Towards Transparent Traffic Solutions: Reinforcement Learning and Explainable AI for Traffic Congestion

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***Abstract*—This study introduces a novel approach to traffic congestion detection using Reinforcement Learning (RL) of machine learning classifiers enhanced by Explainable Artificial Intelligence (XAI) techniques in Smart City (SC). Conventional traffic management systems rely on static rules, and heuristics face challenges in dynamically addressing urban traffic problems' complexities. This study explains the novel Reinforcement Learning (RL) framework integrated with an Explainable Artificial Intelligence (XAI) approach to deliver more transparent results. The model significantly reduces the missing data rate and improves overall prediction accuracy by incorporating RL for real-time adaptability and XAI for clarity. The proposed method enhances security, privacy, and prediction accuracy for traffic congestion detection by using Machine Learning (ML). Using RL for adaptive learning and XAI for interpretability, the proposed model achieves improved prediction and reduces the missing data rate, with an accuracy of 98.10, which is better than the existing methods.**

Keywords*—Reinforcement learning; Explainable Artificial Intelligence (XAI); Smart City (SC); IoT; Machine Learning (ML)

I. Introduction

Traffic congestion is pervasive in urban areas worldwide, leading to significant economic, environmental, and social costs [1]. Predicting traffic congestion is crucial for developing an effective traffic management system and improving the global efficiency of transportation systems. Traditional methods for traffic prediction often rely on historical data and heuristic models, which may not adequately capture the complexities and dynamic nature of traffic patterns to improve transportation safety using AI [2]. Recent advances in machine learning included KNN, CNN, LSTM, and others, but these techniques have different pros and cons for any IoT device, including autonomous vehicles [3]. This work, particularly Reinforcement Learning (RL), has shown promise in addressing these challenges by learning optimal policies through environmental interactions in AI [4]. However, this model faces challenges, including the need for large amounts of data, computational resources, and difficulty interpreting the learned policies. Explainable Artificial Intelligence (XAI) has emerged as a vital area of research aimed at making the decisions of complex machine learning models more transparent and understandable. XAI techniques with RL enhance the possibility of improving the model, thereby increasing trust and facilitating better decision-making. Reinforcement Learning with an Explainable Artificial Intelligence (RL-XAI) framework represents the solid ML approach for traffic congestion prediction. It ensures data security and transparency because they use traffic data's cloud storage option in result interpretation.

Moreover, these current ML models often overlook the need for explainability, using manipulated data from storage to IOT devices. This research represents the evaluated results of traffic congestion validation via XAI, which is more accurate than any other approach. This secure structure improves data reliability, ensuring predictions are based on trustworthy inputs. Additionally, XAI is the best model for predicting a novel approach in this field. Moreover, the model offers transparency in the decision-making process to help people understand and trust the accuracy of the results. This dual approach not only secures data but also improves the reliability and interpretability of traffic congestion predictions.

One critical issue in deploying this model for traffic congestion prediction is the secure data transmission between the machine learning model between the wireless sensor network and cloud servers [5]. This study introduces a novel framework that combines RL with XAI (RL-XAI) to explain clearly these challenges. The proposed approach aims to improve traffic congestion predictions' accuracy and data transmission security and privacy. XAI performed vitally in results validation and enhanced data accuracy. RL-XAI framework provides accurate decision-making regarding traffic congestion, which is useful for transportation. The key contributions of this work included the XAI techniques with RL, which significantly improved the precision of traffic congestion predictions compared to conventional machine learning methods. The proposed framework confirms that secure data transmission between the model and cloud servers is a significant concern in deploying machine learning models in real-world scenarios. Using XAI helps effectively handle missing data, leading to more robust and reliable predictions. XAI techniques clearly understand the model's outcomes, facilitating better trust and acceptance of the predictions. Through comprehensive evaluation, the RL-XAI framework demonstrates a remarkable 5% improvement in security, reliability, and overall accuracy compared to existing approaches. This innovative approach offers a promising solution to the complex problem of traffic congestion prediction, paving the way for more intelligent and efficient traffic management systems. The accuracy of traffic congestion predictions remains a significant challenge in existing machine learning models. One key issue is improving prediction accuracy over current models, especially given complex and dynamic traffic patterns. Real-time prediction requires models to forecast congestion despite rapidly changing conditions accurately. Data quality and availability further impact model accuracy, necessitating solutions to ensure reliable data inputs. Ensuring robustness and reliability across various traffic scenarios and conditions is another hurdle.

Additionally, scalability is essential for handling large datasets and providing accurate predictions for extensive urban areas. Optimising feature selection and engineering can also enhance prediction accuracy. Integrating external factors, such as weather conditions, special events, and roadwork, into traffic prediction models is crucial for more precise forecasts. Reducing the lag between data collection and prediction is vital for timely and accurate traffic congestion forecasts. Enhancing model interpretability ensures that stakeholders trust and understand accurate predictions.

