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Reinforcement Learning (RL)-Based Adaptive Traffic Signal
Control with Emergency Vehicle (EV) Preemption Using
YOLOv12 and SUMO

Research Proposal

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1. Abstract

Urban traffic congestion remains a major challenge in modern cities due to rapid urbanisation and the increasing number of vehicles on the road. Many existing traffic signal systems still operate using fixed-time schedules, which are unable to adapt to real-time traffic variations. This often results in unnecessary delays, higher fuel consumption, and inefficient traffic flow, particularly during peak hours. Furthermore, most conventional systems offer limited support for emergency vehicles, which can negatively affect response times. This research proposes a smart traffic signal control system that combines reinforcement learning (RL), computer vision, and traffic simulation. A YOLO-based object detection model is used to monitor traffic conditions by identifying vehicles, estimating queue length, and detecting emergency vehicles. The extracted data is then used by an RL agent to adjust signal timings dynamically based on current traffic conditions. In addition, an emergency vehicle prioritisation mechanism is incorporated to allow faster movement through intersections by temporarily adjusting signal phases. The proposed system is tested using the SUMO simulation platform under different traffic scenarios, including high congestion and emergency situations. Performance is evaluated using metrics such as waiting time, vehicle delay, and traffic throughput. The expected outcome is improved traffic efficiency and reduced emergency response delays, contributing to smarter and more adaptive urban traffic management systems.

2. Introduction

2.1 Background

Traditional traffic signal systems were originally developed based on predictable traffic patterns, typically using fixed-time control or pre-defined schedules derived from pre-defined information. However, in reality, traffic flow is highly dynamic and often unpredictable, as it is affected by factors such as time-of-day variations, road incidents, weather conditions, and irregular events, including the movement of EVs [1].

ITS have emerged as a promising solution for improving urban traffic management. It integrates communication technologies, computer vision, AI, and real-time data analysis to improve traffic flow and transportation efficiency. One important application within ITS is adaptive traffic signal control (ATSC), which adjusts signal timings based on current traffic conditions instead of relying on static configurations, thereby improving overall intersection efficiency [2]. Earlier adaptive approaches mainly relied on hardware-based solutions such as inductive loop detectors and wireless sensor networks to measure traffic flow and queue lengths [3].

Recent advances in deep learning and computer vision have significantly improved traffic monitoring capabilities. YOLO (You Only Look Once) object detection models can perform real-time vehicle detection with high computational efficiency and detection accuracy. Modern YOLO-based systems can identify multiple vehicle categories, estimate queue length, and recognize EVs under complex urban traffic conditions [4].

At the same time, RL has become increasingly important in traffic signal optimization. It enables intelligent agents to learn optimal traffic control strategies through continuous interaction with the traffic environment. Deep RL methods such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) have demonstrated strong performance in adaptive traffic signal control applications [5].

ATSC systems are considered an important component of ITS because they dynamically adjust signal phases according to current traffic conditions rather than relying on static scheduling methods [6]. Although these methods can provide useful data, they are often expensive to install and maintain, and they do not offer detailed understanding of the traffic environment. In addition, they have limited capability in identifying specific vehicle types, particularly EVs. With recent advancements in computer vision and deep learning, camera-based solutions have become a more flexible and scalable alternative. Object detection models like YOLO (You Only Look Once) can process visual data in real time and provide detailed information about traffic scenes [7]. At the same time, RL has shown strong potential in solving sequential decision-making problems, including traffic signal optimization. RL-based systems learn effective control policies through interaction with

simulated environments, reducing the need for manually designed signal timing rules [8].

However, many existing RL-based ATSC approaches do not adequately consider EV prioritization, or they rely on simple rule-based mechanisms that limit their effectiveness in real-world scenarios [9].

Despite these advancements, many existing traffic systems focus either on traffic detection or traffic optimization independently. Few studies successfully combine computer vision, RL, EV prioritization, and real-time adaptive traffic management within a single framework. Therefore, this study proposes a unified intelligent traffic signal control framework integrating YOLO-based perception, RL, and SUMO simulation.

2.2 Research Problem

Although adaptive traffic control systems have improved significantly, a number of important issues remain.

- **Limitations of fixed-time and sensor-based systems:** Traditional signal control methods, including fixed-time scheduling and sensor-based approaches, are not flexible enough to handle sudden changes in traffic conditions. These systems often depend on costly infrastructure such as embedded sensors, and their rule-based nature makes them difficult to adjust in real time.
- **Insufficient support for EVs:** Many existing ATSC systems do not effectively prioritize EVs. In some cases, emergency handling is ignored altogether, while in others it depends on manual control or simple IoT alerts that lack real-time awareness of the surrounding traffic situation.
- **Disconnection between perception and decision-making:** Current research tends to treat detection and control as separate problems. Systems based on YOLO are mainly used for identifying vehicles but do not include intelligent control mechanisms. On the other hand, RL models often use simplified or abstract traffic data and do not take advantage of real visual inputs from the environment.
- **Absence of an integrated framework:** There is still no widely adopted system that successfully combines real-time visual perception, learning-based traffic optimization, and EV prioritization. Existing RL approaches face difficulties when incorporating live perception data into their decision-making process.

As traffic conditions in urban areas become increasingly complex, the lack of a fully integrated and intelligent control system can lead to higher congestion levels, increased safety concerns, and slower response times for emergency services.

These limitations contribute to increased traffic congestion, longer waiting times, and delayed emergency response services [10].

2.3 Research Aim and Objectives

2.3.1 Aim

The aim of this research is to develop and assess an intelligent traffic signal control system that integrates computer vision techniques with RL. The proposed system will use a YOLO-based detection model to monitor traffic conditions in real time while applying RL methods to improve signal timing and ensure priority for EVs.

