assesses congestion levels on each road segment. This real-time data is then used to dynamically adjust the duration of traffic signal phases, thereby prioritizing heavily congested lanes and optimizing overall traffic movement.

A key aim of the project is to ensure that the system is scalable, adaptable, and suitable for deployment across a wide range of traffic environments, including densely populated urban centers, sparsely trafficked rural intersections, and high-speed highway entry/exit ramps. The system is designed to be cost-effective and compatible with existing infrastructure, using standard CCTV feeds and edge computing solutions for local processing, reducing the need for expensive sensor-based installations.

Furthermore, the project seeks to contribute to environmental sustainability by minimizing vehicle idle times at traffic lights, thus reducing fuel wastage and emissions. It also aspires to improve the daily commuting experience for citizens by reducing delays and enabling smoother, faster travel. From a broader perspective, the system aligns with the vision of smart city development, where technology is integrated into urban infrastructure to improve quality of life, enhance safety, and promote sustainable growth.

In addition to developing the core traffic control algorithm, the project also aims to establish a comprehensive framework for data collection, processing, and decision-making that can be extended to other intelligent transportation applications. This includes potential integration with emergency vehicle prioritization, pedestrian safety systems, and data analytics for urban planning.

In summary, the objective of this research is to create a practical, intelligent traffic management solution that not only addresses current congestion issues but also lays the foundation for future smart transportation systems. By leveraging AI and real-time data, the project strives to deliver a responsive, efficient, and environmentally friendly traffic control mechanism that benefits both city administrators and road users alike.

1.3 Thesis Contribution

In this thesis, our primary focus has been to address the key research questions outlined in the Objective section, particularly those concerning the real-time adaptability, accuracy, and efficiency of the proposed smart traffic management system. The results presented in this chapter reflect a thorough evaluation of how well the system meets these objectives, including its ability to detect and count vehicles accurately, estimate traffic density effectively, and dynamically adjust signal timings based on real-world conditions. Each outcome is critically analyzed to determine how the developed solution contributes to smarter, more sustainable urban traffic control in line with the goals of the Indore Smart City initiative.

1.4 Organization of Thesis

The thesis is organized into five chapters. A summary of each chapter is provided below:

Chapter 1 (Introduction)

In this chapter, we provide a concise summary of our research, including the foundational background necessary for understanding our work, the driving motivations behind it, the unique contributions of our thesis, and the overall organization of the subsequent sections.

Chapter 2 (Literature Survey)

In this chapter, we discuss the related work on this field. All the major techniques used for this purpose is explained in detail.

Chapter 3 (Methodology)

In this chapter, we discuss methodology for this project follows a structured six-step process to develop a real-time smart traffic management system. It begins with data collection from live traffic camera feeds, followed by preprocessing of video frames to create a clean, labeled dataset. A deep learning-based vehicle detection and counting model (like YOLO or SSD) is then trained to identify and count vehicles in real time. Using this data, the system estimates traffic density for each direction at intersections. A dynamic signal control algorithm then adjusts green light durations based on real-time traffic conditions. Finally, the system undergoes evaluation and testing, where its performance in reducing congestion and improving traffic flow is analyzed through real-time simulations and comparisons with traditional traffic systems.

Chapter 4 (Results)

In this chapter, we present and analyze the results obtained from the implementation of our proposed real-time smart traffic management system. The findings are discussed in detail to evaluate the system's performance across various parameters such as vehicle detection accuracy, responsiveness, and the efficiency of adaptive signal control. Through this analysis, we aim to demonstrate the effectiveness of our approach in improving traffic flow and reducing congestion in real-world scenarios.

Chapter 5 (Conclusion and Future work)

In this chapter, we conclude the work in our thesis and discuss the future directions of our research.

Chapter 2

Literature Review

Recent studies have highlighted the growing severity of traffic congestion in major Indian cities. According to a report by TomTom Traffic Index[16], metropolitan areas such as Bangalore, New Delhi, Mumbai, and Pune are among the most severely affected, experiencing substantial delays due to overburdened road networks. In response to such challenges, several researchers have proposed intelligent traffic management solutions leveraging emerging technologies.

Khushi et al.[5] introduced a video-based traffic management system in which live camera feeds are processed prior to transmission to a central server. A C++-based algorithm is then used to analyze the footage and generate results. Their study compares two processing methodologies—hard-coded versus dynamically coded—and demonstrates that the dynamic approach yields a 35% performance improvement, emphasizing the importance of flexible algorithm design in traffic systems.

Zaid et al.[20] explored the application of fuzzy logic for adaptive traffic light control. Their proposed system employs two fuzzy controllers, each designed with three inputs and one output, to independently manage traffic flow on primary and secondary roads. Simulations conducted in VISSIM and MATLAB revealed that the system significantly enhances traffic flow efficiency, especially under low-density traffic conditions.

Srivastava et al.[14] proposed an image-processing-based adaptive traffic light timer system. The architecture incorporates high-resolution image sensors, MATLAB for processing, and microcontroller-driven timers with UART-based communication. While the system successfully adapts to traffic density, it lacks features for emergency vehicle prioritization or accident detection at intersections, which are vital for real-world deployment.