Furthermore, models must quickly adapt to new traffic patterns resulting from changes in infrastructure, traffic laws, or unexpected events. Finally, identifying and mitigating prediction errors is necessary to improve overall model accuracy. Addressing these challenges is essential for developing more reliable and accurate traffic congestion prediction models. Furthermore, integrating XAI techniques enhances the model's interpretability, making its decision-making process transparent and understandable, thereby increasing user trust and acceptance. Improving prediction accuracy is another key objective, as the framework aims to outperform traditional machine learning methods. Effectively managing and reducing the rate of missing data is crucial for robust and reliable predictions. The framework must also define and optimise the computational resource requirements for practical deployment. Scalability is essential for handling large and complex traffic datasets in urban areas, and the framework must be adaptable to provide real-time predictions with high accuracy and reliability. Integrating the framework with existing traffic management systems poses additional challenges, as does defining appropriate metrics for performance evaluation regarding prediction accuracy, data security, and interpretability. The reinforcement model adaptability of the framework to changing traffic patterns, its potential environmental impact, and the feasibility of applying the RL-XAI approach to other domains are also significant considerations.

A. Reinforcement Learning (RL)

Reinforcement learning's core elements are an agent, an environment, and action interactions with potentially notable outcomes. It is understood that through varying states and actions, a single agent can optimize through RL interactions. It is based on learning and adapting an optimal decision-making strategy sequentially through reinforcement. Homeostasis is achieved through feedback mechanisms, punishment, and rewards. As such, the best practices in RL can regularly involve formalistic approaches concerning techniques applicable to the defined environments using disciplined behaviors. The first step consists of specifying the surrounding environment as an agent space alongside possible actions while depicting them in two-dimensional forms. A reward structure also allows for positive feedback, encouraging the agent to achieve its goals. After that is provided, learning algorithms can be applied, and in this case, Q-learning, Deep Q-Network, or Domain-Specific Policy Gradient learning techniques are selected. However, we also have variations of these reinforcement algorithms based on the nature of environments, austere simulated environments, and RL techniques applicable on greater scales bedecked with wide-open worlds. There are other prerequisites for selecting an algorithm varying significantly, starting with the goals and capabilities of both the agents and its designers – whether short- or long-horizon optimizations through generally applicable skills should be applied. Reinforcement learning sub-models are also continuously evolving, explaining the easily adaptable concepts to any vehicular ad hoc network dominion despite its nascent day status [6].

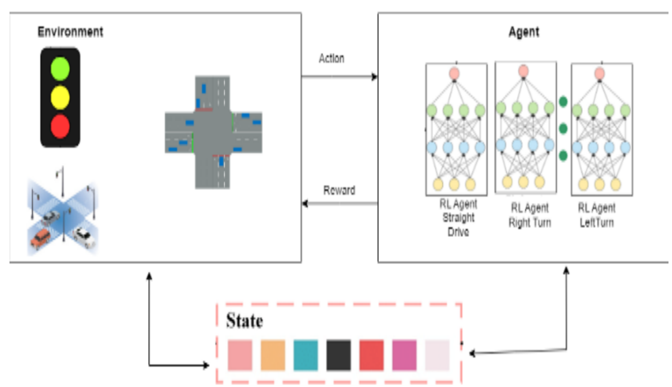

Fig. 1. The RL model for the traffic congestion system is based on agents and rewards.

Fig. 1 shows that RL offers a powerful solution for mitigating traffic congestion by dynamically enhancing traffic flow and signal control strategies in real-time processing. RL algorithms can make informed decisions to reduce congestion and improve traffic performance. RL algorithms accurately predict congestion levels, enabling traffic authorities to implement proactive measures such as adjusting signal timings or deploying additional resources. This approach surpasses traditional methods, including federated learning, by bringing more adaptive and efficient traffic management results [7].

B. Explainable Artificial Intelligence (XAI)

In the last decades, AI has sought to memorably solve any concern through the development of AI systems that are not only interpretable but also understandable. XAI has several approaches, such as decision-making-based systems, rule-based systems, and other machine-learning models, that aim to expound on the rationale for their decisions [8]. Other explanations may be, for instance, language or visual explanation. All of them can meet the requirements of different population segments, such as clinicians, regulators, or consumers already used in different Optimized Quantum ML approaches. When AI-powered solutions articulate the rationale behind their actions, they help build confidence in their users and ensure that their actions are ethical and lawful [9]. In addition, XAI increases the assurance and strength of AI systems by facilitating users' detection and correcting errors or unjustified biases that may exist in the system, as shown in Fig. 3.