2.3.2 Research Objectives

- To review current traffic signal control approaches and identify their limitations, particularly in handling EVs prioritization.
- To develop a real-time detection module capable of identifying different vehicle types using a YOLO-based deep learning model.
- To build an RL model, such as PPO or DQN, that can learn optimal traffic signal strategies based on changing traffic conditions.
- To incorporate an EV priority mechanism into the learning framework so that signals can adapt immediately when such vehicles are detected.
- To test and analyze the performance of the proposed system using SUMO simulation, considering key metrics such as vehicle delay, queue length, traffic throughput, and emergency response time.



Figure 1: Traffic Congestion at a Complex Urban Intersection

This visualization of significant traffic congestion at a multi-lane, complex urban intersection highlights the inefficiencies and limitations of traditional, fixed-time traffic control systems.

2.4 Significance of the Research

This study offers value from both a theoretical and practical perspective. From an academic viewpoint, it addresses an existing research gap by bringing together traffic perception, intelligent decision-making, and emergency prioritization within a unified system. In practical terms, the proposed approach can contribute to smart city development by improving emergency response efficiency, reducing traffic congestion, and lowering fuel usage and environmental impact. In addition, the framework is designed to be scalable and compatible with future camera-based traffic management systems.

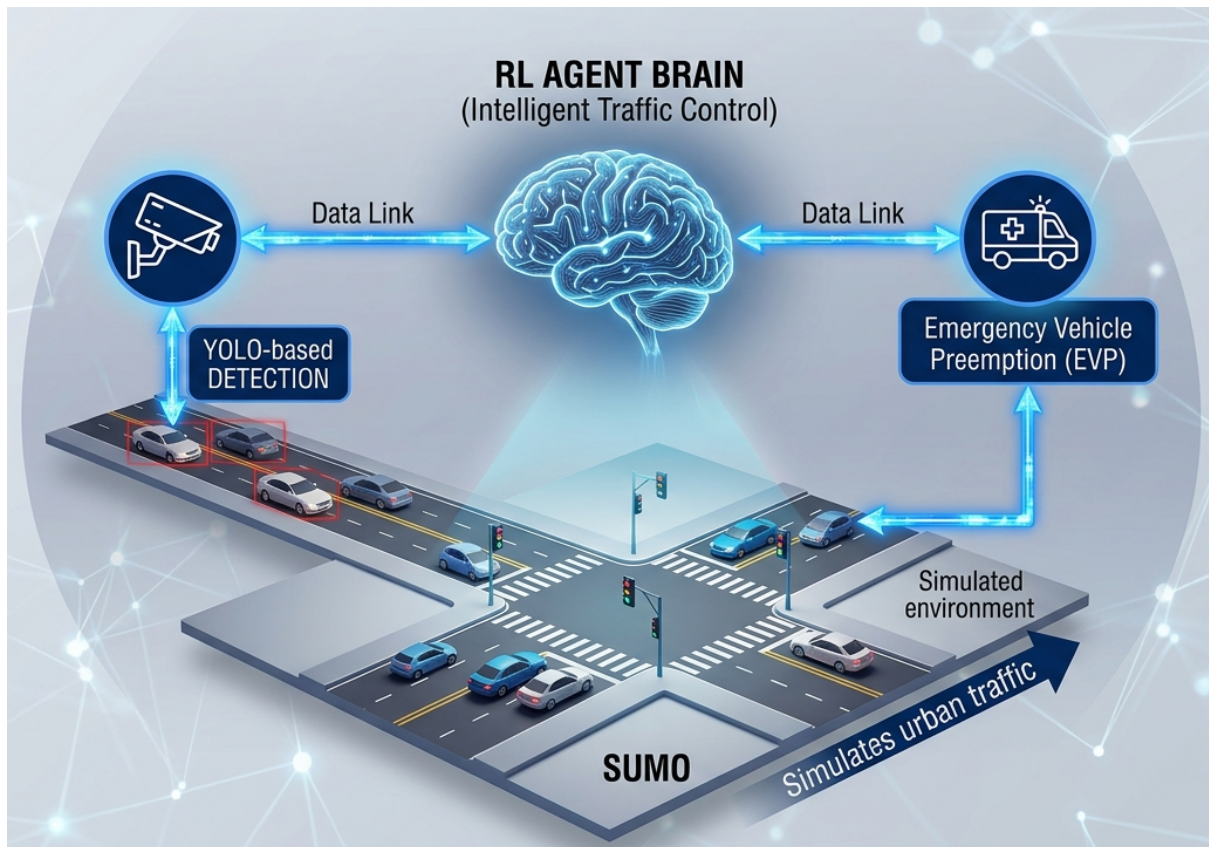


Figure 2: An Intelligent System

This conceptual diagram of the proposed intelligent traffic control (ITC) system. It features real-time detection of vehicles and EVs using YOLO, a RL agent (the 'intelligent brain') that dynamically adjusts signal timings, and an Emergency Vehicle Preemption (EVP) module, all integrated with a smart city data platform.

sectionLiterature Review

2.5 Overview and Scope

Research in intelligent traffic control has progressed significantly over the past two decades, shifting from fixed signal timing systems to more adaptive and data-driven approaches. Recent developments focus on integrating artificial intelligence, real-time data analysis, and computer vision to enhance traffic efficiency. This review examines key contributions related to traffic signal control methods, reinforcement learning techniques, YOLO-based detection models, and emergency vehicle prioritisation [11].

2.6 Conventional and Sensor-Based Traffic Control

Early traffic signal control systems primarily relied on fixed-time schedules and sensor-based monitoring, such as inductive loop detectors and wireless sensor networks [12]. These approaches were effective under predictable traffic patterns but struggled to adapt to dynamic environments. In many cases, they required expensive infrastructure and regular maintenance.

Although sensor-based systems improved traffic monitoring accuracy, they provided limited understanding of complex traffic behaviour. Moreover, emergency vehicle handling in such systems was often basic and dependent on predefined rules rather than intelligent decision-making. These limitations highlight the need for more flexible and scalable solutions.