Malhotra et al.[7] conducted a comparative analysis of leading object detection models, including R-CNN, Fast R-CNN, and YOLO. The study offers valuable insights into the advantages and limitations of each approach, highlighting YOLO's real-time detection capability as particularly suitable for traffic monitoring applications. This comparison serves as a foundation for selecting efficient detection algorithms in intelligent traffic management systems.

Farooq et al.[3] presented a pioneering adaptive traffic control system based on image processing techniques and GSM communication. Their system uses digital cameras strategically placed at intersections to continuously monitor traffic density. The visual data is processed in real time to determine vehicular load and adjust traffic signal durations accordingly. The integration of GSM technology facilitates communication with a central traffic control center, enabling remote monitoring and system updates. This work highlights the scalability and low-cost implementation potential of intelligent traffic management solutions in developing regions with limited infrastructure.

Panda et al.[11] implemented an image processing-based solution for traffic signal optimization. Their approach focuses on analyzing live traffic footage to estimate vehicle density and dynamically adjust signal timings. Using standard filtering and edge detection techniques, the system identifies vehicular clusters and traffic flow trends. The authors demonstrated that their method reduces idle time at signals and enhances traffic fluidity, especially in urban settings where traffic volumes fluctuate throughout the day.

Klein et al.[6] conducted an in-depth evaluation of two major types of traffic monitoring technologies: overhead and in-ground detectors. Their comparative analysis assesses parameters such as installation cost, accuracy under varying weather conditions, and maintenance requirements. Results indicate that while in-ground sensors like inductive loops are more accurate, overhead detectors (e.g., cameras and radar) offer ease of deployment and broader area coverage. Their findings serve as a guideline for city planners and engineers in choosing the right detection technology based on the unique needs of urban or rural environments.

Tavladakis and Voulgaris[15] proposed a novel distributed adaptive traffic control architecture. Their system functions autonomously, making local signal decisions based on real-time traffic input without relying heavily on centralized coordination. The decentralized nature enhances system robustness and responsiveness, particularly in large cities with complex traffic patterns. Their work underscores the importance of scalable traffic solutions that can adapt to unpredictable road conditions and minimize signal delays.

Albagul et al.[1] introduced a sensor-based traffic light control system equipped with real-time decision-making capabilities. By employing infrared and proximity sensors to detect vehicular presence at intersections, their system dynamically adjusts light durations, thereby reducing unnecessary waiting time and fuel consumption. The study emphasizes how sensor integration can transform traditional signal systems into responsive, energy-efficient infrastructure, especially useful in regions experiencing high congestion variability.

Aye[2] developed a LAN-based traffic control network designed to synchronize multiple traffic signals using a centralized computing node. The system facilitates two-way communication between local traffic lights and a control center, allowing for real-time signal coordination and anomaly detection. This method not only reduces traffic delays but also provides a scalable framework for integrating future features such as emergency vehicle prioritization or pedestrian detection.

Wigan [18] provided a comprehensive review of image-processing applications in traffic engineering. He discussed how digital image techniques could be leveraged for a variety of traffic management tasks such as vehicle classification, road damage identification, and congestion pattern recognition. His study also laid the groundwork for incorporating machine vision into modern traffic surveillance and control systems, highlighting early innovations that paved the way for current AI-driven systems.

Choudhary et al.[8] (referred to as My et al. in IEEE) presented a low-latency, real-time traffic monitoring approach using camera-based vehicle detection. Their system leverages frame differencing and object tracking algorithms to count and monitor vehicles in dynamic traffic environments. The prototype implementation confirmed that such a system could function effectively in moderate traffic conditions, making it suitable for cities in developing countries looking for cost-effective smart traffic solutions.

Siyal et al.[13] explored a hybrid approach combining neural networks with image recognition to develop a smart traffic management system. Their model was trained to identify vehicle types, track motion, and predict traffic buildup. The neural-vision system offered higher accuracy in pattern recognition compared to conventional image processing, thus enabling more reliable traffic signal adjustments. This work demonstrates the potential of incorporating artificial intelligence into real-time traffic control for better prediction and responsiveness.

Chapter 3

Methodology

This section outlines the systematic approach employed in this project to develop an automated traffic control system using vehicle detection and counting. The methodology is divided into six sections, each detailing a specific aspect of the process. These sections encompass the techniques, tools, and processes utilized to achieve the project's objectives, including data collection, model training, implementation, and evaluation. By following this structured approach, we ensure that the system is robust, efficient, and capable of addressing the challenges of traffic management.

3.1 Model Selection

RCNN[9], Fast RCNN[19], SSD (Single Shot MultiBox Detector), and YOLO[17] are widely used techniques for object detection. While RCNN and Fast RCNN are slower compared to YOLO and SSD, which both excel in speed and efficiency, YOLO particularly excels in regression tasks over classification. SSD also performs well in real-time detection but may not match the speed of YOLO in certain scenarios. Both RCNN and Fast RCNN struggle with real-time detection capabilities, whereas YOLO and SSD are capable of performing real-time classification with impressive speed and accuracy.

Model	Frames Per Second (FPS)
YOLOv8	40-155
SSD	22-46
Faster R-CNN	5-7

Figure 3.1: YOLOv8 Performance Comparison.