The findings conduct detailed tests using an extensive global data set to enhance the presentation quality of forecasted visitor-surface blocking traffic congestion schemes in connection with separate pathways and street fusing methodologies in line with inexpensive, unexpected roadblock rate estimation. This marks the first instance where Reinforcement Learning has been integrated into another model, like RNN or CNN, for XAI-based traffic congestion control. Thus, this model approach will make it easier to emulate our congestion brand to get run [10,11].

II. Literature Review

Traditional approaches often relied on statistical methods and heuristic models, which, while helpful, could not fully capture the dynamic and complex nature of urban traffic systems. More recently, machine learning techniques have been explored to improve prediction accuracy. Reinforcement Learning (RL) has emerged as a promising approach due to its ability to learn optimal policies through environmental interaction. Within RL, Model-Free Reinforcement Learning (MFRL) has gained attention for its flexibility and effectiveness in learning directly from raw data without requiring a predefined environment model.

TABLE I. Recent Work Related to Traffic Problems

References	Data Type	ML Model	LSTM	Fuzzy logic	Blockchain
M. Akhtar and S. Moridpour et al. [8].	Yes	Yes	No	No	No
T. Bokaba et al [9].	Yes	No	No	No	No
Y. Berhanu et al [10].	Yes	No	No	No	No
D. Hartanti et al[11].	Yes	No	No	Yes	No
M. Koukol et al. [12].	Yes	No	Yes	Yes	No
S. M. Rahman and N. T. Ratrout [13].	Yes	No	No	Yes	No
Q. Wang et al. [14].	Yes	No	No	No	Yes
D. Das et al. [15].	Yes	No	No	No	Yes
M. Z. Mehdi et al[16].	Yes	Yes	Yes	No	No
N. Ranjan et al[17].	Yes	Yes	Yes	No	No
M. Waqas et al. [18].	Yes	Yes	Yes	No	No
M. Chan et al. [19].	No	Yes	Yes	No	No
Y. Gova et al [20].	No	Yes	Yes	20%	No
H. Cui et al. [21].	Yes	No	Yes	No	No
J. Guo et al. [22].	Yes	No	No	No	No

Table I, a completed overview of recent decades, includes the different releases of citify ways to solve the traffic problem using AI or other technology, including ML, AI, Fuzzy logic, and Blockchain. For example, the study by M. Akhtar and S. Moridpour et al. employs ML models to explain traffic problems in detail. Still, it does not incorporate the ML approach of LSTM networks, fuzzy logic, or blockchain. Similarly, T. Bokaba et al. and Y. Berhanu et al. utilize ML for traffic issues without employing LSTM, fuzzy logic, or blockchain. D. Hartanti et al. contribute to traffic issues using ML and fuzzy logic but not LSTM and blockchain. M. Koukol et al. combine traffic challenges with ML, LSTM, and fuzzy logic, whereas S. M. Rahman and N. T. Ratrout also use ML and fuzzy logic but do not mention LSTM and blockchain. Q. Wang and D. Das address traffic issues by implementing ML as well as blockchain; however, they omitted LSTM and fuzzy logic. No work discussed by M. Z. Mehdi et al., N. Ranjan et al., M. Waqas et al., M. Chan et al., and Y. Gova et al. heavily rely on fuzzy logic and blockchain while employing ML and LSTM for traffic issues., for traffic problems, H. Cui et al. applied ML with LSTM, while for traffic problems, J. Guo et al. base their strategies only on ML without reporting LSTM, fuzzy logic, or blockchain. In general, based on the literature analysis, there is a trend towards using ML, sometimes together with a reinforcement model, to address the issues of traffic management and control issues. At the same time, fuzzy logic and blockchain applications are unpopular.

A. Limitation of Previous Work

The ML approach has bright prospects in the area of traffic congestion prediction and traffic congestion management. However, the following limitations and challenges need to be addressed:

- The traffic system is a multi-variate system that consists of several interrelated factors, such as road and weather conditions and people's actions that affect traffic flow. Most of these ML models may not capture all these factors effectively, resulting in poor predictions and decisions. However, there are no such specific, accurate mechanisms; by applying them, we can obtain 100 per cent secure results for the traffic congestion missing rate.
- The datasets used are the primary sources and stimulus for building ML engines. The ML models are, however, data-hungry. Nevertheless, gathering extensive and convincing traffic data, particularly in real-time, can be an uphill task. Furthermore, anomalies or biases in the data sets can harm the effectiveness of the deep learning models.
- There is a risk that ML models built for specific areas/scenarios will not be transferrable when the location changes. Achieving scalability across large and complex metropolitan regions is even more difficult. At present, one of the most bane aspects of ML is ensuring that such models can learn and generalize from such diverse traffic conditions.
- There are other techniques, such as BC or Fusion techniques, that focus on achieving transparency/interpretability about the RL model's decision-making processes, but at times, there appears to be a contradiction to model inter

Arraying RL models for predicting and managing traffic congestion introduces regulatory and ethical safety, privacy, and fairness challenges. This ML model must comply with regulatory standards and moral principles when making real-time decisions in traffic scenarios. Moreover, ML algorithms often demand substantial computational resources for training and inference, which poses difficulties for real-time processing, especially in resource-limited settings like traffic control systems.