2.7 Intelligent Transportation Systems (ITS)

Intelligent Transportation Systems (ITS) aim to improve mobility and reduce congestion through the integration of communication technologies, machine learning, and real-time data processing [11]. Modern ITS solutions focus on adaptive traffic signal control, where signal timings are dynamically adjusted based on current traffic conditions.

Recent studies show that AI-based traffic management systems can significantly reduce congestion and improve traffic flow [13]. However, challenges remain in scalability and real-world deployment, particularly in complex urban environments.

2.8 Reinforcement Learning for Traffic Signal Control

Reinforcement learning has emerged as a promising technique for traffic signal optimisation because it enables systems to learn optimal decisions through interaction with their environment [14]. Unlike traditional rule-based approaches, RL models continuously improve their performance by maximising a reward function, which typically reflects traffic efficiency metrics such as delay reduction and throughput improvement.

Methods such as Deep Q-Networks (DQN) and Proximal Policy Optimisation (PPO) have

been widely used in traffic control research [14, 15]. These approaches have demonstrated improvements in reducing vehicle delay and queue length compared to fixed-time systems [16]. However, many RL-based models rely on simplified traffic data rather than real-time visual inputs, which limits their effectiveness in realistic scenarios.

Recent research has explored multi-agent RL and hybrid models to improve scalability and adaptability [17]. Despite these advancements, integrating real-time perception data into RL decision-making remains a key challenge.

2.9 YOLO-Based Vehicle Detection in Traffic Systems

YOLO (You Only Look Once) models have significantly advanced real-time object detection by providing high accuracy with low computational cost [18]. In transportation systems, YOLO has been used for vehicle detection, traffic density estimation, and queue length measurement.

More recent versions, such as YOLOv8, offer improved performance in complex environments, including poor lighting and high traffic density [19]. While these models are effective for detection, many existing systems use them only for monitoring purposes and do not integrate them with intelligent control mechanisms.

2.10 Emergency Vehicle Priority Systems

Emergency vehicle (EV) prioritisation is an important aspect of modern traffic management. Traditional approaches rely on siren detection or communication-based systems, which may be unreliable in noisy or congested environments.

Recent studies have explored the use of reinforcement learning to dynamically prioritise emergency vehicles [17]. These approaches create adaptive signal changes that minimise delay for EVs while maintaining overall traffic efficiency. However, many existing solutions treat emergency handling as a separate module rather than integrating it into a unified control system.

2.11 Research Gap Summary

The literature highlights several important gaps. First, YOLO-based approaches are mainly used for detection and lack integration with adaptive control systems. Second, RL models often operate without real-time visual data, limiting their ability to respond to complex traffic situations. Third, emergency vehicle prioritisation is often handled separately rather than as part of a unified framework.

Therefore, there is a need for an integrated system that combines real-time visual perception, reinforcement learning, and adaptive emergency handling to improve traffic efficiency and responsiveness.

Table 1: Thematic Literature Review Overview

Theme	Sources	Key Findings	Research Gap
RL-Based Traffic Control	[14]–[17]	DQN, PPO, and attention-based RL improve traffic flow and reduce delay in urban intersections.	Limited integration of real-time visual traffic data.
YOLO-Based Vehicle Detection	[18]–[19]	YOLO enables real-time vehicle detection, queue estimation, and EV recognition.	Most systems focus on detection without adaptive optimization.
EV Prioritization	[17]	RL and computer vision reduce ambulance delay using adaptive green corridors.	Emergency traffic handling is often treated separately from signal optimization.
Smart City Integration	[11],[13]	ITS frameworks improve mobility using AI-based traffic optimization.	Scalability and real-world deployment challenges remain.

3. Research Design and Methodology

3.1 Research Design:

This research follows a simulation-based experimental methodology using the SUMO traffic simulation environment. SUMO is selected because it supports realistic microscopic traffic simulation and allows RL integration through the Traffic Control Interface (TraCI). SUMO also enables researchers to evaluate adaptive traffic management systems under different traffic conditions and urban road structures.