The performance of different object detection models varies significantly in terms of frame rate, making some models more suitable for real-time applications. As shown in Figure 3.1, YOLOv8 achieves the highest frames per second (FPS) range, with values between 40 and 155 FPS. This is significantly higher than SSD, which operates at 22 to 46 FPS, and Faster R-CNN, which achieves only 5 to 7 FPS. This performance advantage makes YOLOv8 particularly effective for real-time vehicle detection in traffic monitoring systems

YOLOv8 builds on the advancements of YOLOv7, offering significant improvements in accuracy, speed, and usability. With an optimized architecture that enhances feature extraction and multi-scale detection, YOLOv8 achieves higher mean Average Precision while maintaining real-time processing capabilities, making it an ideal choice for diverse object detection applications.

3.2 Vehicle Detection System

The proposed system utilizes YOLOv8 for vehicle detection, offering an optimal balance of accuracy and processing speed. A custom-trained YOLOv8 model detects various classes of vehicles such as cars, bikes, tractors, heavy vehicles like buses and trucks. YOLOv8, built on the Darknet-53 backbone, is an advanced convolutional neural network (CNN) that efficiently performs feature extraction and real-time object detection. The algorithm processes the full image in a single pass, segmenting into regions and predicting the bounding boxes along with class probabilities for each segment as seen in Figure 3.2. The bounding boxes are refined based on the predicted probabilities, providing high accuracy and real-time performance, making YOLOv8 suitable for traffic management applications. To measure traffic density, the system calculates incoming and outgoing vehicles in real time, storing the vehicle count over the last 10 seconds to continuously assess traffic volume on each lane. Once the density is calculated, the system estimates the required green light duration for each lane using the Webster method.

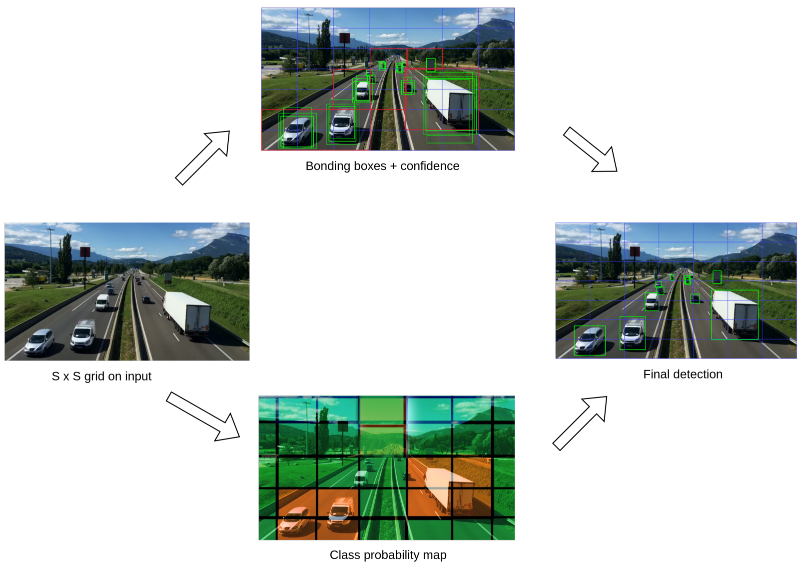


Figure 3.2: Predict bounding boxes and class probabilities in single pass.

3.3 Dataset

The Top-View Vehicle Detection Image Dataset [4] is tailored for YOLOv8 applications, especially beneficial for traffic monitoring and urban planning. This dataset comprises aerial, top-view images, which provide an effective perspective for accurately detecting and counting vehicles. This dataset captures vehicle behavior and traffic patterns from an aerial perspective, providing a comprehensive view that enables AI models to analyze traffic flow effectively. With annotations for various vehicle classes and a consistent image format, this dataset supports the development of robust models capable of making real-time predictions. This unique top-down view not only enhances the accuracy of vehicle detection but also offers insights into traffic dynamics that are difficult to achieve from traditional angles, making it essential for optimizing traffic management and infrastructure planning 3.3.

Specifications:

- Class: Vehicle.
- Total Images: 626
- Image Dimensions: 640x640 pixels
- Format: YOLOv8

Dataset Split:

- Training Set: 526 images, covering varied scenarios for comprehensive model training.
- Validation Set: 100 images, used to assess unbiased model performance.