III. Methodology

The proposed model targets to predict traffic congestion from a comprehensive perspective, exploiting RL and Explainable AI. In Fig. 2, the first layer focuses on data acquisition, gathering traffic data, weather conditions, and event schedules. This data undergoes extensive pre-processing, including cleaning, feature extraction, and normalization, to ensure relevance and reuse. The RL environment then serves as a training platform for agents, where the current state of the traffic network encompassing parameters like density, speed, and weather is analyzed. Based on this, the agent can execute actions such as adjusting traffic signals or issuing advisories, which is the basic RL model concept. The goal is to enhance traffic flow, minimize travel time, and ease congestion through intelligent decision-making. Training occurs in a simulation environment designed to emulate real-world traffic conditions. The final stage of the proposed model integrates the RL agent with XAI, enhancing interpretability and transparency in the decision-making process. Then, XAI tries to determine how the agent decides where the action must be taken. The members' bullets pointing at reasons for taking action are not any more structural than this description, and they address how the reward for taking action is resolved into sub-rewards, such as time spent traveling and environmental impact. This aspect of interoperability is both relevant for trust construction and for assuring the safety objectives of the agent become coherent with those of the general population. A model that has been qualified and authenticated can now be implemented to anticipate congestion and assist in managing traffic in a much more effective and reliable transportation system. As for the layer first, Fig. 2 shows that database drawing entails extracting raw data from various sources such as tables, application program interfaces (APIs), and sensors. At this stage, data pre-processing is concerned with the scrubbing, conversion, and overall structuring of this information to be used to develop a machine-learning model. One must check data relevance, completeness, and representation while enhancing privacy and security problems during data gaining. Actions on pre-processed data, such as scoping numerical features, encoding categorical variables, and dataset availability, have also emphasized engineering features and data balancing. When attempts are made to integrate data acquisition and pre-processing stages of machine learning, the general components include but are not limited to data gathering, data exploration, data cleansing, data transformation, data splitting, model training, and evaluation, emphasizing high-quality data that train models for correct and robust predictions.

Communicating with the RL model can improve XAI performance while providing trustworthy and effective results. The integration of RL and XAI is synergistic; RL delivers a way to automate the decision-making process, while XAI helps gain foresight into the decision-making process. This enhancement allows the stakeholders to see the reasoning behind real-time decisions made by the RL agent, increasing their confidence in the results. Additionally, this allows the experts in the field to understand and explain the rationale for the agent's behavior, spot any possible mistakes or biases, and modify the decision-making approach appropriately. Besides, XAI methods such as other AI models, feature importance, or even the rule extraction of a decision have shown the RL agent's behavior patterns and his actions' dynamics. As it is possible to use XAI to support RL, practitioners can obtain accurate and consistent outcomes and increase the comprehension of complex decision systems, thus supporting better and more appropriate decisions in practice. Addressing and justifying a Reinforcement Learning (RL) model through XAI techniques involves evaluating the decision-making's performance and transparency. Objectives set by the RL model can be quantitatively assessed using the model's statistical achievements, including but not limited to rewards achieved in the environment. Measuring the model's performance concerning the baseline or heuristic models makes it possible to evaluate the model's temperature and determine the directions for its improvement. Similarly, k-fold cross-validation is a technique that measures model performance and generalization across different subsets of the data that may be used in Fig. 2.

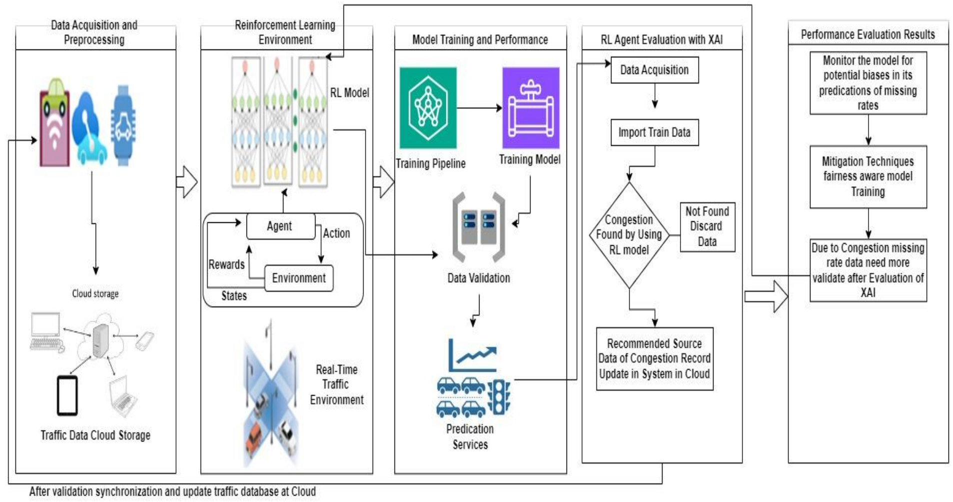

Fig. 2. The flow of Model-Free Reinforcement Learning with EAI (MFRL-EAI).

