Report: Smart Dynamic Traffic Signal Controller for Heterogeneous Traffic and Emergency Vehicles using Reinforcement Learning and Blockchain Technology

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I. INTRODUCTION

Traffic signals in India are controlled by a traffic management system, which uses sensors, cameras, and other devices to monitor traffic flow and adjust the timing of traffic signals accordingly. In India, the traffic system consists of various types of systems and technologies. Given below are the main ones:

1. **Pre-timed Traffic Signal Controllers**: Most of the traffic signal controllers in India are pre-timed in other words, a static system. These controllers follow a fixed timing pattern for signal changes, regardless of the traffic conditions. This system is simple and inexpensive to implement. The signal timings are derived from the statistical data. The duration and order of all green phases are fixed and therefore, it cannot respond to real-time demand.
2. **Adaptive Traffic Control System (ATCS)**: The ATCS is a more advanced solution that automatically adjusts the timings of traffic lights based on real-time traffic conditions. It uses data from vehicle detectors and other sensors to optimise traffic flow and reduce congestion. The ATCS has been tested and successfully deployed at several intersections in India.

Some other traffic systems deployed in India:

1. Delhi – Split Cycle Offset Optimization Technique (SCOOT) is a real-time adaptive traffic control system for coordinating and controlling traffic signals across an urban road network.
2. Mumbai – ITACA (Intelligent Traffic Adaptive Control Area) - it offers a real-time response to current and future traffic flow demands, and brings 'intelligence' to fixed-time pattern control approaches.
3. Jaipur – The Composite Signal Control Strategy (CoSiCoSt-EnV) developed by C-DAC Thiruvananthapuram optimizes a weighted combination of delay and number of stops in real time.

Here are a few common issues associated with pre-timed traffic signals:

1. **Lack of Flexibility**: The signal timings may not be optimized for the current traffic volume or flow – since it follows a fixed timing pattern - leading to potential congestion or delays.

2. **Inefficient Traffic Flow**: Since signals do not adapt to real-time traffic, they may not effectively respond to changes in traffic patterns or unexpected events such as accidents or road closures.
3. **Limited Coordination**: Coordinating pre-timed signals across multiple intersections can be challenging. If the timing plans are not properly synchronized, it can lead to disruptions in traffic progression and cause delays for motorists.
4. **Inadequate Pedestrian Safety**: Pre-timed signals may not provide sufficient time for pedestrians to cross the road safely.

To address these issues, many cities are transitioning to more advanced traffic control systems, such as adaptive traffic control systems (ATCS). ATCS uses real-time data from sensors and detectors to dynamically adjust signal timings based on the actual traffic conditions, optimizing traffic flow and reducing congestion. Traffic-responsive control systems have been introduced to adapt signal timings based on the actual traffic demand at any given time. By continuously monitoring traffic conditions and adjusting signal timings accordingly, these systems help improve traffic flow and reduce delays. Centralized traffic management systems enable authorities to monitor and control traffic signals at multiple intersections from a central location. To enhance pedestrian safety features such as pedestrian countdown timers, pedestrian detection sensors, and exclusive pedestrian crossing phases have been integrated into traffic signal systems.

Using Artificial Intelligence (AI) and Machine Learning (ML) can help address issues related to pre-timed traffic signals by introducing adaptive and dynamic control mechanisms. AI algorithms can analyze real-time traffic data from various sources such as cameras, sensors, and GPS devices to dynamically adjust signal timings based on current traffic conditions. By leveraging predictive modelling and optimization algorithms, machine learning (ML) models can be trained to predict traffic patterns and congestion based on historical data. These ML algorithms can optimize signal timings considering various factors such as traffic volume, vehicle speed, and pedestrian crossings, thereby enhancing traffic flow efficiency.

AI-powered systems can adapt signal timings in real-time to respond to changes in traffic volume and flow, significantly reducing congestion. Integration with smart infrastructure components, such as connected vehicles and smart traffic lights, can create a more cohesive and responsive traffic management system. Additionally, ML models can incorporate feedback loops from traffic cameras and sensors to continuously learn and improve signal control strategies over time, leading to more effective decision-making. AI systems can also prioritize emergency vehicles by dynamically adjusting signal timings, allowing for faster passage and improved response times during emergencies

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II. LITERATURE SURVEY

Traffic management is crucial for regulating roadway traffic and enhancing overall transportation efficiency. With technological advancements, there is increasing interest in leveraging machine learning techniques to automate traffic control systems. ML algorithms, through the analysis and processing of vast amounts of traffic data, can make informed decisions that enhance safety, alleviate congestion, and optimise traffic flow. This literature review provides an overview of the latest research on autonomous traffic control using machine learning.