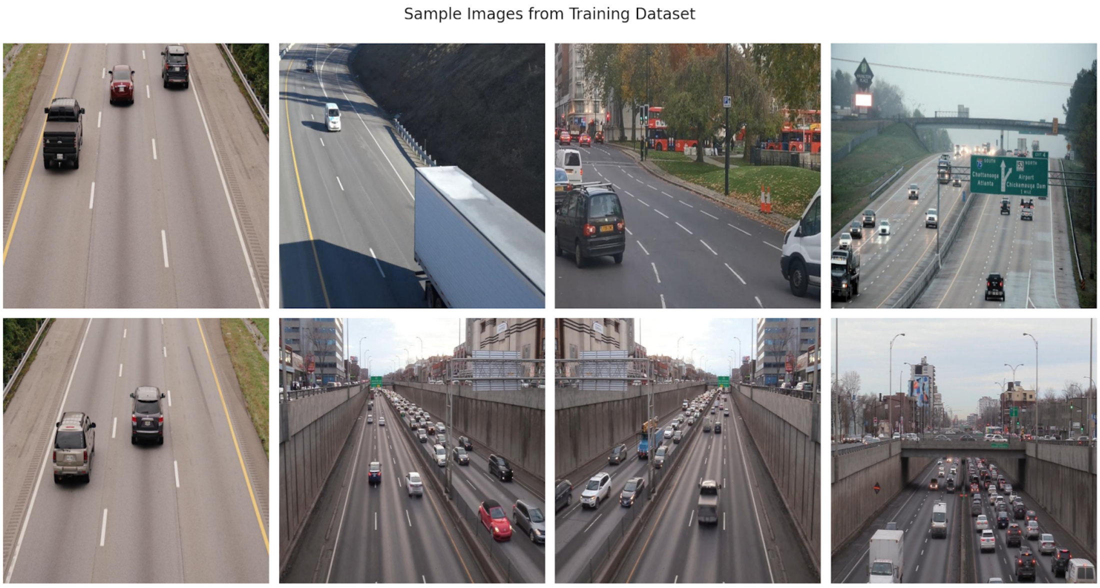


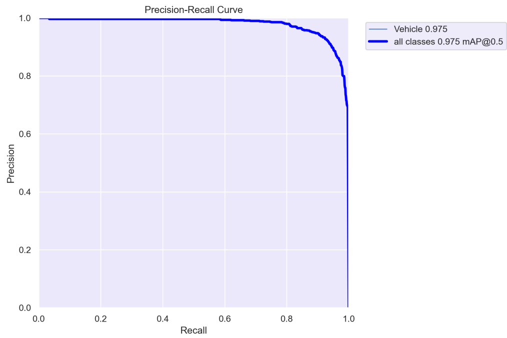
Figure 3.3: Sample Images from Training Dataset[4].

3.4 Transfer Learning

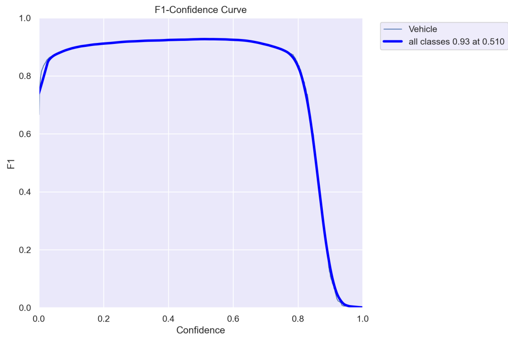
Fine-Tuning for Enhanced Detection Accuracy

To improve the model's performance, transfer learning is employed, allowing the pre-trained YOLOv8 model to be fine-tuned for a more specialized task—detecting vehicles from aerial views. This involves retraining the model on a custom dataset that captures vehicles from top-down perspectives, optimizing it to handle the nuances of aerial imagery. The goal of this refinement is to achieve higher precision and recall, ensuring more accurate vehicle detection, even in complex scenarios like traffic monitoring or urban planning.

Through this method, the fine-tuned YOLOv8 model becomes highly specialized, significantly improving its ability to detect vehicles with greater accuracy and reliability from unique aerial angles, thereby enhancing its overall utility in real-world applications.



(a) Precision-Recall Curve



(b) F1-Confidence Curve

Figure 3.4: Precision-Recall Curve and F1-Curve for Vehicle Detection Model

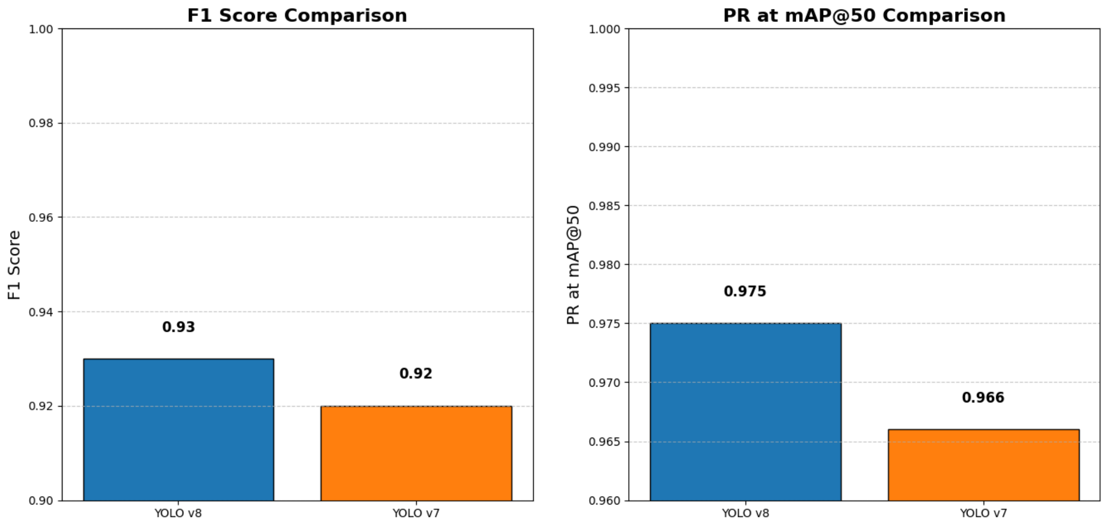


Figure 3.5: Comparison with previous YOLOv7 model.

