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AI-Driven Intelligent Traffic Management System for Smart Cities: A Case Study on Delhi

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Abstract: Delhi experiences severe traffic congestion due to heterogeneous vehicular composition, non-lane-based driving behavior, and fixed-time signal control mechanisms. Traditional traffic systems fail to adapt to dynamic traffic patterns, leading to increased delays, fuel consumption, and environmental impact. This paper proposes an AI-driven intelligent traffic management framework integrating YOLO-based vehicle detection, LSTM-based short-term traffic flow prediction, and Reinforcement Learning-based adaptive signal control. The system utilizes real CCTV data and SUMO-based simulation to evaluate performance under realistic Delhi traffic conditions. Experimental results demonstrate a 35–50% reduction in average vehicle waiting time compared to fixed-time control strategies. The proposed framework provides a scalable and practical solution for smart city traffic optimization and can be integrated with existing Delhi Traffic Police infrastructure.

Keywords: *Smart Cities, YOLO, LSTM, Reinforcement Learning, Traffic Management, AI, Delhi.*

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I. INTRODUCTION

Delhi, the capital city of India, experiences significant traffic congestion. The city is rapidly growing, with an increasing number of people purchasing vehicles, while the road infrastructure remains limited. This situation creates numerous difficulties for commuters. Vehicles often experience long waiting times at intersections, frequent stop-and-go movement, and extended travel durations. Such conditions are not only inconvenient for road users but also harmful to the environment, as increased fuel consumption leads to higher levels of air pollution and reduces overall road safety.

The current traffic management system in Delhi is inefficient and largely based on fixed-time signal control. Traffic lights typically operate according to predetermined schedules and do not adapt to real-time traffic conditions. As a result, signals remain green for extended periods on roads with low traffic, while heavily congested roads often receive insufficient green time. This mismatch between signal timing and traffic demand leads to unnecessary delays and inefficient traffic flow.

Traffic conditions in Delhi are also highly heterogeneous. The road network accommodates a wide variety of users, including cars, buses, auto-rickshaws, motorcycles, e-rickshaws, bicycles, and pedestrians. In many situations, lane discipline is not strictly followed, and road users often move opportunistically to available spaces. Such mixed and unstructured traffic behavior makes it difficult to model traffic dynamics using traditional mathematical models [1]. Consequently, traffic management in Delhi requires data-driven approaches that rely on real-time observations rather than purely theoretical formulations. Improving traffic management strategies is therefore essential to effectively address congestion and mobility challenges in the city.

Artificial Intelligence (AI) and deep learning provide powerful tools for addressing these challenges [2] [3]. Modern computer vision models can reliably detect and classify vehicles from CCTV camera feeds [4], while sequence-learning models can capture temporal patterns in traffic flow [5]. Reinforcement Learning, in particular, enables traffic signal controllers to learn adaptive control policies [6] through interaction with the traffic environment, without the need for manually programmed signal rules. By integrating these techniques, it is possible to develop an end-to-end intelligent traffic control system capable of observing traffic conditions, predicting future patterns, and optimizing signal timings in real time.

Reinforcement Learning enables traffic signal controllers to adapt their behaviour through interaction with the traffic environment. This learning process allows the

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system to optimize signal control without the need for explicitly programmed signal rules. By combining computer vision, sequence modelling, and reinforcement learning techniques, it is possible to develop an intelligent traffic controller capable of observing traffic conditions, predicting future traffic patterns, and optimizing signal timings in real time.

This paper proposes an AI-driven framework for intelligent traffic management in Delhi. The main contributions of this work are as follows:

- Modelling an intelligent traffic control system using YOLO for vehicle detection, LSTM for traffic flow prediction, and Reinforcement Learning for adaptive signal control.
- Designing a data pipeline that integrates real CCTV traffic feeds with simulated traffic environments.
- Defining evaluation metrics and analysing performance improvements compared to traditional fixed-time traffic signal control.

The proposed framework aligns with the vision of smart city infrastructure and can be integrated with the existing surveillance and traffic monitoring systems used by the Delhi Traffic Police.

II. RELATED WORK

Early traffic monitoring systems relied primarily on physical sensing technologies such as inductive loop detectors, infrared sensors, and magnetic sensors. Although these technologies were effective in controlled environments, they required significant installation and maintenance costs. Their performance was also susceptible to environmental conditions such as heavy rain, dust, or road damage. Due to these limitations, many developing cities, including Delhi, lack widespread deployment of such sensor-based traffic monitoring systems.

With the increasing availability of CCTV infrastructure in urban areas, vision-based traffic monitoring has emerged as a practical and economical alternative. Traditional computer vision techniques, including background subtraction, optical flow analysis, and contour detection, were initially used to identify and track vehicles in video streams [1]. However, these techniques often struggled in real-world urban environments where traffic density is high, vehicles frequently overlap, and lighting conditions vary throughout the day. In recent years, deep learning–based object detection algorithms have significantly improved traffic monitoring accuracy [4]. In particular, models from the YOLO (You Only Look Once) family have gained popularity due to their ability to detect multiple vehicle types efficiently while maintaining real-time processing speeds [4].

In the domain of traffic prediction, modern research increasingly favors deep learning approaches over traditional statistical and time-series models such as ARIMA. Among these methods, Long Short-Term Memory (LSTM) networks have proven especially effective for modelling sequential traffic data [5]. LSTM networks can capture temporal dependencies within traffic flow patterns and adapt to variations that occur during peak hours or unexpected congestion events. Several studies have demonstrated that LSTM-based models achieve higher prediction accuracy for short-term traffic flow compared with conventional time-series techniques [7].