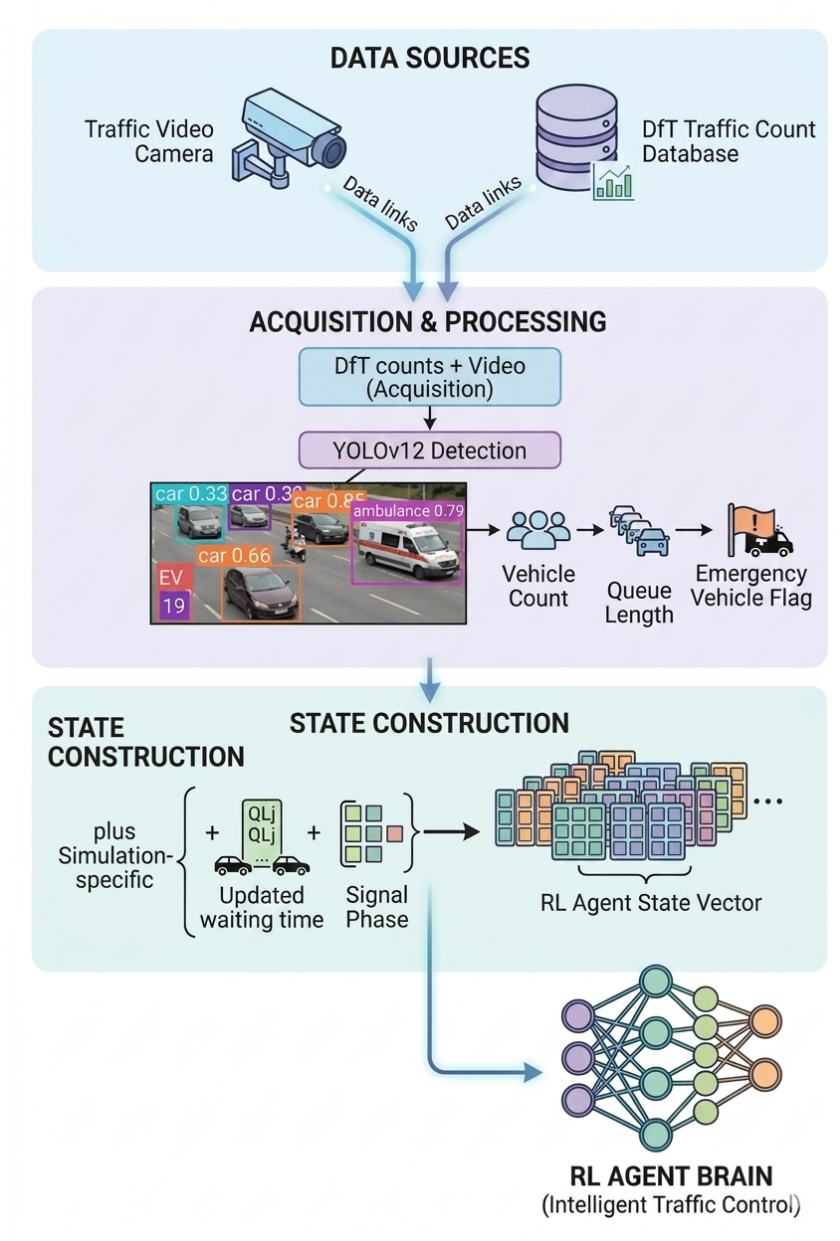


Figure 3: YOLOv12-Based Data Processing and RL State Construction for Traffic Control

The approach involves collecting multi-source data, processing it through an object detection model, constructing a comprehensive traffic state, and applying a learning-based agent to dynamically optimize traffic signals, including prioritization of EVs.

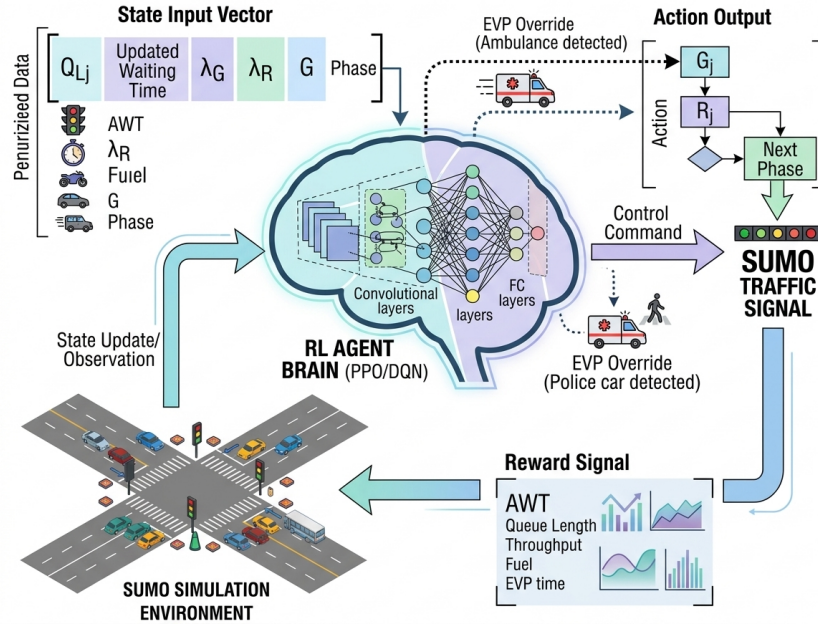


Figure 4: RL Control Architecture (Perception and Decision-Making).

Here is shown how real-time traffic information obtained from the perception module is transformed into a structured state representation. Key inputs, such as vehicle counts and waiting times, are used to form the agent's state. This state is then passed through an RL model, such as PPO or DQN, which determines the most appropriate signal control action. The mapping from state to action enables the system to optimize traffic signal timings based on current conditions.

3.2 RL Module

In this study, the traffic signal system is represented as an RL agent that interacts with its environment. The agent observes the current traffic conditions. Based on this information, it selects an appropriate action. The effectiveness of each action is evaluated using a reward function, which considers factors. For implementation and comparison, PPO and DQN are used, as both methods are widely adopted and have shown stable performance in traffic control applications [20], [21]. These algorithms are considered due to their strong performance in adaptive traffic management applications [22].

