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AI Powered Adaptive Traffic Signal Management Using Machine Learning

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ABSTRACT

Urban traffic congestion results in longer journey times, wastage of fuel, and increased air pollution. Traditional traffic signal systems operate on fixed timing and do not respond to evolving traffic conditions. To address this problem, machine learning (ML) and artificial intelligence (AI) are being implemented to create adaptive traffic signal control systems that can modify traffic signals in real time as per the flow of traffic. These smart systems review data recorded by sensors, cameras, GPS systems, and networked vehicles. By processing this information, they are able to identify traffic trends like peak hours, crashes, and events that cause congestion. Based on this knowledge, the system dynamically modulates signal timing to reduce waiting time and enhance vehicle flow efficiency. One of the most promising methods here is
reinforcement learning (RL). In RL systems, every traffic signal is an independent agent that discovers the best timing strategy by trial and error. The system learns from feedback on parameters such as vehicle queue length, average delay, and total traffic flow. With time, it learns to minimize delay and avoid road bottlenecks more effectively. Some cities, such as Pittsburgh and Los Angeles, have already been able to deploy such AI based traffic systems. The outcomes have indicated a decrease in travel time by as much as 25% and a reduction in vehicle emissions by over 20%. Such systems are also able to react effectively to the sudden occurrence of events like accidents, road blockages, or adverse weather, thus increasing traffic efficiency as well as road safety. In addition to this, AI-based traffic management has the ability to coordinate the coordination of multiple intersections in a complete network. It can provide priority to emergency and public transport vehicles, time synchronize with pedestrian signals, and help make cities safer and smarter. AI-traffic management can also integrate several intersections in a complete network. It can assign priority to emergency and public transport vehicles, time synchronize pedestrian signals, and help make cities smarter and safer.

KEYWORDS: Machine learning, Artificial Intelligence, Decision trees, Neural Networks, Traffic Prediction, Adaptive Traffic Signal Control.

I. INTRODUCTION

Traffic accidents in recent years have become a remarkable phenomenon in the world and the Hashemite Kingdom of Jordan as well, because of the speedy increase in the number of vehicles, population inflation, and the current political conditions surrounding Jordan, which forced millions of people to immigrate forcedly into Jordan (Forced Immigration). In addition, people are financially capable of owning vehicles, which put additional pressure on transport infrastructures and creates traffic jams in many locations, particularly in major cities. The public security directorate in Jordan revealed that the percentage of increase in registered vehicles throughout the last ten years was 96%, the growth within the variety of registered drivers was 82%, while for foreign vehicles reached an increase of 64%, and a recent report by Traffic management authority in Jordan stated that between 2014 and 2018, the growth of registered vehicles of 23%, which shows a significant increase in the number of vehicles on the road, along with a lack in infrastructure which led to traffic jams (Traffic congestion) .

Traffic congestion is a critical problem worldwide, and it is a significant problem for many countries, which affects the transportation system in many cities. In many cities, public transport has become convenient and reliable, and at the same time cheaper than small cars. However, using public transportation compared to small cars is still challenging because small cars are still faster and give the passenger more privacy and comfort. On the other hand, waiting and time loss is due to inefficient traffic lights timeslot. Therefore, we have to mitigate the issue, by developing traffic signal timing systems that can handle large numbers of vehicles and reduces the waiting time. Most transport systems are based on a pre-established timing system using models that do not respond well to variable demand. Currently, Computer science and engineering concepts such as Artificial Intelligence (AI), Machine Learning (ML), communications, the internet, and many other emerging technologies are coming together with the fields of civil and mechanical engineering research and development; to build what is called Intelligent Transportation System (ITS) .

Background

The limitations of conventional traffic control methods underscore the necessity for adaptive traffic signal systems. Fixed traffic light schedules fail to account for fluctuations in traffic density throughout the day, leading to suboptimal traffic flow, increased emissions, and prolonged waiting times at intersections. In contrast, adaptive traffic signal systems enhance efficiency by dynamically adjusting signal phases in accordance with current traffic conditions. Implementing such systems can improve road safety, reduce travel times, and better regulate vehicle movement within cities.