The Traffic Signal Controller (TSC) is the pivotal component used at signalised junctions to manage traffic with safety confirmation. A variety of solutions are available to operate traffic signals using different technologies like genetic algorithms, fuzzy logic, Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF) etc.

Sl. No	**Title of the paper**	**Year of publication**	**Problem Statement**	**ML Technique used**	**Final Outcome**
1	Boosted Genetic Algorithm Using Machine Learning for Traffic Control Optimization	2022	Optimising traffic control during severe, non-recurrent incidents (accidents, breakdowns) affecting multiple lanes/intersections.	1. Genetic Algorithm 2. Machine Learning Algorithms 3. BGA-ML Integration	1. The complex BGA-ML improves travel time by 43%-45% compared to the regular GA for traffic control optimization. 2. BGA-ML avoids lengthy simulations during real-life operations by learning quickly from previous traffic models. 3. It provides a 25% improvement in travel time under normal, non-incident conditions due to repeating traffic patterns. 4. BGA-ML reduces computational time by pre-training models, benefiting traffic modellers and planners.

2	State-of-the-Art Review on Traffic Control Strategies for Emergency Vehicles	2022	Emergency vehicles (EVs) like ambulances and fire trucks need swift response times to save lives. Delayed responses can escalate mortality rates, underscoring the importance of optimising traffic control to minimise EV travel time. Current strategies encompass route optimization, signal preemption, lane reservation, and mixed traffic control. These approaches face complexity due to static (rescue distance, intersections) and dynamic factors (traffic flow, speed). Despite efforts, efficiently reducing EV response times during emergencies remains a challenge.	1. Route Optimization: Uses ML algorithms to dynamically select the best routes for EVs to minimise travel time. 2. Signal Preemption: Employs ML models to predict and adjust traffic signals to prioritise EVs. 3. Lane Reservation: Utilises ML to guide regular vehicles away and clear paths for EVs. 4. Hybrid Strategies: Combines ML techniques across different strategies to optimise overall traffic control for EVs.	1. Emphasises the necessity for enhancing the dynamism of optimised response times in emergency management services. 2. Highlights the predominant focus of current research on individual strategies, often limited to simulation testing and challenging for commercial implementation. 3. Advocates for future investigations to explore the integration of multiple strategies to effectively reduce response times. 4. Suggests broadening the scope of evaluation beyond just the response time of emergency vehicles to include the broader impact on traffic flow. 5. Identifies the potential for significant advancements in emergency services by addressing the negative impact of vehicles on urban environments through comprehensive research initiatives.
3	Density-based Automatic Traffic Control using Machine Learning	2023	Traditional traffic light control systems suffer from inefficiencies due to their reliance on offline data, leading to long delays and energy wastage. .	1. The proposed system utilises YOLOv8 for real-time vehicle detection and analyses of previous traffic conditions. 2. ML algorithms are employed to optimise traffic signal timings	1. The evaluation considers various congestion scenarios, presenting results comparing actual and predicted vehicle numbers within different ranges, and showcasing density variance. 2. Utilises the Precision-Recall (PR) curve to assess the

				based on vehicle density.	YOLOv8 model's accuracy and reliability in detecting and classifying vehicles, aiding in understanding its performance. 3. Calculates precision (P) and recall (R) values to evaluate the model's ability to correctly identify and capture relevant vehicles within specified ranges. 4. Displays the precision-recall curve for different vehicle types, providing insights into the model's performance. 5. Shows traffic density of four lanes in a junction and the vehicle count after running the YOLOv8 algorithm, identifying the lane having the maximum density and calculating the corresponding Time of Need (TON). 6. Identifies open security issues related to storing and securing confidential data, emphasising the importance of addressing these challenges.
4	Traffic Signal Optimization by Integrating Reinforcement Learning and Digital Twins	2023	Existing machine learning (ML) methods for traffic signal optimization are often centralised, lacking scalability and adaptability in large traffic networks. Training such models is challenging due to limited training platforms and the high cost of deploying	1. Integrating decentralised graph-based multi-agent reinforcement learning (DGMARL) with a Digital Twin (DT) to optimise traffic signals. 2. DGMARL	1. 24-Hour Scenarios: - Overall Eco PI improved by 44.27% compared to the baseline vehicle actuated signal timing plan. - Improvements ranged from 11.23% to 81.47% across 11 intersections in the MLK Smart Corridor. 2. PM-Peak Hour