Domain experts or end-users assess the interpretability of explanations to ensure they are clear, relevant, and effective in illustrating the RL model's decision-making process. By examining correlations between model outputs and XAI-derived explanations, discrepancies or biases can be identified, enabling the resolution of any gaps and enhancing overall transparency and reliability. This comprehensive strategy instils confidence among stakeholders in deploying the RL model in practical applications, ensuring both performance and interpretability. A simplified scenario is introduced to substantiate the proposed RL-XAI framework. Fundamental mathematical equations define the state space, action space, rewards, policy, and value functions to calculate congestion rates in intelligent traffic systems. Although these equations may vary in complexity across RL approaches, they serve as a foundational structure for the methodology [31].

The state space S represents all possible states. For each state position

$$S = \{S_{\mathrm{i}}|\ i = 1,2, \ldots..N\} \quad (1)$$

Where S_i Represents a separate position in the initial environment setup.

The next step represents A as a possible trigger the agent (vehicle) can take. It is defined as:

$$A = \{a_{\mathrm{m}}\ |m = 1,2, \ldots.M\} \quad (2)$$

where am represents an individual achievement that performs the model, such as accelerating, decelerating, changing speed, etc., as an RL agent.

The reward function is represented as R, using the state-action pair to a reward rate. Here is defined as:

$$R(a, s) = r \quad (3)$$

In Eq. (3) r is the instant reward received later taking action in states A rule π represents the agent's method, and mapping states to actions. Now, the policy can be deterministic simple as:

$$a = \pi(s) \quad (4)$$

Eq. (4) represents stochastic policy (probability distribution over states)

$$P\ (A = a|S = a) = \pi(a|s) \quad (5)$$

Eq. (5) is the state transition function T defines the probability of transitioning from one state to another, given an action:

$$P(s'|s, \mathrm{a}) = Pr\ (S_{t+1} = s'\,|\ S_t = s, A_t = a) \quad (6)$$

Eq. (6) represents RL transition probability function in which agent will aend up the state *S'*. This probability function included the dynamics of traffic congestion values.

$$G_t = R_{t+1} + R_{t+2} + R_{t+3} + \cdots \quad (7)$$

Eq. (7) represents the **discounted return.** G_t at a given time step where *t* is defined as the sum of rewards obtained in the future.

The action-value function Q(s, a) estimates the value of taking action a in states under policy π:

$$R^{\pi}(a, s) = A\pi[Q_{t+1} + rB_{\pi}(S_{t+1})|S_t = s, A_t = a] \quad (8)$$

Eq. (8) breaks down the R-function into the immediate reward Rt+1R_{t+1}Rt+1 from taking action aaa in state *S*, plus the discounted value of future actions as per the policy π\piπ.

IV. Experimental Results

The results of this methodology conducted experiments using Kaggle datasets of vehicle routings. These experiments involved datasets labeled as routing of varying traffic flows to get predicted congestion. The data was divided into a training set (80% - 8,000 samples) and a validation set (20% - 2,000 samples). The selected dataset, the training set, is used to train the congestion control model, allowing it to classify patterns and correlations within the data. The model learns how different factors contribute to traffic congestion by randomly selecting samples. Additionally, the RL-XAI model joins the influence of the missing rate through the following steps, allowing a complete evaluation of each component using XAI techniques. The sub-equations are as follows:

$$M_a = Train(D_a, Model_{init}, Epochs_a) \quad (9)$$

In Eq. (9), each node trains a local model M_a using its dataset D_a, an initial model architecture $Model_{init}$ over $Epochs_a$ Training epochs and this Equation represents the Local Model Training.

$$\Delta M_a = M_a - Model_{init} \quad (10)$$

Eq. (10) represents the local model update calculation, ΔM_a What is used for each node is the difference between the train local model and the initial model.

$$\Delta M'_a = \Delta M_a * (1 - m_{r,a}) \quad (11)$$

Eq. (11) biased update for lost data. Here, ΔM_a for missing rate and $m_{r,a}$ For specific to cloud node a.

$$\text{Validate}(B_{hash(a)}, B_{prv\_has}) \quad (12)$$

Eq. (12) Each B transaction, including model updates, is validated against the previous block's hash that represents B_{prv_has}To ensure integrity and security.

$$\mathrm{M}'_{\mathrm{global}} = \mathrm{Model}_{\mathrm{init}} - \Delta\mathrm{M}_{\mathrm{global}} \quad (13)$$