As illustrated in Figure 3.5, YOLOv8 demonstrates a noticeable improvement over YOLOv7 when evaluated on our custom traffic dataset. Specifically, YOLOv8 achieves higher F1 scores and better Precision-Recall (PR) curves at mAP@50, indicating superior performance in terms of both precision and recall. This suggests that YOLOv8 not only detects a greater number of vehicles correctly but also minimizes false positives and false negatives more effectively. The improved F1 score reflects its ability to maintain a balanced trade-off between precision and recall, which is critical for real-time traffic monitoring applications where both detection accuracy and consistency are essential. Consequently, YOLOv8 proves to be a more reliable and efficient model for deployment in intelligent traffic systems that require fast and accurate vehicle detection under varying environmental and traffic conditions.

System Flow to Update traffic light timer

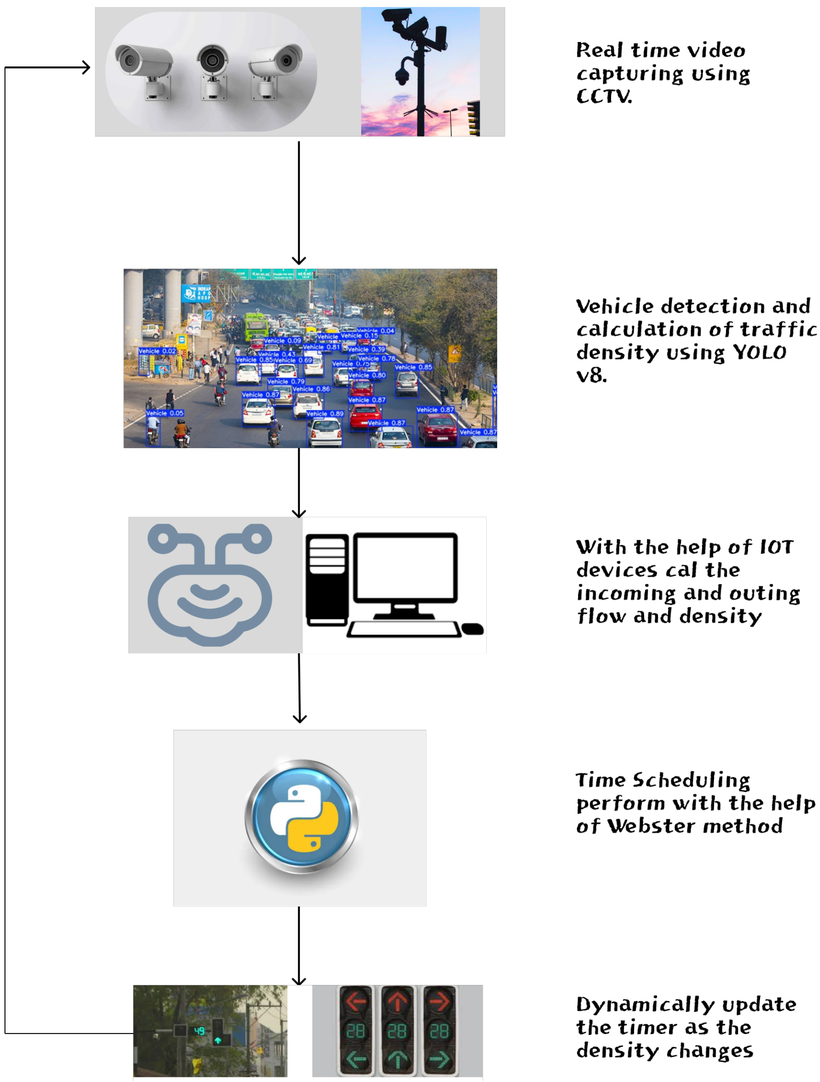


Figure 3.6: Flow Chart.

3.5 Counting the Incoming and Outgoing Flow

We have traffic coming from four different directions, and by using our fine-tuned vehicle detection model, we can accurately calculate the incoming and outgoing traffic for each phase. This allows us to determine the traffic density, or observed volume, for each phase. With this data, we calculate the saturation flow of the traffic, which is then used in the Webster method to determine the optimal cycle length for setting the most efficient signal timings at the intersection. As shown in Figure 3.7, our prototype at the four-way junction enables real-time calculation of traffic density per hour on each approach, storing this data for use in the Webster method. Additionally, it analyzes traffic flow to dynamically control signal timing based on density across phases.