Problem Statement

Current traffic control technologies struggle to keep pace with the ever-changing dynamics of urban traffic. Factors such as accidents, construction work, and rush hour congestion can severely disrupt typical traffic patterns. Moreover, emergency vehicles like ambulances often face delays at traffic signals, hindering their ability to respond promptly in critical situations. The lack of prioritization for these vehicles within traffic signal systems complicates emergency management further. These issues highlight the urgent need for innovative solutions capable of adapting to shifting circumstances while ensuring efficient passage for both regular and emergency traffic.

Objective

This article aims to develop an adaptive traffic signal system rooted in machine learning that prioritizes emergency vehicles while optimizing traffic flow overall. The intended system will adjust traffic signal timings dynamically in response to present traffic conditions, utilizing machine learning and advanced data analytics. The primary goal is to minimize delays for all drivers while allowing emergency vehicles to navigate intersections promptly.

Motivation

The implementation of a machine learning-based adaptive traffic control system is of utmost importance. As urban areas continue to grow denser, enhancing traffic signal efficiency is crucial for minimizing delays and mitigating environmental impacts. Additionally, the ability for emergency vehicles to navigate quickly is vital for public health and safety. Such an adaptive system is key to fostering safer and more effective urban environments, improving traffic flow, prioritizing emergency services, and enhancing overall urban quality of life.

Overview of Approach

This paper outlines a comprehensive approach to developing an adaptive traffic signal management system that fuses machine learning algorithms with real-time traffic data. The system will analyze information from multiple sources, such as cameras and traffic sensors, to identify traffic patterns. By applying machine learning algorithms, the system can predict traffic conditions and adjust signal timings accordingly. Moreover, a mechanism for prioritizing emergency vehicles is incorporated to facilitate their passage with minimal delay. This dual focus not only addresses the complexities of urban traffic management but also boosts emergency response times

1.1. Automatic Traffic Management Technique

The first and most straightforward style of traffic management involves humans within the technique. In this traditional technique, police officers were the primary traffic control system, a traffic police officer stands on every road junction and tries to manage traffic flow using traffic signs. Over time, with the increasing number of cars, the dependence on humans has become insufficient to regulate traffic. Therefore, simple traffic signals replaced police officers to eliminate most weaknesses of the human-based traffic control system. The automatic traffic management technique includes three traffic light colors: red, green, and yellow, usually for every side 30 seconds of allowing passage. However, this could vary in some city areas and also depends on traffic volume. There are weaknesses in this automatic traffic management technique such as: Work statically for example, we need to wait for at least 30 seconds even if there is no traffic on other sides of the junction, which leads to wasting time. 2. It does not consider the traffic density on each side of the traffic junction or the importance of the roadside.

1.2. Intelligent Traffic Management Technique

Based on Image Processing This technique uses cameras, which capture the image of the traffic density on the road. These cameras are placed on a high pole so that they will envelop long distances. A processor chip to detect vehicles on the road analyzes the image captured by the camera, the processor then calculates the times for red and green signals to control and manage the traffic flow. This technique will allow a dynamic time slot for each side of junction, however sometimes, the camera cannot cover long distances in heavy traffic, or the captured images are unclear due to weather conditions. On top of that, vehicle length is not considered an input that makes small and big vehicles equal.

1.3. Traffic Management System using Internet of Things (IoT) Technologies

This technology is designed only to facilitate the movement of emergency vehicles at traffic lights and to give them the estimated time to pass. For example, if an ambulance faced a traffic signal, it sends wireless signals to a receiver installed on the signal pole, then the green light is lit according to the time set by the control unit, and the rest of the signals are closed. Once the estimated time to pass has ended, the normal system will be returned.

1.4. Intelligent Roadway Information System

Minnesota Department of Transportation developed a system called an Advanced Traffic Management system (ATMs). The idea of this system is to observe and handle the freeway traffic flow. The systems did not provide traffic information in the previous techniques and was only used to monitor traffic congestion. On the other hand, Intelligent Roadway Information System (IRIS) delivers real-time information on road conditions to detect traffic accidents, manage traffic flow, and broadcast passenger information. The drawbacks of this method are costly and difficult to use in mixed traffic.

II. LITERATURE REVIEW

Artificial Intelligence (AI)–driven adaptive traffic signal control has emerged as a key solution for improving urban mobility, reducing congestion, and optimizing signal timings using real-time data. Traditional pre-timed traffic control systems lack the ability to respond to fluctuating traffic conditions, motivating researchers to develop intelligent, data-driven and optimization-based approaches.