			them in real traffic networks. Additionally, traditional simulation models rely on assumptions and simplified models, lacking accuracy in representing real-world traffic scenarios.	agents learn traffic state patterns and make decisions regarding traffic signal control, assisted by a DT module that simulates real traffic behaviours.	Scenarios: - Average Eco PI improved by 29.88% from ten replicate trials with different random seeds. - Improvements ranged from 6.07% to 43.90% across the 11 intersections. - Average reduction in stops by 10.48% and stop delay by 49.68% compared to the baseline actuated signal timing scenario. - Carter intersection exhibited the largest improvement in stop delay by 65.01%, while Pine intersection showed the least improvement of 5.96%. These outcomes demonstrate the effectiveness of the proposed DGMARL signal timing plan in reducing traffic congestion and network-wide fuel consumption related to stopping in both 24-hour and PM-peak-hour scenarios on the MLK Smart Corridor.
5	Intelligent traffic signal controller for heterogeneous traffic using reinforcement learning	2023	Traditional solutions focused on infrastructure improvements, but constraints like resources and space have led to exploring alternative methods leveraging technology with existing infrastructure. While Adaptive Traffic Signal Controllers show promise in alleviating congestion, their implementation requires advanced techniques beyond traditional static or	Reinforcement learning using Multi-agent	The study demonstrates that using reinforcement learning, particularly a multi-agent approach, can optimise traffic signal green times, leading to reduced waiting delays and improved traffic flow efficiency.

			actuated controllers.		

III. PROPOSED METHODOLOGY

The report presents proposed methodologies for enhancing traffic signal control using reinforcement learning (RL) and utilising blockchain technology in Vehicle-to-Infrastructure (V2I) communication for emergency vehicles. These methodologies aim to optimise traffic flow, reduce congestion, and prioritise emergency vehicle passage in urban environments.

A. Proposed Methodology for Dynamic Traffic Signal Control:

- **Multiagent Reinforcement Learning (MARL):** Utilizing MARL to develop a dynamic traffic signal controller. Inputs from YoloV8 and CNN Model eg., queue length, vehicle density. Agents interact with the environment to learn optimal traffic signal policies.
- **Input from YOLOv8 Model**: The YOLOv8 model is employed for vehicle density estimation and vehicle detection. Provides real-time input to the traffic signal controller regarding traffic conditions.
- **Significance of YOLOv8 Model:** The YOLOv8 model is crucial for real-time vehicle detection and density estimation. Enables the traffic signal controller to make informed decisions based on accurate traffic data. A higher version **YoloV9** can also be adapted for the same.
- **CNN Model for Vehicle Detection:** Utilizing the Convolutional Neural Network (CNN) model for accurate vehicle detection enhances the accuracy and reliability of traffic data input.
- **Reinforcement Model Output:** The output of the reinforcement model comprises optimised traffic signal sequences. The proper cycle for red, yellow, and green lights is determined based on learned policies.
- **Feedback Loop Mechanism:** Incorporating a feedback loop mechanism to evaluate controller performance. Feedback in the form of reduced waiting time for vehicles in the lane.
- **Emergency Vehicle Handling:** Incorporates image detection using the CNN and GPS data fed into the **V2I communication** system and then fed into the MARL model. Identifies emergency vehicles for priority passage through signal preemption
- **Edge Computation and Cloud Databases:** Implements edge computation for real-time processing of traffic data—Utilises cloud storage for efficient data management and scalability.