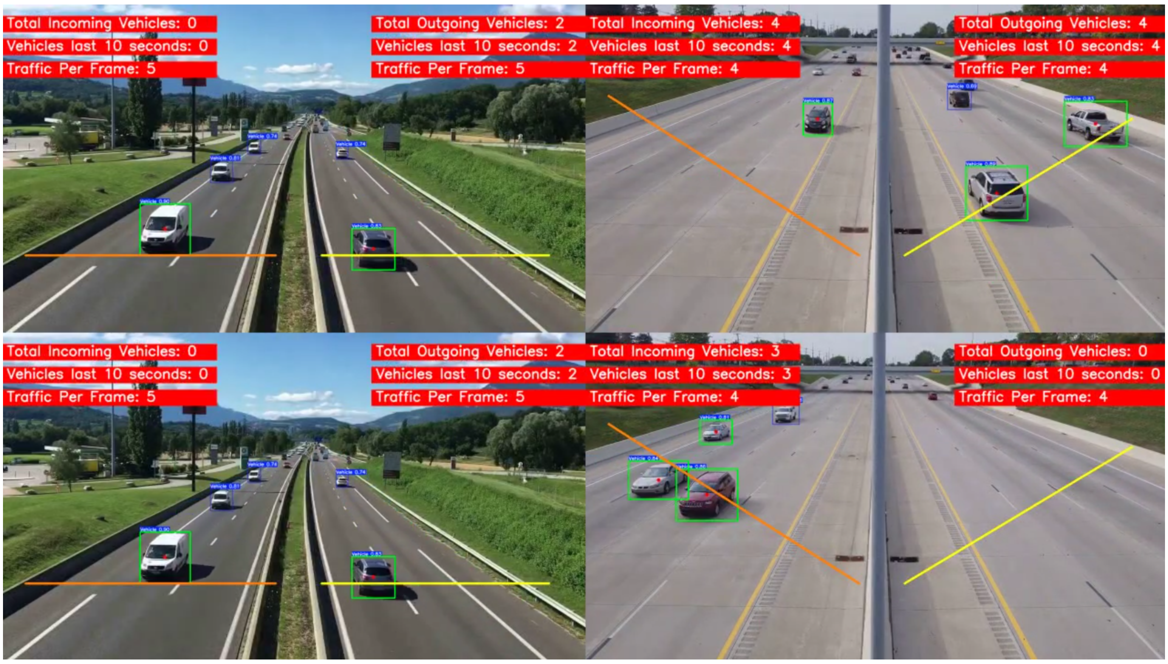


Figure 3.7: Calculating incoming and outgoing traffic flow at 4 way junction.

3.6 Webster Method for Traffic Optimization

The Webster method is a widely used traffic signal timing optimization technique developed by F.V. Webster in 1958. It focuses on optimizing traffic signal timings at intersections to reduce vehicle delay and traffic congestion. Here's how the Webster method is applied for traffic optimization:

3.6.1 Key Concepts

The method is based on the idea of minimizing delays by optimizing the cycle time of traffic signals. The cycle time is the total time taken for a complete sequence of signal phases (e.g., red, yellow, green). Webster's formula calculates the optimum cycle time based on several parameters like traffic flow, saturation flow, and lost time at an intersection.

With our vehicle detection model, we can now accurately calculate the traffic flow for each phase, which is a critical component of the Webster method. The other two parameters in this method are determined based on the type of intersection and can be set accordingly. Using these parameters, we can calculate the optimal cycle time, enabling more efficient and responsive traffic signal control.

3.6.2 Key Parameters

- **Saturation Flow (s)**: The maximum rate at which vehicles can pass through an intersection when the green signal is continuously on.
- **Flow Rate (q)**: The number of vehicles arriving at the intersection.
- **Lost Time (L)**: Time lost at the start of the green phase and during phase changes.

3.6.3 Steps to Apply the Webster Method

1. **Determine Flow Rates and Saturation Flows**: Measure or estimate the traffic flow and saturation flow rates for each approach at the intersection.

2. **Calculate Lost Time**: Estimate the lost time due to vehicles starting up and slowing down, usually around 2-3 seconds per phase change.

3. **Compute the Critical Flow Ratio**: Calculate the sum of the ratios y_i for all critical approaches.

4. **Calculate Optimum Cycle Time**: Use Webster's formula to determine the best cycle length C_0 that minimizes delays.

5. **Distribute Green Time**: Allocate green time for each approach based on the critical flow ratios.

The Webster method helps optimize traffic flow at intersections by adjusting traffic light cycle times based on traffic demand, leading to reduced vehicle delays and improved traffic management.

Using object detection to measure incoming and outgoing traffic flow, our system can determine the flow rate and critical flow ratio for each approach in the Webster method. These metrics are essential for calculating the optimal cycle length of a signal. The Webster method also includes additional parameters that are adjusted based on road type and phase structure. With our proposed model, we effectively calculate the key components of the Webster method, enabling accurate computation of optimal cycle time for traffic signals.

Chapter 4

Results

In this section, we present the results obtained from our experimental phase. We trained each of the models discussed here under identical conditions, utilizing the same dataset and a consistent hardware setup: Ubuntu 22.04.4 LTS, Intel Core i9-13900 CPU, and Nvidia GeForce RTX 3070 GPU. Alongside comparative accuracy metrics, additional comparisons are included to provide a clearer perspective on our objectives.

Figure 4.1: Detection Comparison before and after fine-tuning

4.1 Vehicle Detection Model Performance Evaluation

To evaluate the effectiveness of our YOLOv8-based vehicle detection model for traffic analysis, we analyzed the F1-Confidence and Precision-Recall (PR) curves, both of which highlight the model's ability to maintain high precision and recall.