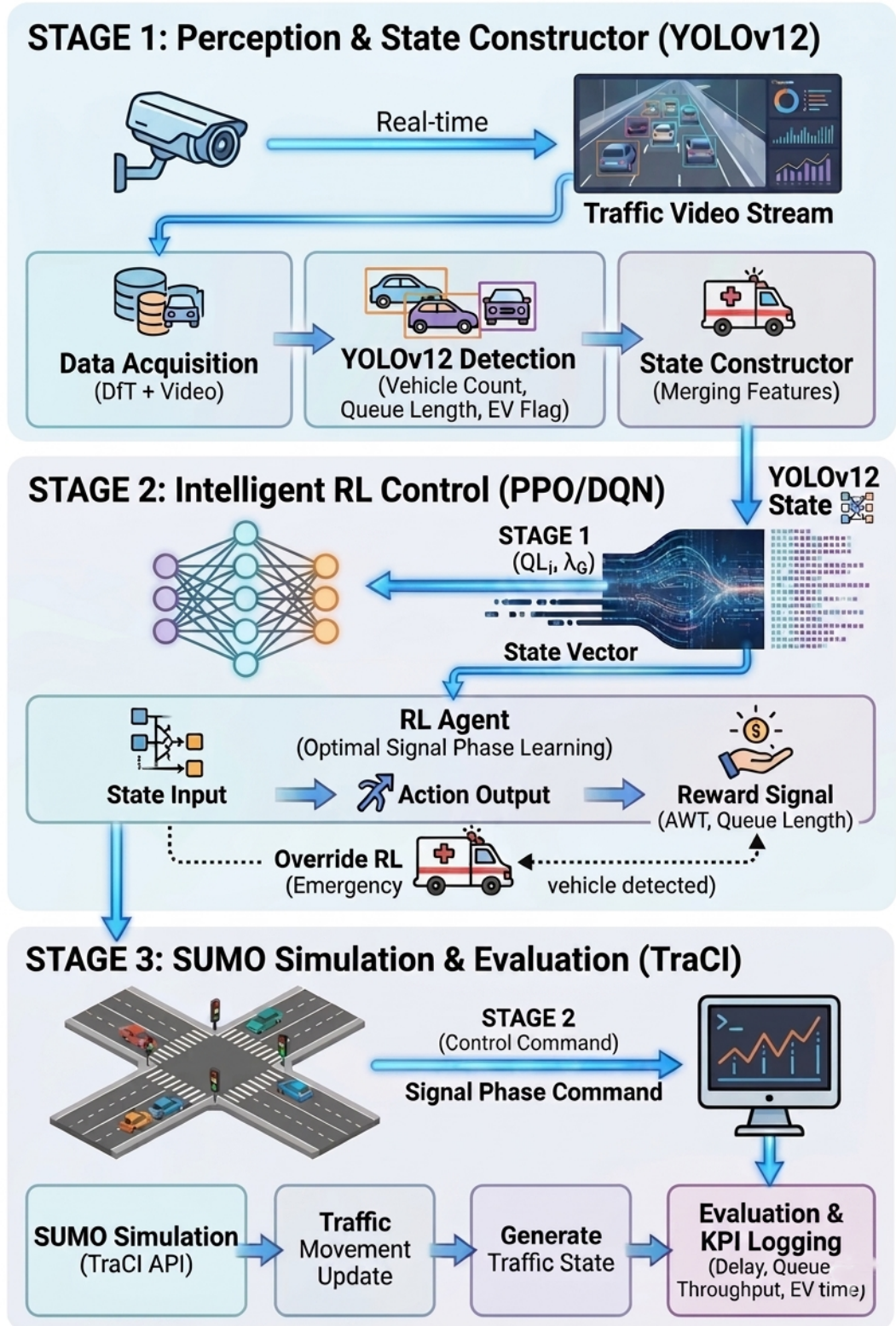


Figure 5: System Methodology Diagram.

This figure presents the overall workflow of the proposed intelligent traffic signal control system. The framework is divided into three major stages that work together to manage urban traffic more efficiently.

In the first stage, traffic information is collected from cameras and DfT traffic data sources. Live video streams are processed using the YOLOv12 detection model, which identifies vehicles in real time. The model is responsible for detecting different traffic features such as vehicle count, queue length, and the presence of EVs. After detection, the extracted information is combined in the state constructor to create a structured traffic state representation. This state contains the important traffic conditions that will later be used by the learning model for decision-making.

The second stage focuses on intelligent traffic control using RL algorithms such as PPO or DQN. The generated state vector is provided to the RL agent as input. Based on the current traffic situation, the RL agent learns the most suitable traffic signal phase to reduce congestion and improve traffic movement. The system continuously receives feedback through a reward signal, which depends on factors such as average waiting time and queue length. If an emergency vehicle is detected, the emergency override mechanism temporarily changes the normal RL decision to give priority access and create a faster route for the emergency vehicle.

The final stage involves traffic simulation and system evaluation using the SUMO simulator through the TraCI interface. The signal control commands generated by the RL model are applied inside the simulated road network. SUMO then updates traffic movement according to the selected traffic signal actions. During simulation, important performance indicators are recorded, including traffic delay, queue length, traffic throughput, and emergency vehicle travel time. These evaluation results help measure the effectiveness of the proposed adaptive traffic control framework under different traffic conditions.

3.2.1 System Architecture and Workflow

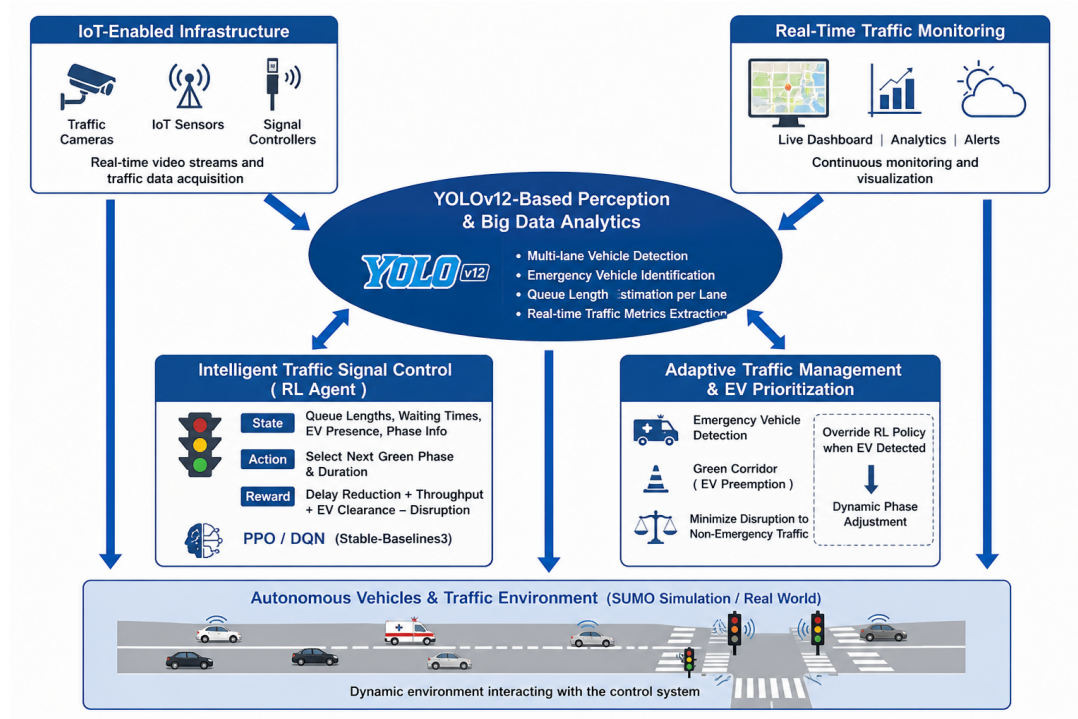


Figure 6: System Architecture

The figure presents a unified traffic management framework that integrates computer vision with RL for adaptive signal control. Traffic data collected from camera-based systems and connected infrastructure is analyzed using a YOLO-based perception module. These outputs are then transformed into state information for an RL agent, which selects appropriate signal timings based on current traffic conditions. In addition, the system includes an EV priority mechanism that adjusts signal phases dynamically to reduce delays for critical vehicles while maintaining efficient overall traffic flow. The performance of the framework is assessed within a simulation environment or a real-world traffic scenario [23].