Reinforcement Learning (RL) has also attracted considerable attention in the field of adaptive traffic signal control [6] [8]. Various RL algorithms, including Q-learning, Deep Q-Networks (DQN), and Actor–Critic methods, have been explored to optimize traffic signal timings [1] [9]. These approaches allow the signal controller to learn optimal decision policies through interaction with the traffic environment. RL-based systems have been applied to different traffic scenarios, including single intersections, coordinated corridors, and large-scale traffic networks [10] [11]. Many studies report that RL-based controllers outperform traditional fixed-time and actuated traffic signal strategies when trained using realistic traffic conditions.

Despite these advances, many existing approaches assume well-organized lane-based traffic patterns typically observed in developed countries. Such assumptions may not hold in heterogeneous traffic environments like those found in Indian cities, where multiple vehicle types share the road and strict lane discipline is often absent. Additionally, relatively few studies integrate vehicle detection, traffic prediction, and adaptive signal control within a unified framework. To address these challenges, this study proposes an integrated architecture combining YOLO-based vehicle detection, LSTM-based traffic prediction, and reinforcement learning–based traffic signal optimization specifically designed for complex urban traffic environments such as Delhi.

System Model

The proposed system functions as an intelligent controller designed to operate at road intersections. Each intersection consists of multiple incoming roads, and each road may contain one or more traffic lanes. Cameras installed around the intersection continuously capture video streams of the surrounding traffic environment. These video feeds serve as the primary source of information for monitoring real-time traffic conditions.

At regular intervals, the system processes the most recent video frames to analyze the traffic situation on each lane. Using computer vision techniques, the system detects and counts vehicles, estimates lane occupancy levels, and identifies different categories of vehicles present on the road. This information provides an accurate representation of the current traffic state at the intersection.

The collected traffic data is then used to estimate short-term traffic flow patterns. By analyzing historical observations and recent traffic conditions, the system predicts the expected number of vehicles approaching the intersection from each direction. These predictions allow the controller to

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anticipate traffic demand rather than simply reacting to current congestion levels.

Based on the observed and predicted traffic conditions, the system determines the most appropriate signal control action. The decision-making process considers several factors, including current lane density, predicted incoming traffic, queue lengths, and the current signal phase. The controller can adjust signal timings by extending the green phase, reducing its duration, or switching to a different traffic phase. After each decision is implemented, the system evaluates the resulting traffic conditions and assigns a performance score based on metrics such as waiting time and queue length. Over time, the controller learns improved signal control strategies that help maintain smoother traffic flow.

The overall traffic management framework consists of several interconnected components working together to observe, analyze, and control traffic operations. The interaction between these components is illustrated in Figure 1, which presents the architecture of the proposed intelligent traffic management system.