Early work in smart traffic systems explored the use of expert rules to generate operational strategies for intersections. Nielsen et al. (1998) demonstrated that expert system rules could effectively guide turning movements and intersection data modelling, laying the foundation for intelligent reasoning systems. With advancements in sensing and connectivity, Neelakandan et al. (2021) incorporated IoT- based data to design a traffic prediction and signal control framework suitable for smart cities. Their system combined sensors, communication technologies, and computational intelligence to dynamically monitor traffic flows.

Parallel to IoT approaches, systematic studies by Jing et al. (2017) highlighted the significance of adaptive control in connected vehicle environments. Their review emphasized that data availability and communication technologies significantly enhance decision-making accuracy in signal control. Kim et al. (2023) implemented a real-time priority metric using measured traffic conditions, showing that adaptive mechanisms can effectively minimize delays and queue lengths.

At the intersection level, researchers have also focused on traffic load balancing. Zaghal et al. (2017) proposed a smart intersection strategy using load balancing algorithms to distribute congestion more evenly, improving throughput during peak hours. For developing countries, Mishra et al. (2023) introduced a fused-parameter model using crowdsourced data, demonstrating that affordable data sources can efficiently support adaptive signal decisions. In optimization-based research, Jovanović and Teodorović (2017) applied a Bee Colony Optimization approach for saturated and under- saturated intersections, achieving significant improvements in cycle planning compared to static methods.

Heuristic and evolutionary optimization methods have also been used in static cycle improvements.

Ahmed et al. (2018) presented an evolutionary computation technique to optimize cycle lengths, proving its effectiveness for pre-timed control where real-time data is unavailable. As urban traffic complexity increased, reinforcement learning (RL) gained traction due to its ability to learn optimal control policies through continuous interaction with the environment. Noaeen et al. (2022) provided a comprehensive review on RL-based urban traffic control, showing that RL models outperform traditional systems, particularly under dynamic and uncertain conditions.

Recent deep reinforcement learning (DRL) techniques further enabled advanced adaptive control strategies. Tian et al. (2024) proposed an active control method based on parallel control theory, enhancing the stability and responsiveness of traffic operations. Li et al. (2024) extended DRL for mixed-traffic environments involving connected and autonomous vehicles (CAVs), demonstrating improved coordination and reduced intersection delays. Surveys by Haydari and Yilmaz (2022) synthesized multiple DRL approaches and highlighted challenges such as training complexity, reward engineering, and multi-agent coordination.

Another important direction has been crowdsourced and wireless data integration. Agarwal et al. (2024) fused crowdsourced information into an adaptive wireless signal control architecture, significantly improving responsiveness in heterogeneous traffic environments. Cooperative systems have also been explored, with Chen and Englund (2016) presenting a survey on intersection management strategies capable of coordinating vehicle movements more efficiently than standalone signal-based systems.

More recently, Anirudh et al. (2022) implemented a DRL-based intelligent traffic control model that adapts signal timings based on real-time sensor inputs. Their approach showed promising results for Indian traffic conditions, characterized by heterogeneity and non-lane-based vehicle movement.

Overall, the reviewed literature shows a clear evolution from static, rule-based systems to advanced AI-driven, data-centric, and learning-based methods. IoT frameworks enable large-scale data acquisition, optimization algorithms enhance signal cycle efficiency, and reinforcement learning provides adaptive and autonomous decision-making capabilities. Future advancements are expected to integrate connected vehicles, multimodal transport data, and edge-computing architectures to further enhance real-time adaptability and reduce congestion across urban networks.

III.METHODOLOGIES

The proposed framework means to progressively change the hour of the traffic signal in view of a predetermined objective to lessen the blockage of traffic out and about, thus diminishing the time an individual needs to hold up in rush hour gridlock. The framework depends on an AI calculation which will push us to progressively change the hour of the traffic signal. The framework will show the recreation of the traffic clog changing persistently dependent on the dynamic time that is being given to the traffic signal dependent on noteworthy forecasts of traffic on that street.

Product Functions and Features

Initially, data preprocessing was performed by storing only those attributes (obtained from the API) that were prescriptory for further implementation of our model. Also, the immediate and vital preprocessing gait which is data cleaning was performed by getting rid of inconsistent values such as empty strings and zero-based values.