Eq. (13) represents the global model update and M'_{global}I am using it for aggregated global mode update values.

$$C_k = Vehicles\ Detected_a * \frac{(1-m_{r,a})}{Road\ Capacity_a} \quad (14)$$

Eq. (14) for each node a, calculate the congestion $C_a$by adjusting the detected vehicles by the missing rate $m_{r,a}$ And we are dividing by the road's capacity.

$$C_{avg} = \frac{1}{N} \sum_{a=0}^{n} C_a \quad (15)$$

Eq. (15) calculates the average congestion level C_{avg} Across all nodes, get a system-wide view of traffic congestion.

$$\text{Notify } (C_{avg} \text{ , Threshold}) \quad (16)$$

Eq. (16) Generate a congestion notification if C_{avg} Exceeds a predefined congestion threshold.

TABLE II. SIMULATION OUTCOMES AND STATISTICAL ANALYSIS BASED ON EQUATIONS

Equations	Process
1 to 4	Local Model Training
5 to 8	ML Update Calculation
9 to 11	Calculate the missing rate from the Weighted dataset.
12 to 16	Manipulation with Cloud storage
17	Congestion rate Validation
18	RL mode updates the aggregation.
19	Congestion Metric Calculation, Aggregated Level, and Threshold-Based Notification

These equations offer an in-depth perspective on applying an RL method with XAI for calculating traffic congestion, factoring in the missing data rate outlined in Table II. Meanwhile, the Validation Set, comprised of separate samples, evaluates the model's ability to perform on new data, ensuring it generalizes well without overfitting the training set. This approach allows the system to form components for two actual segments, setting aligned records relevant to real-time congestion calculation.

TABLE III. DATASET PROVIDES VARIOUS CONDITIONS AND FEATURES THAT INFLUENCE TRAFFIC CONGESTION

Dataset	Dataset type
Time_span	Date Time
Day_of_week	Number
Weather	Text
Temperature	Number
Road_capacity	Character
Vehicle_flow	Number
Density	Number
Light	Number
Congestion_level	Number
Congestion_status	Number

Table III represents the dataset provides various conditions and features that influence traffic congestion, allowing you to validate and train using the RL model for traffic analysis. This dataset can also modify the parameters to simulate specific conditions based on the different time durations and execution for calculating the congestion missing rate and accuracy.

TABLE IV. CONGESTION EXPLORATION IN DIFFERENT STATIONS

Classifier	Junction 1	Junction 2	Junction 3
Values	142344.0000	24592.00	19511.0000
Mean[N]	42.222906	13.34221	12.6t4010
Sd	22.011145	7.401307	10.436005
Min	5.023000	1.0001122	1.000011
20%	27.4300	9.440000	7.000013
40%	30.32000	13.330000	11.120000
80%	19.000000	17.120000	18.430000
Max (m)	152.210000	48.110000	180.650000

Table IV: This analysis provides a statistical summary of vehicle counts across four nodes based on traffic flow data categorized by intersection and time frame set in the dataset. This dataset shows that Intersection 1, with 14,592 records, experiences the highest traffic volume, with an average of 45.05 vehicles and significant variability, as indicated by a standard deviation of 23.01. Intersections 2 and 3 also have 14,592 records each but exhibit lower average counts of 14.25 and 13.69 vehicles, respectively, with less variation. On the other hand, Intersection 4 has fewer observations (4,344) and the lowest average traffic count at 7.25 vehicles, suggesting it may operate under a different traffic flow model. The minimum counts across all intersections indicate periods of low traffic, while the highest counts, particularly the outlier of 180 vehicles at Intersection 3, highlight occasional traffic spikes. Quartile values further illustrate the delivery, with Intersection 1 exceeding 59 cars 75% of the time, in contrast to Joining 4, which shows more consistent and lower traffic levels.