- **Precision-Recall Curve 3.4a**:
  - The model attains a mean average precision (mAP) of **0.975** at an IoU threshold of 0.5, underscoring high detection accuracy across varying traffic densities.
  - High precision is maintained across most recall values, with a slight decline only at maximum recall, showing that the model consistently minimizes false positives.
  - The PR curve's near-flat shape confirms reliable performance, ensuring effective detection for real-time traffic monitoring.
- **F1-Confidence Curve 3.4b**:
  - The model achieves an optimal F1 score of **0.93** at a confidence threshold of **0.51**, providing a balanced trade-off between precision and recall.
  - The F1 score remains above **0.9** within a confidence range of **0.3 to 0.7**, indicating consistent performance suitable for real-time applications.
  - At confidence levels above **0.8**, the F1 score drops due to a decline in recall, suggesting that high thresholds reduce false positives but may miss some vehicles, impacting traffic density measurements.

4.2 Traffic Flow Calculation and Model Performance

To assess traffic flow effectively, we utilized our fine-tuned model to analyze various phases, producing a normalized confusion matrix ??. This matrix demonstrates the classification performance of our model in identifying vehicles against background elements, providing insight into the model's accuracy and potential for real-world deployment.

4.2.1 Confusion Matrix Analysis

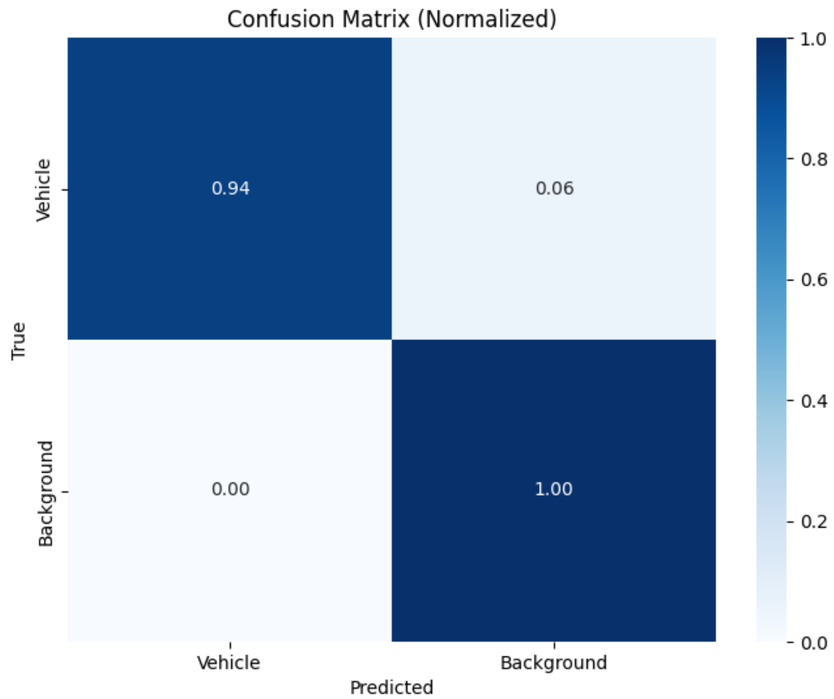


Figure 4.2: Normalized Confusion Matrix

- **True Positive (TP)**: 94% of vehicles were correctly identified by the model, which is reflected by the value in the top-left cell (0.94). This high TP rate indicates that the model is reliable in identifying vehicles accurately.

- **True Negative (TN)**: All background elements were correctly classified as non-vehicles, as shown in the bottom-right cell (1.00). A TN rate of 100% suggests the model is highly precise in not falsely classifying background elements as vehicles.
- **False Positive (FP)**: There were no instances of background elements being incorrectly identified as vehicles, indicated by the zero value in the bottom-left cell. This low FP rate is crucial for ensuring that the model does not overestimate traffic density by misclassifying background elements.
- **False Negative (FN)**: The model misclassified 6% of vehicles as background (top-right cell, 0.06). Although this FN rate is low, these instances represent a slight undercount in the traffic flow. However, this level of misclassification is within an acceptable range for real-time applications.

4.2.2 Practical Implications and Real-Time Suitability

The high true positive and true negative rates demonstrate that the model achieves a high degree of accuracy, making it suitable for real-time traffic flow analysis in urban environments. The minimal false positives ensure that non-vehicle elements do not interfere with traffic density calculations, while the low false negative rate suggests the model can reliably capture most vehicles. This robust performance means that our model can provide accurate traffic flow information, a critical component for dynamic traffic management systems. Such performance in identifying vehicles and non-vehicles accurately is essential for calculating optimal cycle times and adjusting signals in real time, leading to more efficient traffic management across various types of intersections.

Chapter 5

Conclusion and Future Work

In conclusion, the proposed system actively adjusts the green signal duration based on real-time traffic density, providing longer green signals to directions with heavier congestion and shorter ones to areas with lighter traffic. With the help of our fine-tuned model, we achieve precise vehicle counting, enabling accurate density calculations. This approach minimizes unnecessary delays, reduces congestion and waiting times, and ultimately lowers fuel consumption and pollution levels. Figure 7 illustrates the functionality of our prototype at the four-way junction.