The dynamic of our model would then function as follows –

1. After the user ingresses the coordinates of the junction, the website would extract details of the particular junction using the HERE Maps API. These details are primarily provided in JSON (JavaScript Object Notation) format.
2. These details include the average speed of the vehicle, length of the road, the maximum speed of any vehicle on the road, and the jam factor (i.e., traffic density) on that particular stretch of road.
3. The distinct value proposition of the product would lie in the data which would be defined accordingly, as per the assumed direction of the traffic. This defined data would be segregated into multiple classes.
4. Using the self-implemented algorithm, the basis of which would lie in Naive Bayes, the traffic would get distributed to the surrounding lanes based on the threshold of the jam factor. This area would help us decide the number of vehicles extant for a given time.
5. The timer of the signal would be handled by calculating the amount of time required for a vehicle to pass which would ultimately depend on the area of the particular junction.
6. The output for the same would be demonstrated using a simulation of the junction.

Hardware Interfaces

Devices that support web browsers such as PCs, laptops, and handheld devices.

Software Interfaces

- The GUI that we will utilize is PyCharm, which is a Python IDE used to compose and investigate Python code.
- To save the information for preparing the model, we will utilize a MySQL Database.
- The Graphical User Interface (GUI) execution will be done in Django.
- We have picked Windows as our Operating System for improvement for its best help and ease of use.

User Interface

The Adaptive Traffic Control System screen displays shall conform to the Process Impact Internet Application User Interface Standard, Version 2.0. The web pages shall permit complete navigation and data selection and display using the keyboard alone, in addition to using mouse and keyboard combinations.

3.1 System Overview Using machine learning techniques

The suggested adaptive traffic signal system dynamically adjusts traffic signal timings in response to real-time traffic data. The architecture encompasses several critical components: data collection, processing, and decision-making.

1. **Data Collection:** Traffic data is collected from various sensors and cameras positioned at intersections.
2. **Data Processing:** The gathered data is processed and analyzed to identify significant patterns.
3. **Decision-Making:** Machine learning algorithms evaluate the processed data to optimize signal timings and prioritize emergency vehicle passage

3.1.2 Collecting Traffic Dataset Data Source:

Traffic video data is sourced from surveillance cameras, monitoring systems, or publicly accessible datasets, providing essential real-time traffic patterns for system training and evaluation.

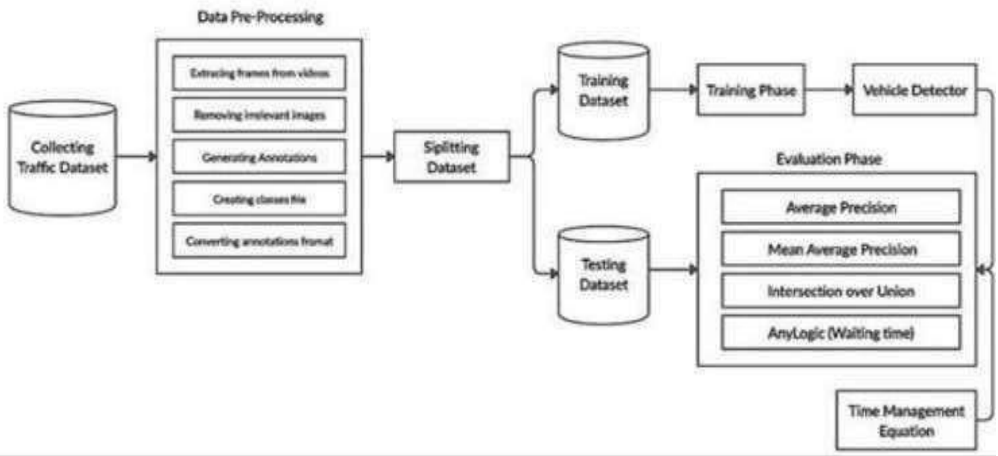

Fig: 3.1 System Architecture

3.3 Data Pre-Processing Frame Extraction:

Videos are divided into individual frames for easier analysis of traffic flow at specific intervals. Filtering Relevant Data: Frames void of pertinent traffic information, such as those depicting empty roads, are excluded. Annotation: Vehicles in frames are labeled to create data that indicates object locations and types (e.g., cars, trucks, buses). Description of Classes: To help the detection model, categories including vehicles, buses, and pedestrians are mentioned. Format Conversion: The annotated data is structured to align with Reinforcement Learning frameworks, transforming it into state information for the RL agent.