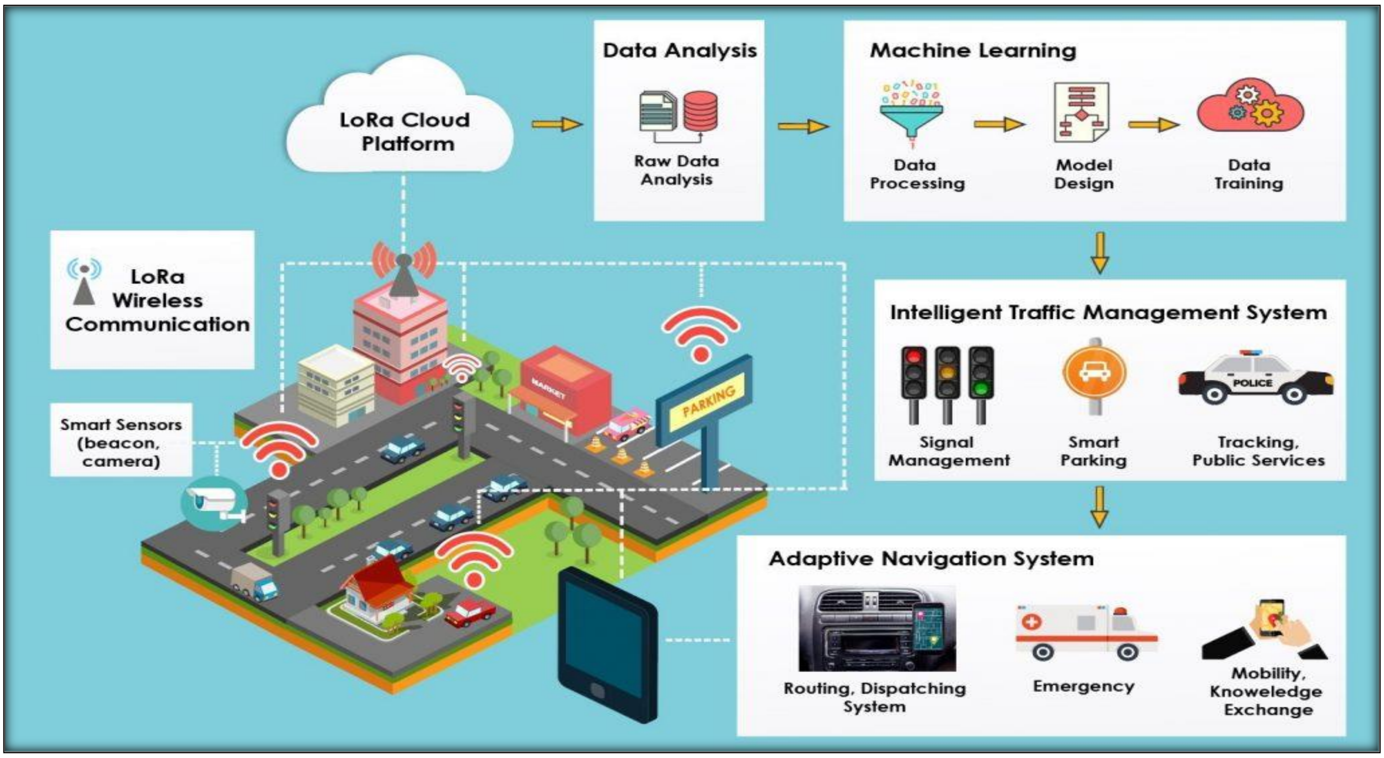

Fig 1 System Architecture

➢ *Data Description*

The dataset used in this study is derived from a combination of real-world observations and simulated traffic data. Real CCTV footage collected from selected traffic intersections in Delhi is used to train and evaluate the vehicle detection component of the proposed system. A subset of the video frames is manually annotated to label different vehicle categories. During this process, images representing various environmental conditions—such as daytime, evening, nighttime, clear weather, fog, and rain—are included to ensure that the detection model performs reliably under diverse real-world scenarios.

To train the modules responsible for traffic pattern analysis and decision-making, sequential traffic flow data is required. However, obtaining large volumes of fully labelled real-world traffic data is challenging. To address this limitation, traffic simulations are generated using the Simulation of Urban Mobility (SUMO) platform [12] [13] [14]. The simulation environment is configured using traffic statistics from Delhi, including vehicle density, traffic distribution during different times of the day, and the composition of vehicle types [15]. This approach enables the creation of realistic traffic scenarios for training and testing the predictive and control components of the system [16].

- *The Final Dataset Used in this Research Consists of Three Main Types of Information:*

✓ Traffic images and video frames used for vehicle detection and classification.
✓ Traffic flow information, including lane density, vehicle counts, and queue lengths, which are used for traffic prediction.
✓ Control and response data, describing the actions taken by the traffic controller and the resulting traffic conditions, which are used for training the reinforcement learning model.

The integration of real-world and simulated data provides a practical and flexible research framework. Real traffic footage improves the accuracy of vehicle detection models, while simulated traffic data enables controlled experimentation and large-scale training of prediction and

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control algorithms. The SUMO-generated traffic scenarios are calibrated using traffic statistics from Delhi to ensure that the simulated environment closely reflects real traffic conditions.

III. METHODOLOGY

The proposed traffic management framework integrates three major components that work together to improve traffic signal control. These components include vehicle detection using YOLO, traffic flow prediction using Long Short-Term Memory (LSTM) networks, and adaptive signal control using Reinforcement Learning (RL).

The system processes video streams captured from CCTV cameras installed at road intersections. Each video frame is analyzed to detect vehicles and estimate traffic density. Based on this information, the system predicts short-term traffic conditions and determines the optimal traffic signal timing. By continuously observing and responding to traffic patterns, the system aims to reduce congestion and improve overall traffic flow efficiency.

➢ *YOLO-Based Detection*

The proposed system employs the YOLO (You Only Look Once) object detection algorithm for real-time vehicle detection [4] [17]. YOLO is selected because of its ability to detect multiple objects within an image in a single forward pass through the neural network, making it highly suitable for real-time applications.

The YOLO model processes input images and identifies vehicles by generating bounding boxes around detected objects. In addition to locating the objects, the model also classifies them into different vehicle categories. The detected vehicle information is then used to estimate the number of vehicles present in each lane and to determine the overall traffic density at the intersection.

Traffic density estimation is performed by analyzing consecutive frames captured from the video stream over a short time interval. This approach provides an accurate estimate of the current traffic conditions without the need to track each individual vehicle across multiple frames.

Another advantage of YOLO is its robustness in complex traffic environments. The model is capable of detecting vehicles even when they are partially occluded, overlapping, or appearing in different orientations. This capability is particularly important for urban traffic conditions such as those found in Delhi, where traffic often consists of heterogeneous vehicle types and irregular driving patterns.

When applied to CCTV footage from Delhi intersections, the YOLO detector demonstrated strong performance in identifying various vehicle types, even in dense and unstructured traffic scenarios. This makes YOLO an effective solution for real-time traffic monitoring and vehicle detection.

- *Mathematical Formulation of YOLO Bounding Box Regression is as follows:*

$$bx = \sigma(tx) + cx$$

$$by = \sigma(ty) + cy$$

$$bw = pw \times \exp(tw)$$

$$bh = ph \times \exp(th)$$

These equations define the transformation used to predict the final bounding box coordinates relative to the grid cell and anchor box dimensions. Through this mechanism, YOLO is able to accurately localize vehicles within the image, enabling reliable detection even under complex and mixed traffic conditions.