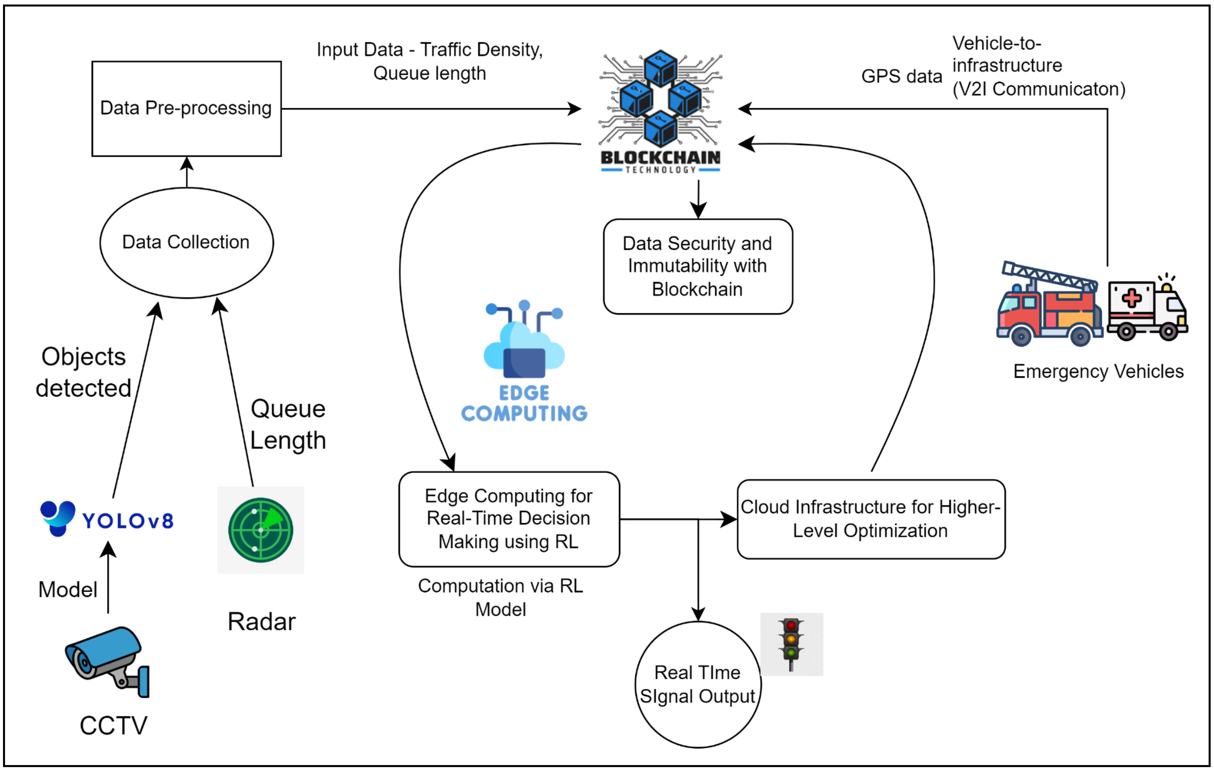

Figure 1. Proposed methodology for the dynamic traffic signal controller

B. Proposed Methodology for Blockchain in V2I Communication:

A decentralized V2I communication network leveraging blockchain technology will securely exchange information between emergency vehicles and infrastructure components. Blockchain's immutable ledger will record critical data such as emergency vehicle routes, status updates, and priority requests, ensuring data integrity and preventing tampering. Smart contracts will automate and enforce agreements between emergency vehicles and traffic management systems, facilitating priority access at intersections and dynamically adjusting traffic signals. Encrypted data sharing between emergency vehicles and infrastructure will protect sensitive information from unauthorized access. Additionally, all interactions and transactions will be recorded on the blockchain to enhance transparency and accountability in traffic management decisions, allowing stakeholders to audit and verify the system's operations.

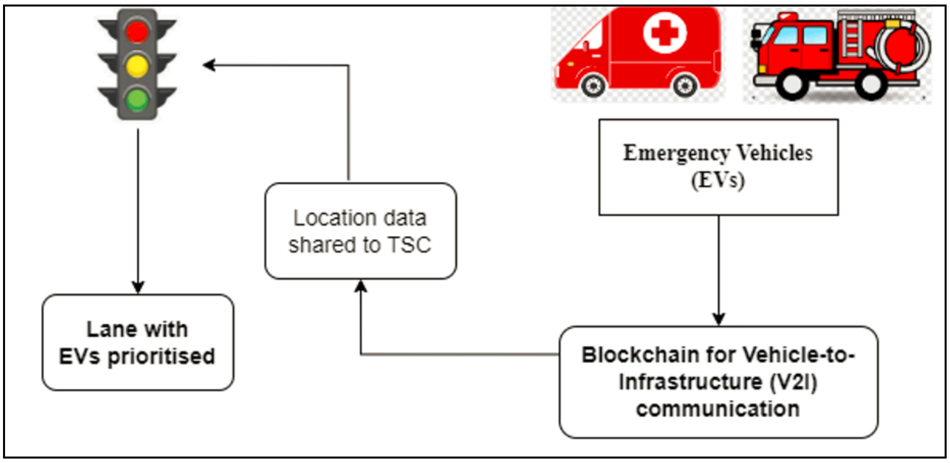

Figure 2. Strategy for reducing EV response time

The proposed methodologies for RL in traffic signal control and blockchain in V2I communication present innovative approaches to improve traffic management efficiency and prioritise emergency vehicle passage. By leveraging RL algorithms and blockchain technology, urban traffic systems can become more adaptive, secure, and responsive to dynamic conditions, ensuring safer and more efficient transportation networks.

IV. NOVELTY OF THE PROPOSED METHODOLOGY

The proposed methodology differs from existing machine learning (ML) solutions in traffic management by integrating reinforcement learning (RL) algorithms with blockchain technology in a holistic approach. Unlike traditional ML approaches that may focus solely on optimising traffic signals or V2I communication, our solution combines RL-based traffic signal control with blockchain-enabled V2I communication to create a dynamic, adaptive, and secure traffic management system.

The novelty lies in this synergistic integration, which allows for real-time traffic signal adjustments based on RL algorithms while ensuring secure and transparent communication between emergency vehicles and infrastructure components through blockchain technology. This comprehensive approach addresses key challenges in urban traffic management, such as congestion reduction, emergency vehicle prioritisation, and data security, making it a novel and effective solution for improving urban transportation efficiency and safety.

V. REFERENCES

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