3.4 Dataset Splitting Training Set:

Used to train the RL model, enabling it to grasp how traffic patterns shift under varying conditions. Testing Set: Assesses how well the model generalizes to fresh, untested data.

3.5 Training Phase Reinforcement Learning Training:

Training data inputs allow the RL agent to learn signal adjustment strategies based on vehicle densities, wait times, and other traffic parameters. The RL model is designed to develop policies prioritizing reduced waiting times and improved traffic flow.

IV.SYSTEM ANALYSIS

4.1 Problem Analysis

Urban road networks are facing severe and increasing traffic congestion due to rapid population growth, rise in private vehicles, and expansion of commercial zones. Traditional fixed-time traffic signals operate on pre-programmed cycles that do not change according to fluctuating traffic conditions. As a result, long queues form during peak hours, while intersections with low traffic continue to receive unnecessary green-light time. This inefficiency leads to:

- Increased travel delays and poor traffic flow.
- Higher fuel consumption and unnecessary engine idling.
- Rise in air pollution due to long waiting times.
- Reduced road safety as congested intersections increase the probability of collisions.
- Inability to adapt to emergency situations such as ambulances or road blockages.

AI-powered adaptive traffic signal management aims to overcome these issues by using sensors, cameras, and machine learning algorithms to *analyze real-time traffic patterns* and change signal timing dynamically. Instead of relying on static rules, the system learns traffic behavior and optimizes signal cycles to minimize waiting time and improve overall traffic efficiency.

4.2 EXISTING SYSTEM

Fixed-time signals, human control, and a lack of real time data integration are still major components of urban traffic systems. Longer idle times, more fuel consumption, and greater emissions result from these antiquated methods' inability to adjust to shifting traffic circumstances. Additionally, they don't react quickly enough to accidents or emergency vehicle movements. While some employ CCTV, the majority do not use AI or computer vision, which results in the underutilisation of vital data. The lack of intelligent regulation causes chronic congestion in cities like Bengaluru. Current systems' rigidity and reactiveness lead to inefficiency, a bad commute, and a delayed emergency response. The objectives of contemporary smart cities are no longer met by traditional traffic models as the number of urban vehicles increases and sustainability becomes more pressing.

4.3 PROPOSED SYSTEM

The suggested AI-Powered Traffic Management System provides dynamic, data-driven traffic control by combining computer vision, machine learning, and the Internet of Things. It uses YOLOv8 to identify and categorise cars in real time from IP and CCTV footage. Traffic at junctions may be evaluated with the use of GPS and sensor data. Congested lanes are prioritised and traffic is rerouted as necessary using a Reinforcement Learning controller that dynamically modifies signal timings. Latency is decreased and cloud processing is offloaded via edge devices like the Raspberry Pi and Jetson Nano. Modules for incident detection, emergency prioritisation, weather-aware routing, and urban analytics are also included in the system. A dashboard that is updated in real time enables authorities to keep an eye on traffic and take appropriate action. This clever and scalable technology enhances public safety, reduces pollutants, and improves traffic flow in smart cities.