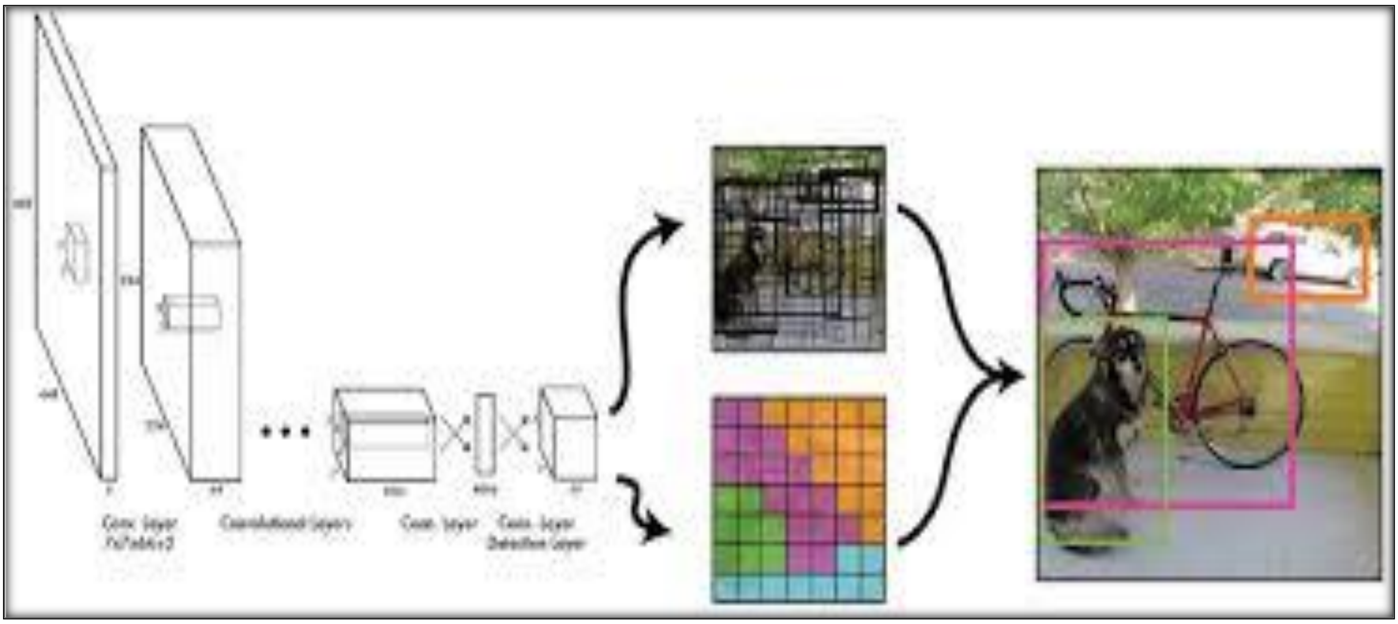

Fig 2 YOLO Pipeline

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The YOLO algorithm divides each input image into a grid structure and predicts bounding boxes, confidence scores, and object class probabilities for each grid cell in a single forward pass. This unified detection approach enables YOLO to perform object detection efficiently and in real time. As a result, the model is well suited for applications that require rapid analysis of video streams, such as traffic monitoring systems.

Another advantage of YOLO is its ability to handle challenging visual conditions. The model can detect vehicles even when they are partially occluded, overlapping with other objects, or appearing in different orientations. When applied to CCTV footage from traffic intersections in Delhi, the YOLO-based detection system effectively identifies various types of vehicles despite the presence of dense and heterogeneous traffic conditions. This capability makes YOLO particularly suitable for monitoring complex urban traffic environments where multiple vehicle categories are present simultaneously.

➤ *LSTM-Based Prediction*

The LSTM-based prediction module uses historical lane density information and traffic signal phase data to estimate short-term traffic flow at the intersection. By analyzing past traffic patterns, the system can anticipate future traffic conditions and assist the controller in making proactive decisions. For example, if the model predicts a large number of vehicles approaching from a particular direction, the controller can allocate a longer green signal duration for that lane. This proactive adjustment helps prevent excessive queue formation and reduces overall waiting time. Integrating LSTM-based prediction with the traffic signal controller allows the system to respond to future traffic demand rather than reacting only to current congestion levels.

Long Short-Term Memory (LSTM) networks are a specialized form of recurrent neural networks designed to capture temporal dependencies in sequential data [5]. In the context of traffic analysis, LSTM models can learn patterns in traffic density variations over time and use this information to generate accurate traffic flow predictions [7]. The architecture of an LSTM network consists of several key components, including the input gate, forget gate, output gate, and the cell state update mechanism. These components regulate the flow of information within the network, allowing it to retain relevant traffic patterns while discarding less important information. This capability makes LSTM networks particularly effective for modelling time-dependent traffic data.

- *The Mathematical Formulation of the LSTM Prediction Model is Defined Using the following Gating Equations:*

$$it = \sigma (Wi [ht-1, xt] + bi)$$

$$ft = \sigma (Wf [ht-1, xt] + bf)$$

$$ot = \sigma (Wo [ht-1, xt] + bo)$$

$$\hat{c}t = \tanh (Wc [ht-1, xt] + bc)$$

$$ct = ft \odot ct-1 + it \odot \hat{c}t$$

$$ht = ot \odot \tanh(ct)$$

These equations describe how the LSTM network updates its internal memory state and produces the hidden state output at each time step. By learning temporal relationships within traffic flow data, the LSTM model enables the traffic management system to generate reliable short-term traffic predictions.