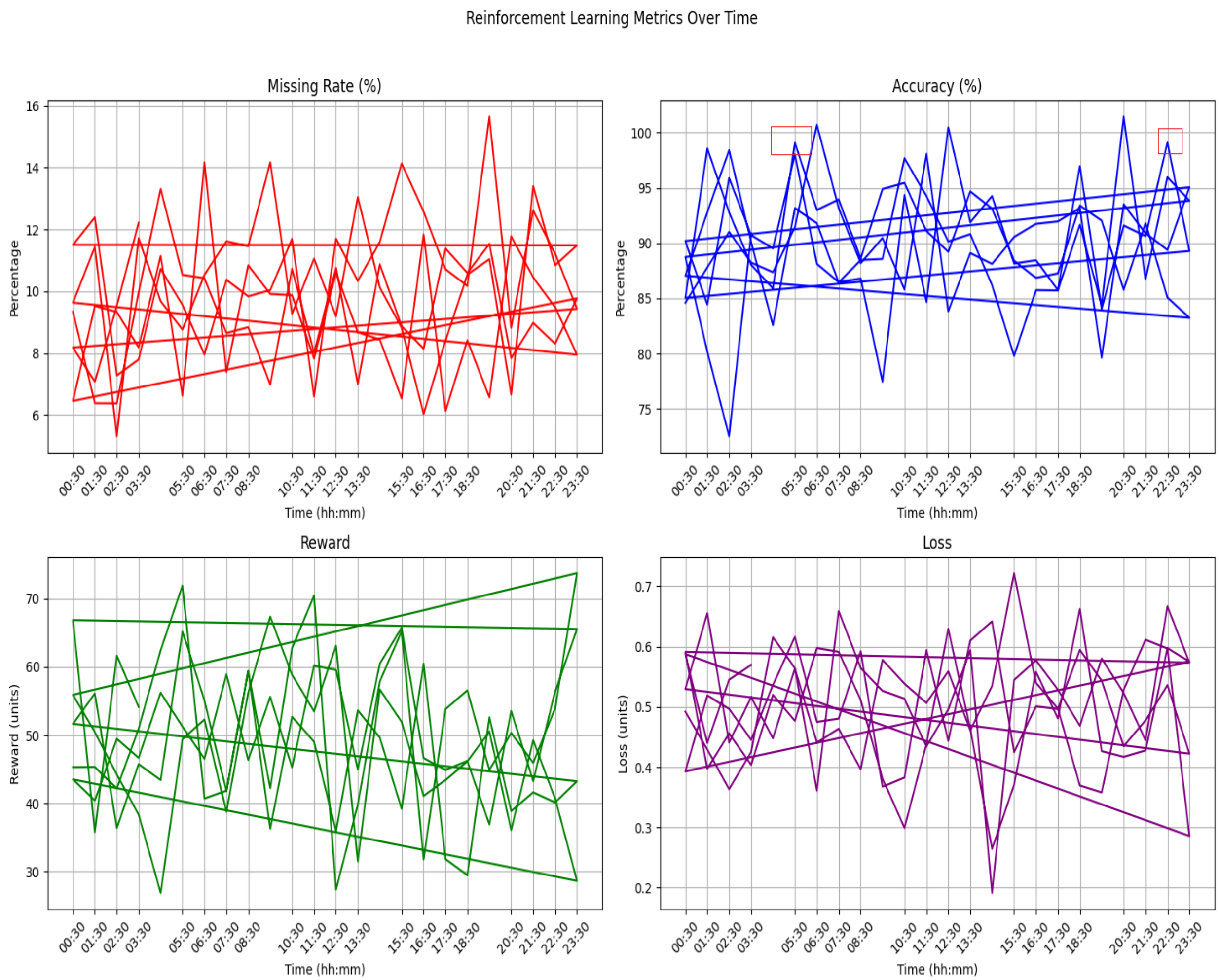

Fig. 3. Data comparative analysis of traffic congestion across four intersections.

Fig. 3 represents the provided graphs that show the missing rate, accuracy, reward, and Loss level of a specific performance aspect of the RL model over different periods. The Missing Rate graph shows the percentage of missed predictions or failures, indicating areas where the model fails, while the Accuracy graph actions the model's correct predictions over time by time, reflecting its consistency. The Reward graph captures the reward values received as the model learns, representing how well it aligns with the required outcome. Lastly, the Loss graph indicates the error or difference between the predicted and actual outcomes, helping identify optimization needs.

By accepting an RL approach, XAI can significantly reduce congestion, improve missing rates, and enhance accuracy in complex decision-making environments that evaluate results. Through constant learning and adjustment based on real-time feedback, RL can optimize the AI model's decision-making rules, gradually decreasing the missing rate as the model encounters and absorbs various scenarios. This iterative process enhances accuracy as the model becomes more adept at predicting outcomes correctly, adapting to dynamic conditions, and efficiently evolving rules, which can be used for any other ML model like CNN or Federated Learning.

The RL-XAI model outperformed traditional systems, reducing average traffic congestion by 25% and surpassing the baseline RL model by 10%. Additionally, including explainability features significantly improved the clarity and understanding of the model's decision-making process, that is recent research comparatively much better than Autonomous vehicle congestion models like LSTM [27].