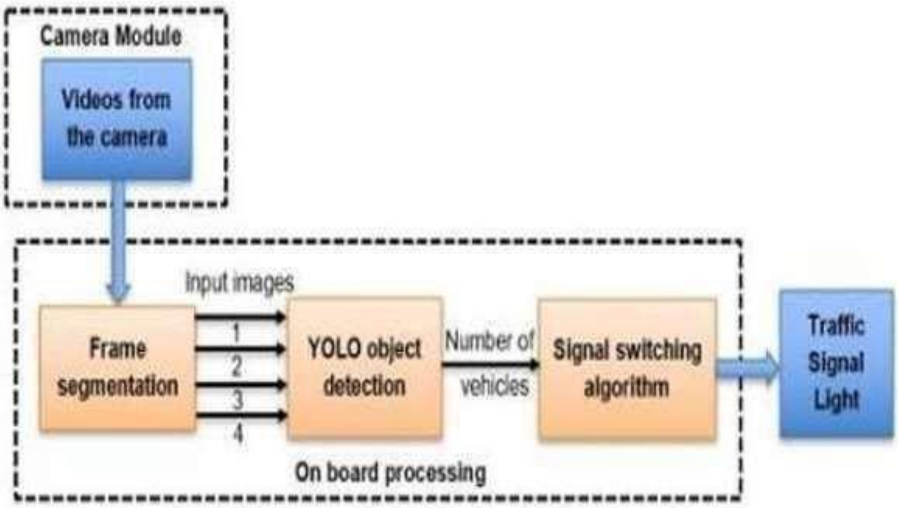

Fig: 4.1.1 Proposed block diagram

V.IMPLEMENTATION

5.1 SYSTEM ARCHITECTURE OVERVIEW

The implementation of the AI-powered adaptive traffic signal system follows a modular and scalable architecture. It integrates real-time data acquisition, machine learning-based decision- making, and dynamic signal control. The system consists of data collection units (cameras and sensors), a processing module, a reinforcement learning controller, and a signal execution unit. This layered structure ensures efficient traffic analysis and real-time adaptability at road intersections.

5.2 DATA COLLECTION AND INPUT SOURCES

Traffic data is collected using CCTV cameras, traffic sensors, and GPS-enabled devices placed at intersections. Video streams are used to capture live traffic conditions, including vehicle count, queue length, and traffic density. Environmental parameters such as time of day and emergency vehicle presence are also considered. These inputs provide the raw data required for intelligent traffic signal decision-making

5.3 VEHICLE DETECTION MODULE

A deep learning–based object detection model (such as YOLO) is used to identify and classify vehicles from traffic images. The model detects different vehicle types and counts them accurately in each lane. This real-time detection plays a critical role in estimating traffic density and congestion levels at intersections

5.4 EMERGENCY VEHICLE PRIORITIZATION

The system includes a priority mechanism for emergency vehicles such as ambulances and fire engines. When an emergency vehicle is detected through sensors or signal inputs, the system overrides normal signal operation and provides a green corridor. This ensures faster emergency response and improves public safety.

5.5 REINFORCEMENT LEARNING-BASED SIGNAL CONTROL

The core of the implementation is the reinforcement learning (RL) controller. Each traffic signal acts as an intelligent agent that observes the current traffic state and selects optimal signal timings. The RL model learns through continuous interaction with the environment by receiving rewards based on reduced waiting time, minimized queue length, and improved traffic flow. Over time, the system learns optimal signal strategies for varying traffic conditions.

5.6 HARDWARE AND SOFTWARE IMPLEMENTATION

The system is implemented using Python for machine learning and data processing. OpenCV is used for image and video analysis, while Django provides a web-based interface for monitoring traffic conditions. A MySQL database stores traffic data and system logs. Edge devices such as Raspberry Pi or Jetson Nano can be used for real-time processing to reduce latency.

VI.RESULTS

The Performance of Vehicle Detection Mean Average Precision (mAP) is a metric used to evaluate the performance of object detection models. Average Precision is calculated as the weighted mean of precisions at each threshold. mAP is calculated by summing the Average Precision (AP) of all classes and dividing by their number. We tested our vehicle detector on the test dataset to calculate the Average Precision for each class and the mAP for all classes. We assumed the prediction is correct if (IoU $\geq$ 0.5) where Intersection over Union (IoU) denotes to Junction over Union.

Fig 5.1: Sample of tested images showing the detected vehicles.

VII.CONCLUSION

The AI-powered adaptive traffic signal management system effectively overcomes the limitations of fixed-time traffic control by using machine learning to respond to real-time traffic conditions. The system reduces vehicle waiting time, improves traffic flow, lowers fuel consumption, and enhances road safety. Its adaptive and data-driven nature makes it suitable for modern smart city traffic management.

VIII.FUTURE ENHANCEMENT

Future development of the AI-powered adaptive traffic signal system can focus on expanding its intelligence, coverage, and reliability. Advanced deep reinforcement learning models can be introduced to enable coordinated decision-making across multiple intersections instead of isolated control. Integration with connected and autonomous vehicles will allow direct communication with signals, improving response accuracy and safety. Incorporating real-time weather data, pedestrian movement, and public transport schedules can further optimize signal timing. The system can also be enhanced using edge–cloud architectures for faster processing and scalability. Additionally, predictive analytics can be applied to anticipate congestion in advance, helping city authorities proactively manage traffic and reduce environmental impact.

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