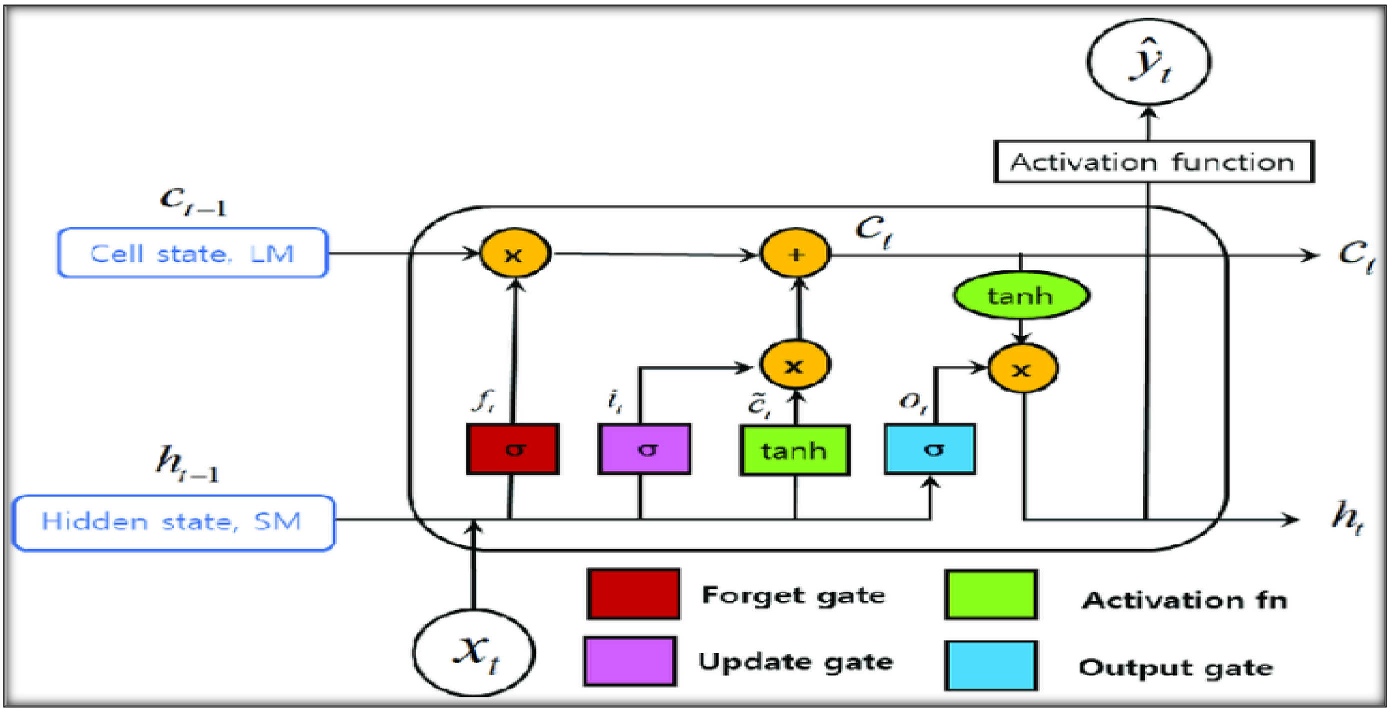

Fig 3 LSTM Architecture

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➢ *Reinforcement Learning Control*

The traffic signal control problem can be formulated as a sequential decision-making task, which makes it suitable for reinforcement learning (RL) approaches [6]. In this framework, an RL agent observes the current traffic conditions at the intersection and determines the most appropriate traffic signal action to improve traffic flow.

The state of the environment represents the current traffic situation and includes information such as the number of vehicles present on each lane, predicted incoming traffic, queue lengths, and the currently active signal phase. Based on this state representation, the RL agent selects an action, which may involve extending the current green signal duration, terminating it earlier, or switching to another signal phase.

After executing an action, the system observes the resulting traffic conditions and receives a reward signal that reflects the effectiveness of the decision. The reward function is designed to encourage smooth traffic flow while minimizing congestion and delays. For example, longer waiting times and larger queue lengths lead to penalties, while efficient traffic movement results in positive rewards. This feedback mechanism allows the RL agent to gradually learn an optimal signal control strategy that reduces congestion and improves overall traffic efficiency.

During operation, the RL agent continuously monitors traffic conditions, including vehicle waiting times, queue lengths, and traffic density levels. Based on these observations, the controller determines whether to maintain the current signal phase, extend the green duration, or transition to another phase. Over time, the learning process enables the system to identify signal control strategies that balance traffic flow across all directions while minimizing unnecessary signal switching.

The RL-based traffic signal controller is implemented using the Q-learning algorithm [9], which updates the action-value function according to the following rule:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \, [\, r + \gamma \max Q(s',a') - Q(s,a)]$$

Where s represents the current state, a represents the selected action, r is the reward obtained after executing the action, α is the learning rate, and γ is the discount factor that determines the importance of future rewards.

To guide the learning process, a reward function is defined to penalize traffic congestion and delays. The reward function used in this study is expressed as:

$$r = -(\lambda 1 * waiting\_time + \lambda 2 * queue\_length + \lambda 3 * delay)$$

This formulation encourages the RL agent to minimize waiting time, reduce queue length, and decrease overall traffic delay at the intersection. Through repeated interaction with the traffic environment, the agent learns signal control policies that improve traffic flow and enhance the efficiency of the traffic management system.