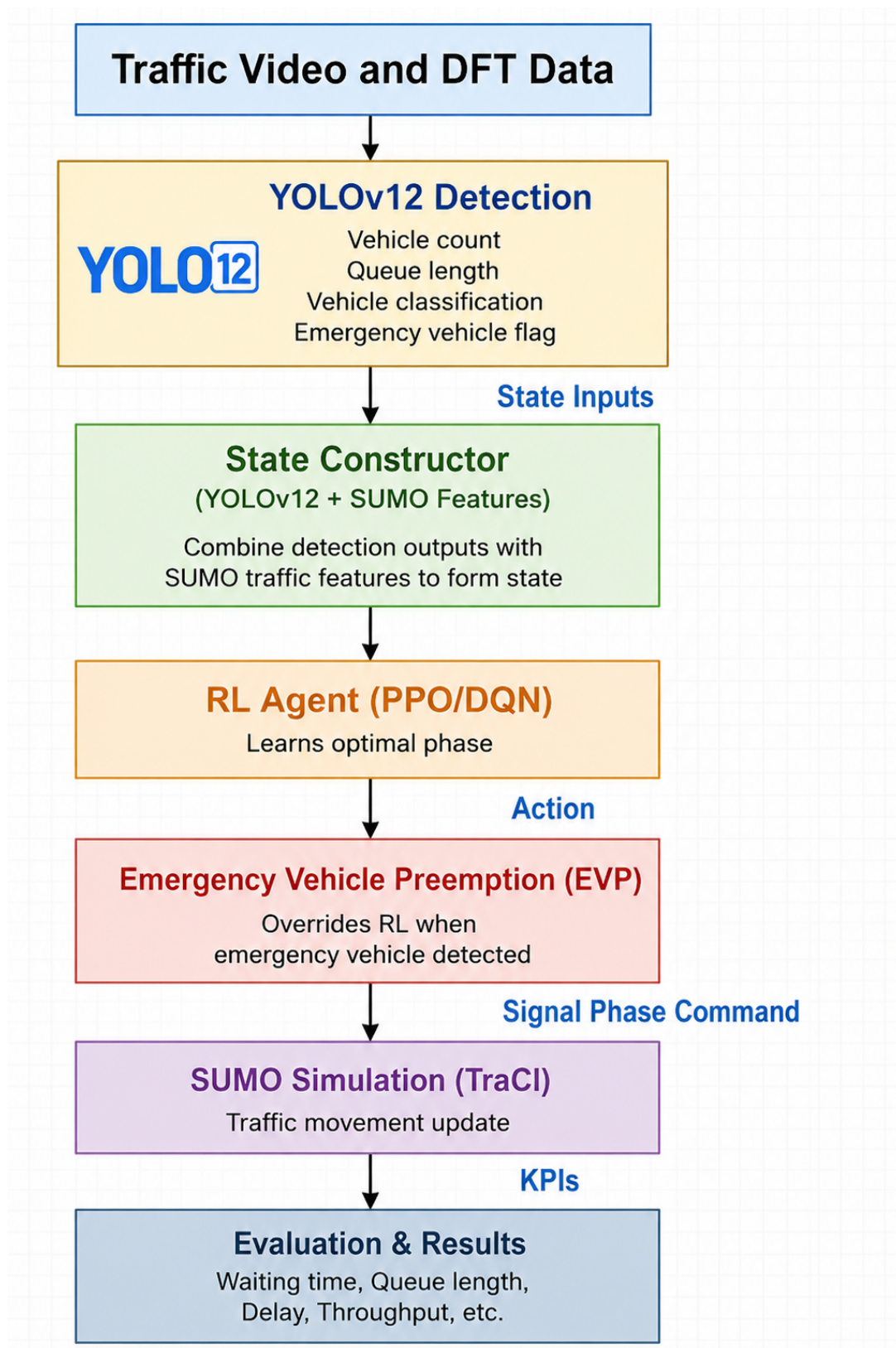


Figure 7: System Workflow

The system starts by collecting traffic video footage and DFT traffic data. YOLOv12 is then used to identify vehicles, calculate vehicle count, measure queue length, and detect

EVs. These outputs are combined with SUMO traffic features in the state constructor to create the input data for the RL agent. The RL agent, using PPO or DQN algorithms, learns the best traffic signal phase based on current traffic conditions. If an EV is detected, the EVP module temporarily overrides the RL decision to provide faster signal access for the EV. The selected signal commands are applied in the SUMO simulation through TraCI, which updates traffic movement in real time. Finally, the system performance is evaluated using key indicators such as waiting time, queue length, and traffic flow efficiency.

3.2.2 Justification for using YOLOv12

In this study, YOLOv12 (or a comparable stable version) is adopted due to its effective balance between accuracy and computational cost. It provides enhanced feature representation and attention-based improvements compared to earlier models, which supports more reliable detection under conditions such as partial occlusion and varying illumination. While newer versions of YOLO are continuously being introduced, they may still be in early stages of development or lack stable integration support. Therefore, YOLOv12 is considered a practical choice for ensuring consistent performance and compatibility when combined with RL and real-time traffic applications [24].