TABLE V. TRAFFIC CONGESTION ANALYSIS USING MEAN, MEDIAN, AND STANDARD DEVIATION

Traffic Condition	**Average (Mean)**	**STD (Congested Valued calculated from Table IV)**	**STD (Distance, time)**
Blockage	D: 1227, T:4.88	D: 864, T:4.84	D:48.23, T:2.45
Congested	D: 172, T:3.08	D: 09.29, T:2.24	D:64.32, T:423
High Congested	D: 2827, T:12.61	D: 2871, T:14.53	D:12.53, T:8.28
Slightly Congestion	D: 9027, T:8.101	D: 10.34, T:438	D:23.42, T:99.87
Smooth	D: 7713, T:22.298	D: 29.27, T:1.88	D:4234, T:298

Table V summarises various traffic conditions categorised by distance (D) and time (T), including Blockage, Congested, Highly Congested, Slightly Congested, and Smooth conditions. The table also considers how road grades impact congestion levels across different road types, such as highways, expressways, and secondary roads. Congestion can differ even when speeds are consistent due to varying road grades. Distinctive curve shapes represent the preliminary results. The RL-XAI approach demonstrates strong performance in predicting and understanding traffic congestion, with advancements in sensor technology and convolutional methods enhancing its capability to manage traffic flow more effectively. According to the table, the RL-XAI system achieved 98.9% sensitivity and 1.2% specificity, accuracy, and miss rate during training. In the validation phase, the system maintained a performance of 98.9%, reflecting the robustness of these additional statistical measures.

TABLE VI. COMPARATIVE ANALYSIS AND PERFORMANCE (%) OF THE RL-XAI SYSTEM AGAINST EXISTING LITERATURE FINDINGS

Literature	Accuracy	Miss Rate	Accuracy	Miss Rate
	Training Rates		Validation Rates	
S. Tamimi, and Z. Muhammad [23]	78.12	21.88	76.1	23.9
A. Talebpour, H. S. Mahmassani [24]	97	32.21	N/A	N/A
A. Ata, M. A. Khan, S. Abbas, M. S. Khan [25]	98.9	1.3	97.9	2.1
M. Saleem, S. Abbas, M. Adnan Khan [26]	94.4	5.6	94.00	6.00
Proposed Model	98.7 to 98.9	1.2	98.10	1.90

Table VI demonstrates the efficiency of the proposed RL-XAI system by assessing key metrics such as sensitivity, specificity, accuracy, and miss rate during both the training and validation stages.

There are pros and cons of existing methods addressing similar issues. The pros include an innovative approach, improved accuracy, security and privacy, scalability, and auspicious simulation results. Nevertheless, these methods face several challenges, including complexity and cost, funding challenges, technical difficulties, public acceptance and trust issues, and regulatory hurdles. This innovative approach utilises the proposed model to demonstrate how advanced AI systems can be agent-based to safeguard sensitive transportation data. Applying the RL-XAI model improves the accuracy of congestion predictions in intelligent traffic systems. Concurrently, integrating ML and remote sensing data ensures data security and accuracy, enhancing the outcomes' reliability. Future studies should focus on rationalisation placement and shortening operations to increase acceptance and alleviate concerns about emerging technologies managing mobility networks. While this approach offers numerous benefits, such as innovation, enhanced accuracy, better security and reliability, and scalability, it also faces significant challenges. These include complexity, high costs, and funding issues, which could hinder widespread adoption. Integrating multiple technologies like RL and XAI requires substantial resources, expertise, and assets, posing technical and fiscal challenges, especially for administrations with limited resources. Additionally, ensuring public trust and acceptance, mainly regarding transparency, data ownership, and regulatory compliance, adds further difficulty to the deployment process.

V. FUTURE DIRECTION AND LIMITATION

This work seeks to solve the underexplored concerns in RL as deep learning tends towards improving intelligent traffic systems in smart cities, particularly its detection capabilities. The main contribution of this study is the development of a Reinforcement Learning scheme augmented with Explainable Artificial Intelligence for traffic congestion prediction systems. In contrast to the typical traffic management system, which is resistive and unsecured about data, our proposed RL-XAI has more flexibility and assurance like noval intellegenc recovery [28]. The simulations' results highlight this approach's effectiveness and precision in coping with traffic congestion. Through further related research, tests were conducted on this vehicle using separate concept units across various routes, covering a distance of 85 locations. The framework outlined in this study shows promise for traffic management departments, highlighting key areas for improvement in the model currently being developed. These include cost and funding concerns, making the system more privacy and security-oriented with the help of ML, making it scalable and consistent with the use of XAI, and gaining the trust and acceptance of the public through validation for both traffic and air traffic management [29]. Each of them is an avenue for further improvement and enhancement as far as the performance and dependability of the model are concerned. Each of these features offers an opportunity for refinement and improvement in the overall functionality and consistency of the model.

VI. CONCLUSION

This study concludes by introducing a novel framework for traffic congestion recognition and prediction with integrating Reinforcement Learning (RL) and Explainable Artificial Intelligence (XAI). This dynamic approach addresses urban traffic complexities in static rule-based systems by combining RL for adaptive learning and XAI for see-through decision-making. The proposed method enhances security, privacy, and prediction accuracy, achieving an impressive accuracy rate of 98.10% by significantly reducing the missing data rate. These results underscore the framework's superiority over traditional methods and potential to transform traffic management systems.

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