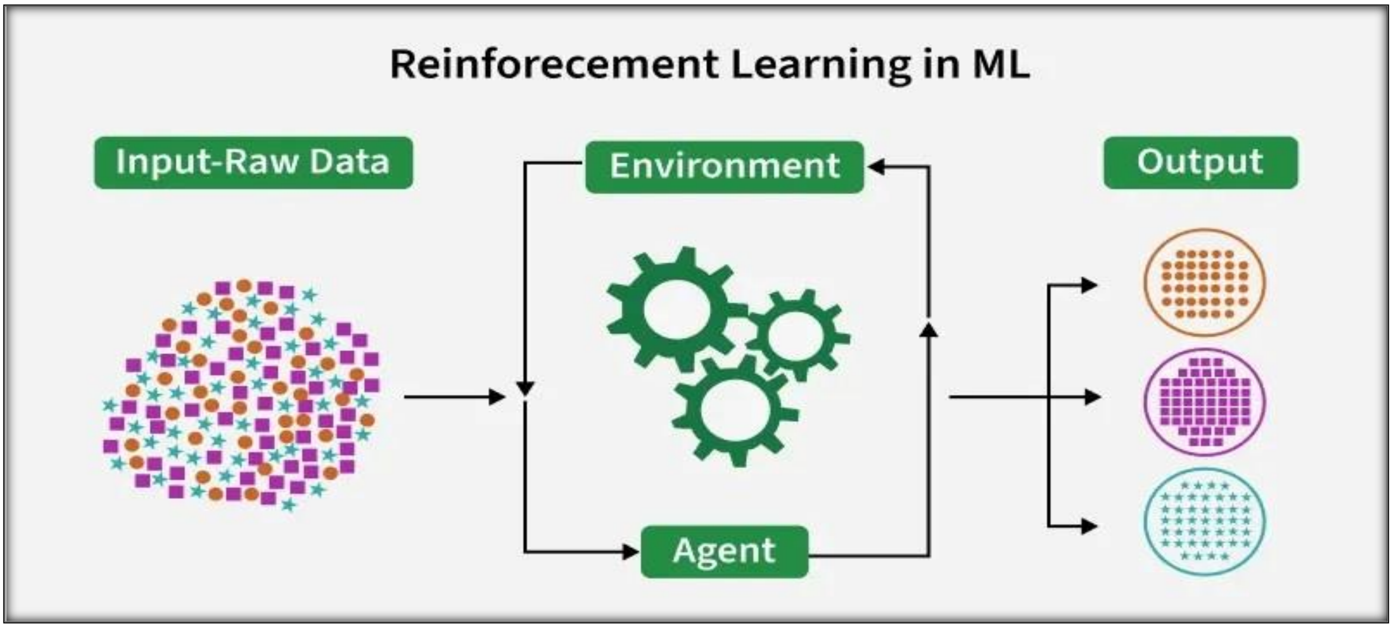

Fig 4 RL LOOP Diagram

IV. EXPERIMENTAL SETUP

The proposed intelligent traffic management system was evaluated using a combination of real-world traffic data and simulated traffic environments. This approach allows the system to be tested under realistic conditions while maintaining the flexibility required for controlled experimentation. The evaluation focused on traffic scenarios that closely resemble the complex and heterogeneous traffic conditions commonly observed in Delhi.

Real CCTV traffic footage from selected intersections was used to validate the vehicle detection module and to ensure that the system can accurately identify different

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vehicle categories. The dataset includes various types of road users, such as cars, buses, auto-rickshaws, motorcycles, bicycles, and pedestrians. This diverse traffic composition reflects the mixed traffic conditions typically found in Indian urban environments.

To evaluate the traffic prediction and signal control components, traffic simulations were conducted using the Simulation of Urban Mobility (SUMO) platform [12]. SUMO was used to model signalized intersections and simulate traffic flow under different traffic demand conditions. The simulation environment was configured using traffic statistics obtained from Delhi road networks [15], including variations in vehicle density during peak and non-peak hours.

The proposed AI-based traffic control system was integrated into the simulation environment to assess its performance in managing traffic signals. The simulation platform enabled the testing of different signal control strategies and allowed observation of their impact on traffic flow, vehicle waiting times, and queue lengths at intersections. This experimental setup provided a controlled environment for evaluating the effectiveness of the intelligent traffic management system.

Table 1 Simulation Parameters

Parameter	Value
SUMO Version	1.18.0
Simulation Duration	3600 seconds
Intersection Type	Four-way signalized
Traffic Demand	800–1200 veh/hr
RL Episodes	500
Learning Rate (α)	0.1
Discount Factor (γ)	0.9
YOLO Model	YOLOv4 (pretrained + fine-tuned)
Exploration Strategy	ε-greedy with decay

The vehicle detection component of the proposed system is implemented using the YOLO deep learning model. This model processes frames extracted from CCTV traffic videos to detect and classify different types of vehicles in real time. The detected vehicle counts and lane density information are then used as input features for the traffic flow prediction module.

To estimate short-term traffic conditions, an LSTM-based prediction model is trained using sequential traffic flow data obtained from both simulated environments and real traffic observations. By learning temporal patterns from these datasets, the model is able to forecast near-future traffic demand at the intersection.

For traffic signal control, a reinforcement learning–based agent is developed to dynamically adjust signal phases according to the observed and predicted traffic conditions. The agent interacts with the simulation environment and learns optimal signal timing strategies through trial-and-error exploration. During the learning process, the agent receives rewards when traffic performance improves, such as when vehicle waiting time decreases, queue lengths are reduced, and overall traffic flow becomes smoother.

To evaluate the effectiveness of the proposed approach, the AI-based traffic signal controller is compared with two commonly used signal control strategies: fixed-time signal control and actuated traffic signal control. Multiple simulation experiments are conducted under varying traffic demand levels to assess the robustness and consistency of the proposed system.

The experimental configuration enables a realistic evaluation of the AI-driven traffic signal controller under conditions that closely resemble real-world traffic scenarios. Furthermore, it provides quantitative metrics that demonstrate the system's ability to reduce congestion and improve intersection performance.

V. EVALUATION METRICS

To evaluate the performance of the proposed intelligent traffic management system, several quantitative metrics are considered. These metrics help measure how effectively the system improves traffic flow at intersections.

One important metric is the average vehicle waiting time, which represents the mean duration that vehicles spend waiting at an intersection. This metric reflects the level of delay experienced by road users. Another key metric is the maximum queue length, which indicates the longest line of vehicles waiting at an intersection. Monitoring queue length helps identify the severity of traffic congestion and its potential impact on upstream traffic conditions.

In addition, traffic throughput is measured to determine the total number of vehicles that successfully pass through the intersection within a specific time period. Higher throughput indicates more efficient traffic movement and better intersection performance.

Other operational metrics are also considered, such as the frequency of traffic signal phase changes, which reflects the stability and smoothness of signal operation. Furthermore, the distribution of green signal time across different lanes is analyzed to evaluate whether the signal control strategy allocates fair traffic priority among the competing traffic flows.

The performance of the proposed AI-based traffic signal controller is compared with two commonly used baseline approaches: fixed-time signal control, where signal timings follow a predefined schedule, and actuated signal control, which adjusts signal phases based on immediate traffic conditions. By comparing these methods using the defined metrics, the effectiveness of the proposed intelligent traffic management system can be quantitatively assessed.