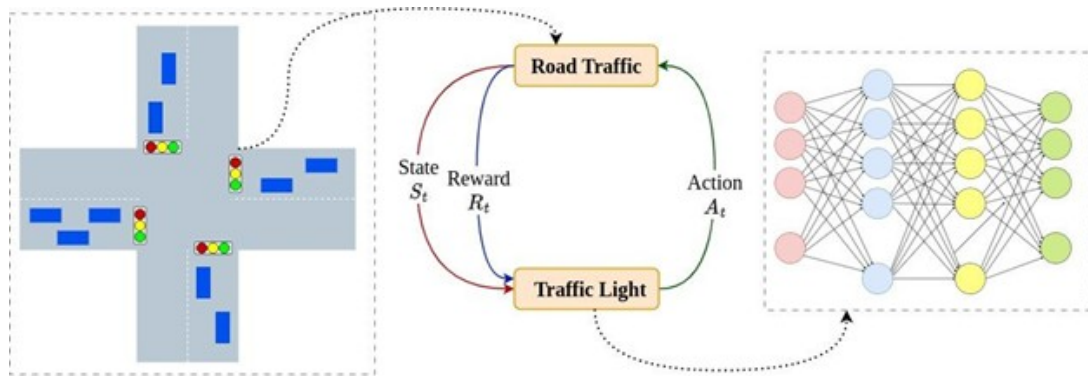


Figure 8: : RL-Based Traffic Signal Control Framework

This figure shows the road traffic environment provides the current state with the RL agent. A neural network is used to learn the optimal policy by mapping states to actions, allowing the system to continuously improve traffic signal decisions over time.

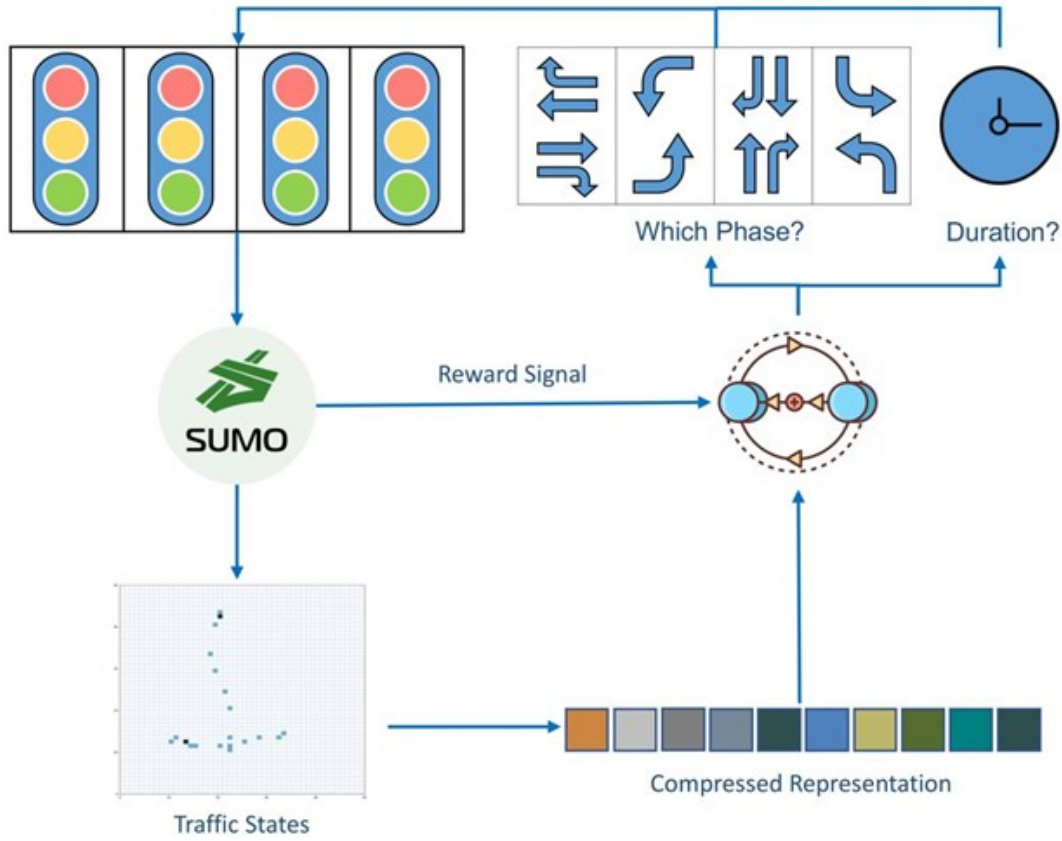


Figure 9: RL-Based Traffic Signal Control with SUMO Simulation

This figure shows how an RL system interacts with a traffic simulation environment to control signal timings. Traffic conditions are first captured as state information from the SUMO simulator. These states are then converted into a compact representation and passed to the RL model. Based on this input, the model decides the appropriate signal phase and its duration. The simulation environment returns a reward signal reflecting traffic performance, which helps the model learn better control strategies over time. This closed feedback loop allows the system to gradually optimize traffic signal decisions [25].

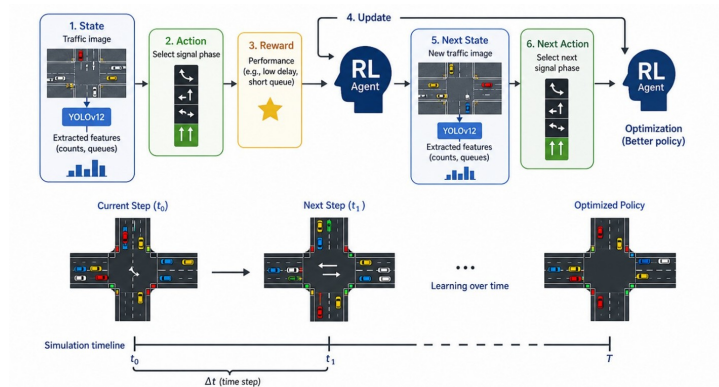


Figure 10: YOLOv12-DQN Framework for Adaptive Traffic Signal Control

Here is a simplified learning process where YOLOv12 is used to extract traffic features from images. These features form the state input for the RL agent. The agent selects an action, such as changing the traffic signal phase, and receives a reward based on traffic performance. This process repeats over time, allowing the system to gradually improve its control strategy and optimize traffic flow [26].