5.1 Future Work

Although the current system lays a solid foundation for intelligent traffic signal control, there are several opportunities to enhance its capabilities and extend its functionality. By addressing additional traffic-related challenges, the system can evolve into a more holistic and robust traffic management platform. The following are proposed directions for future work.

1. **Traffic Violation Detection**

An important enhancement would be the integration of a traffic violation detection module. Beyond optimizing traffic flow, intersections are also critical points for monitoring road rule compliance. Using computer vision techniques, the system can detect violations such as vehicles running red lights, crossing stop lines prematurely, or making unauthorized turns. By implementing motion tracking and defining virtual boundaries (e.g., stop lines or lane boundaries), the system can identify when vehicles breach these limits during red signals.

Moreover, Automatic Number Plate Recognition (ANPR) can be used in conjunction with the violation detection module to identify and log license plate numbers of offending vehicles. These records can then be sent to enforcement authorities for issuing fines or warnings. Real-time detection of such violations can significantly improve road safety and compliance with traffic laws.

Additionally, this feature can help generate valuable analytics, such as the most common types of violations and peak times for rule-breaking behavior. These insights can be used to modify traffic enforcement policies or launch awareness campaigns in specific zones.

2. **Emergency Vehicle Prioritization**

   In critical situations, delays caused by regular traffic can be life-threatening, especially for emergency services like ambulances, fire trucks, and police vehicles. Integrating an emergency vehicle prioritization mechanism into the traffic control system would enhance public safety and save valuable time in emergency response.

   This functionality would involve detecting sirens or flashing lights, or using a wireless signal (e.g., from a GPS-equipped emergency vehicle) to communicate with the traffic control system. Once an emergency vehicle is detected approaching an intersection, the system can automatically adjust the signal timing to provide a green corridor, allowing the vehicle to pass through with minimal delay.

Implementing this feature would require real-time communication protocols, advanced sensor integration, and possibly coordination between vehicles and traffic infrastructure. While this adds complexity, it greatly enhances the responsiveness and social value of the system.

3. **Dynamic Route Optimization and Guidance**

   In addition to managing traffic flow at intersections, future versions of the system can include a feature for dynamic route optimization. By analyzing real-time traffic data from multiple intersections, the system can identify congested zones and recommend alternative routes to drivers via integration with navigation apps or in-vehicle systems.

   This would involve deploying a centralized traffic data analytics module that aggregates inputs from various intersections and road segments. Using AI-based routing algorithms, it can suggest the fastest or most fuel-efficient path for individual vehicles, depending on current traffic density, road conditions, and predicted congestion patterns.

   Dynamic routing helps distribute traffic more evenly across a city, preventing bottlenecks and improving overall traffic fluidity. It also enables proactive traffic management, where authorities can take measures to alleviate upcoming congestion before it escalates.

4. **Pedestrian and Non-Motorized Vehicle Detection**

Another potential enhancement is the inclusion of pedestrian and non-motorized vehicle (e.g., bicycle, e-rickshaw) detection. In urban environments, ensuring pedestrian safety is paramount. The system can be extended to detect pedestrians waiting to cross the road and allocate sufficient green time for them based on real-time demand.

This functionality may require the integration of additional sensors or overhead cameras dedicated to pedestrian crossings. For example, heatmaps or clustering techniques can be used to detect groups of pedestrians. Similar logic can be applied to detect bicycle or two-wheeler lanes to prevent conflicts between motorized and nonmotorized traffic.

5. **Environmental Impact Monitoring**

   To further align with the goals of sustainable development, the system can be extended to monitor environmental parameters such as air quality and noise levels at intersections. IoT-based air quality sensors and decibel meters can be installed to collect data over time, allowing authorities to assess the environmental benefits of improved traffic flow.

   By correlating traffic patterns with pollution levels, cities can implement targeted interventions such as restricting heavy vehicles during peak hours, promoting electric vehicles, or redesigning traffic zones.

6. **Integration with Smart City Platforms**

   The long-term vision of this system is to serve as a key module within a comprehensive smart city framework. Integration with platforms such as city surveillance, emergency response units, and urban planning tools would make the traffic management system more powerful and interconnected. Real-time dashboards, alert mechanisms, and predictive analytics can be used by city administrators to make informed decisions and prepare for events such as parades, roadblocks, or festivals that may disrupt traffic.

Such an integration would also support mobility-as-a-service (MaaS) platforms, public transport coordination, and shared mobility services such as ride-hailing or bike-sharing schemes. The more interconnected the system becomes, the more value it can provide in terms of efficiency, safety, and citizen convenience.

5.1.1 Closing Remarks

The work presented in this thesis demonstrates the promising potential of combining artificial intelligence with traffic control to create adaptive, responsive, and intelligent infrastructure solutions. By focusing on real-time data, computer vision, and automation, we have built a system that not only addresses current congestion issues but also lays the groundwork for future improvements that respond to the evolving needs of urban transportation.

Looking ahead, as smart cities continue to develop and the Internet of Things (IoT) becomes more widespread, traffic systems must evolve beyond basic automation to embrace holistic, intelligent decision-making. Our project represents a small but meaningful contribution to that future, one where roads are safer, travel is smoother, and cities are smarter.

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