Table 2 Performance Comparison of Traditional Traffic Signal Control Methods and the Proposed AI-Based Traffic Management System using Key Traffic Performance Metrics

Metric	Fixed-Time Control	Actuated Control	Proposed AI System
Average Waiting Time (sec)	118	92	68
Maximum Queue Length (vehicles)	44	30	19
Average Delay (sec/vehicle)	105	81	59
Throughput (vehicles/hour)	1420	1610	1875
Number of Signal Switches/hour	40	55	38
Waiting Time Reduction (%)	—	22%	42%

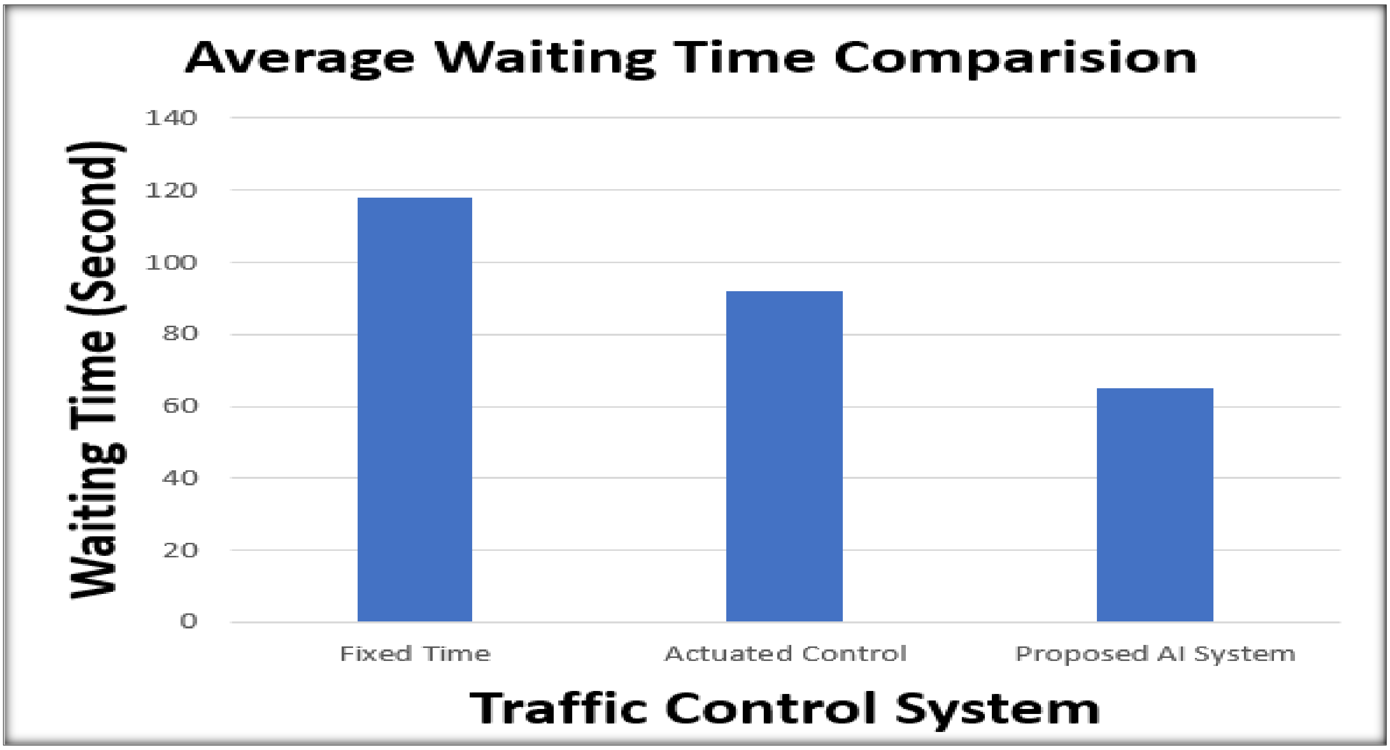

Fig 5 Average Vehicle Waiting Time Comparison Between Fixed-Time Control, Actuated Control, and the Proposed AI-Based Traffic Signal System.