3.2.3 EV Pre-emption Logic

When an EV is detected, the traffic controller temporarily overrides standard optimization policies to create a green corridor. Signal phases are dynamically adjusted to minimize EV delay while reducing disruption for ordinary traffic flow. RL enables adaptive EV prioritization according to current traffic conditions [27].

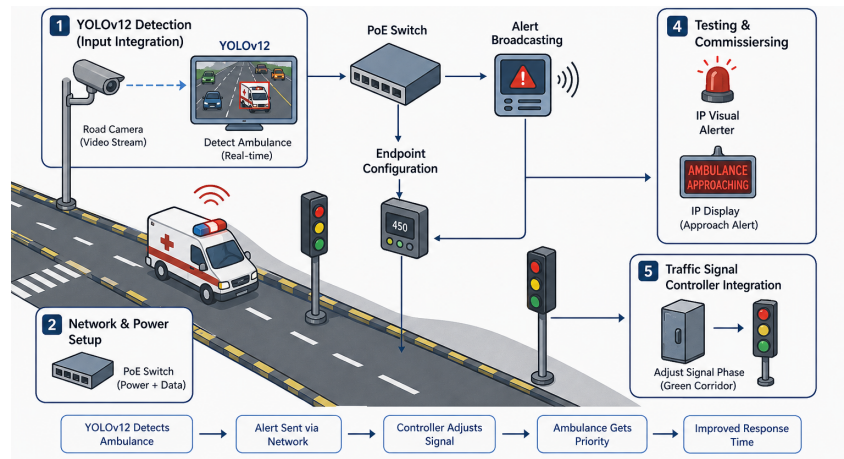


Figure 11: YOLOv12-Based Smart Traffic Signal for Emergency Vehicle Priority

Here, priority is given to an ambulance using a YOLOv12 model. A roadside camera captures video, and YOLOv12 detects the ambulance in real time. Once detected, a signal is sent through the network to the traffic controller. The system then adjusts the signal phase to create a clear path (green corridor) for the EV. Alerts can also be displayed to notify nearby systems. This process helps reduce delays and improves emergency response time. RL enables adaptive emergency vehicle prioritization according to current traffic conditions [28].

3.2.4 Materials and Tools

The implementation of this study relies on a combination of software tools, data sources, and computing resources. The system is developed using Python, alongside platforms such as SUMO and TraCI for traffic simulation, Stable-Baselines3 for RL, and OpenCV for image processing tasks. In terms of data, the study makes use of publicly available traffic information, including UK Department for Transport (DfT) traffic counts and open-source

traffic video datasets. The computational requirements are modest, with a multi-core CPU being sufficient for most tasks, while a GPU may be used to accelerate model training where available. From an ethical perspective, the research uses only publicly accessible datasets and does not involve any personal or sensitive data.

3.2.5 SUMO Simulation Environment

SUMO simulation is used to evaluate traffic performance under multiple traffic scenarios including normal traffic conditions, peak-hour congestion, EV movement, and multi-lane urban intersections. Performance metrics include average vehicle delay, queue length, traffic throughput, waiting time, and emergency response time.

4. Expected Outcomes

The proposed framework is expected to outperform conventional fixed-time traffic systems across multiple performance indicators. Adaptive signal optimization using RL is expected to significantly reduce vehicle waiting time and traffic congestion. Real-time traffic monitoring combined with intelligent decision-making can improve traffic throughput and reduce queue length at urban intersections [29]. EV prioritization mechanisms are expected to reduce ambulance delays and improve emergency response efficiency. Multi-agent RL frameworks previously demonstrated substantial reductions in EV travel time, indicating strong potential for intelligent emergency traffic management [30]. The proposed framework also supports smart city integration because it relies primarily on camera-based traffic monitoring rather than expensive embedded traffic sensors. The scalability and adaptability of RL systems make them suitable for future intelligent transportation infrastructure development [31].

5. Project Timeline

Table 2: Research Project Timeline

Duration	Phase	Key Tasks	Milestone
June–August	Literature Review	Review RL, YOLO, SUMO, and emergency traffic management papers from IEEE, Springer, and ACM databases.	Research gap finalized.
June (1st week)	Research Design	Finalize methodology, framework architecture, and simulation setup.	Methodology completed.
June (2nd and 3rd week)	Data Preparation	Prepare traffic datasets, SUMO scenarios, and preprocessing configuration.	Dataset prepared.
June (last week)	Feature Engineering	Queue extraction, emergency vehicle labeling, and traffic feature optimization.	Features confirmed.
July (1st and 2nd week)	YOLOv12 Development	Train and validate YOLOv12 vehicle detection model.	Detection model completed.
July (3rd week)	RL Development	Implement PPO/DQN adaptive traffic control algorithms.	RL model finalized.
July (last week)	System Integration	Integrate YOLOv12, RL controller, and SUMO through TraCI.	Integrated framework ready.
August (1st week)	Testing	Evaluate congestion reduction and emergency vehicle response performance.	Experimental results collected.
August (2nd week)	Result Analysis	Analyze waiting time, queue length, and throughput metrics.	Performance evaluation completed.
August (3rd and last week)	Dissertation Writing	Complete discussion, conclusion, formatting, and references.	Final dissertation completed.

6. Conclusion

The proposed framework brings together real-time traffic observation and intelligent control to improve how intersections are managed. By using YOLO-based detection, the system can identify vehicles and estimate traffic build-up with good accuracy. At the same time, a reinforcement learning approach is used to adjust signal timings based on current road conditions, rather than relying on fixed schedules. In addition, the system includes a mechanism to give priority to emergency vehicles. This allows signals to be adjusted temporarily to create a clear route, helping reduce delays for ambulances and similar services. Overall, the approach supports the development of smarter urban traffic systems by combining detection, learning, and decision-making within a single framework.

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