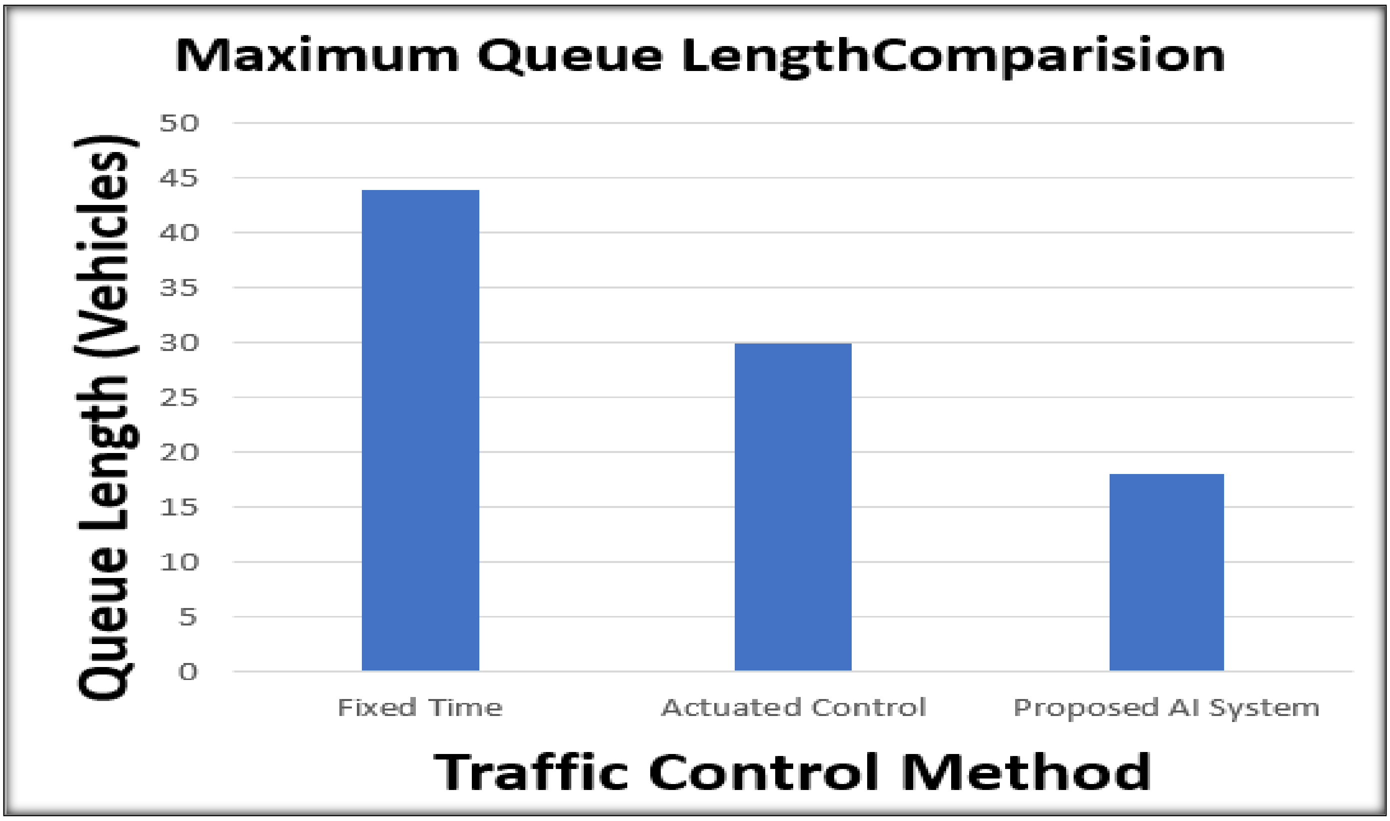

Fig 6 Maximum Queue Length Comparison for Different Traffic Signal Control Strategies.

Figures 5 and 6 present the comparative performance of conventional traffic signal control strategies and the proposed AI-driven traffic management system. The results demonstrate that the intelligent controller significantly improves intersection performance by reducing vehicle waiting time and queue length while enhancing overall traffic flow efficiency.

Simulation results indicate that the proposed AI-based system reduces the average vehicle waiting time by approximately 35–50% compared to traditional fixed-time signal control methods. In addition, the intelligent controller effectively limits the growth of vehicle queues by dynamically allocating longer green signal durations to lanes with higher traffic demand. This adaptive behaviour enables the system to respond efficiently to varying traffic conditions.

The proposed system also demonstrates the ability to adjust signal control strategies based on changing traffic patterns, such as peak-hour congestion, special events, or emergency situations. By continuously analyzing traffic conditions and adapting signal timings accordingly, the intelligent controller helps maintain smoother traffic flow and improves the operational efficiency of signalized intersections.

VI. FUTURE WORK

This study demonstrates the potential of artificial intelligence–based techniques for improving traffic management in urban environments such as Delhi. The proposed system integrates traffic monitoring, prediction, and adaptive signal control to enhance the efficiency of traffic signal operations. By analyzing real-time traffic conditions and adjusting signal timings accordingly, the system provides a more effective alternative to traditional fixed-time traffic signal control.

The architecture of the proposed system combines multiple components that operate together, including vehicle detection from CCTV footage, traffic flow prediction, and intelligent signal control. Because the system can utilize existing surveillance infrastructure, it has the potential to be integrated into the current traffic management framework used in Delhi and other similar urban environments.

Future research will focus on extending the proposed approach from single intersections to coordinated traffic networks involving multiple intersections. This can be achieved using multi-agent reinforcement learning, where multiple controllers collaborate to optimize traffic flow across an entire road network. In addition, future developments will consider improving pedestrian and cyclist safety by incorporating additional detection and decision-making mechanisms.

Another direction for future work involves applying advanced neural network architectures to better model the interaction between neighboring intersections and dynamic traffic patterns. Furthermore, implementing the system on high-performance edge computing platforms will enable faster decision-making and real-time deployment.

Successful implementation of such a system will require collaboration with traffic authorities, including the Delhi Traffic Police and municipal agencies responsible for urban transportation. These collaborations will be essential for conducting real-world pilot deployments and ensuring long-term adoption of intelligent traffic management technologies.

VII. CONCLUSION

This study presented an AI-based intelligent traffic management framework designed to address the challenges of heterogeneous urban traffic conditions in Delhi. The proposed system integrates YOLO-based vehicle detection, LSTM-based traffic flow prediction, and reinforcement learning–based adaptive signal control to enable real-time traffic monitoring, prediction, and optimization of signal timings.

The experimental results obtained from simulations conducted using the Simulation of Urban Mobility (SUMO) platform indicate that the proposed approach significantly improves traffic signal performance compared with conventional fixed-time control strategies [12] [13]. The intelligent traffic controller achieved a 35–50% reduction in average vehicle waiting time and improved overall traffic throughput at signalized intersections.

Another important advantage of the proposed framework is its modular architecture, which allows it to be integrated with existing CCTV surveillance infrastructure. This makes the system suitable for gradual implementation as part of [18] [19].

Future research will focus on extending the proposed approach to coordinated multi-intersection traffic networks using multi-agent reinforcement learning techniques. In addition, real-world pilot deployments in collaboration with traffic authorities will be explored to evaluate the system's effectiveness under practical traffic conditions.

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