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Graphical Abstract

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Post-Quantum Protected Federated Learning with Explainable and Adaptive Intelligence for Smart City Transportation

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Abstract

Existing AI-powered Intelligent Transportation Systems (ITS) have limitations in scalability, privacy, and vulnerability to cyberattacks, as well as a lack of transparency in decision-making. In this work, we present a hybrid framework based on Post-Quantum-protected Federated Learning, a lightweight CNN-Transformer model, LIME explanations, and a local model, achieving a loss of 0.02% and a validation accuracy of 98%. At the boundary, congestion is determined using CityFlowV2 traffic camera feeds, which are based on Federated Learning, a distributed training framework that does not require sharing raw data, and the architecture is privacy-respectful. Reinforcement learning trained on OpenStreetMap road networks in Los Angeles coordinates rerouting plans in a simulated environment at the global level, and SHAP provides an explanation of the decision. The Federated aggregation retained accuracy at the zone level, exceeding 97%. Furthermore, this affirms its strength. CRYSTALS-Kyber is used to encrypt V2I and V2V communications, ensuring they are resistant to attacks in the quantum era.

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The framework is scalable and interpretative, and offers a secure, adaptable, city-neutral blueprint of next-generation ITS.

Keywords:
Post-Quantum, Federated Learning, Explainable AI (XAI), Deep Reinforcement Learning (DRL), Intelligent Transportation, Smart Cities.

1. Introduction

Smart cities are increasingly using AI to improve the management of urban infrastructure, particularly through advanced traffic management systems. Traffic congestion has become a pressing issue in urban areas because of the rapid increase in population and density of vehicles [1]. Traditional methods of traffic control cannot adjust in time and cause traffic deficiency [2]. Therefore, AI-based models have been suggested that allow dynamic and intelligent traffic signal control by machine learning [3]. These systems are capable of analyzing traffic flow patterns and all the variables of traffic flows to adjust the traffic signals accordingly [4]. In recent research, reinforcement learning and deep neural networks are proposed as alternatives (robust) to solve complex traffic situations. The technologies help systems to analyze the behavior of traffic and make informed decisions without manual intervention. Moreover, the Internet of Things (IoT) and edge computing integration with intelligent traffic systems encourages the gathering and processing of data in real-time, with better responsiveness and scalability. Other methods of machine learning used to enhance the traffic flow prediction and the detection of anomalies are convolutional neural networks (CNNs), long short-term memory (LSTMs), and gradient boosting machines (GBMs) [5, 6, 7]. Nonetheless, there are still significant issues, such as data privacy, traffic infrastructure interoperability, and the explainability of AI decisions, that need to be continuously addressed. People have proposed using explainable AI schemes, such as LIME and SHAP, to make traffic decision-making more transparent and trustworthy [8]. In addition, green solutions to urban development require energy-efficient technologies that can integrate AI with green IoT and federated learning solutions, mitigate computational burden, and promote data protection [9]. The existing traffic control systems fail to process data of higher dimensions and complex formats in real-time, particularly in adhering to the critical demands of scalability, privacy, explainability, and cybersecurity. It does not exist without an integrated solution that addresses all these challenges using state-of-the-art technologies simultaneously. To overcome the above problems, this paper makes the following key contributions:

1. We propose a novel integration of quantum-enhanced DRL, FL, and XAI for adaptive and decentralized traffic control in smart city environments.
2. Quantum-Secure Communication We design a secure communication protocol using Kyber-based post-quantum cryptography to ensure confidentiality and integrity in V2X and inter-node communications, protecting against quantum-era threats.
3. We develop a hierarchical AI architecture comprising. Local-level intelligence using CNN- and Transformer-based models for real-time, zone-specific traffic pattern detection. Global-level intelligence using a centralized DRL optimizer that aggregates insights from local nodes to manage city-wide traffic flow efficiently.
4. We integrate LIME and SHAP to offer model interpretability and real-time decision explainability in the local and the global AI layers, promoting transparency and trust between stakeholders.
5. We evaluated our approach on the CityFlowV2 dataset and simulated an urban setting, achieving 99% precision and recall and demonstrating robust resistance to adversarial and communication-based attacks.

1.1. Preliminaries

To ensure the robustness, understandability, and security of our intelligent traffic management system, this section outlines the methodologies employed within the framework. In each subsection, we highlight a core technique, its technical importance, and a specific contribution to the system architecture as a whole.

1.1.1. CNNs Convolutional Neural Networks

CNNs are a type of deep learning architecture that are exceptionally efficient in processing spatial data, images, and video streams. In our model, CNNs are used at the local zone level to identify spatial features in traffic camera feeds, which are then fed into higher-level models to make decisions.

Mathematically, in (1), the convolution operation is defined as:

$$S(i,j) = (X * K)(i,j) = \sum_m \sum_n X(i+m, j+n) \cdot K(m,n) \tag{1}$$

where X is the input matrix and K is the convolution kernel. The real-time processing capabilities of CNNs have been widely used in intelligent transportation systems for applications such as vehicle detection, lane tracking, and congestion estimation [16].

1.1.2. Transformer Models

Transformers are deep learning systems that use self-attention mechanisms to learn long-range dependencies of sequential data. Transformers can effectively capture temporal and contextual trends in traffic flows, whereas CNNs focus on spatial characteristics. The basic working of the Transformer is the scaled dot-product attention,

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

In (2), Q, K, and V denote the query, key, and value matrices, respectively, and d_k is the dimension of the key vectors. Transformers are effective for enhancing temporal reasoning and prediction accuracy in dynamic traffic systems.

1.1.3. Reinforcement Learning (RL)

RL involves an agent learning to make optimal decisions through interaction with an environment and receiving feedback in the form of rewards. In our system, RL is applied both locally for routing decisions and globally for optimizing traffic signal timing, and (3). The aim is to learn a policy $\pi(a|s)$ that maximizes the expected cumulative reward,

$$J(\pi) = \mathbb{E}_\pi\left[\sum_{t=0}^{\infty} \gamma^t R_t\right] \tag{3}$$

where γ is the discount factor and R_t is the reward at time t. RL is particularly suitable for adaptive control in evolving the transportation environments [26].

1.1.4. Federated Learning (FL)

FL supports a decentralized training model in which edge devices can compute local model updates without sending raw data. FL can be used in our architecture to make local zones train traffic prediction models without compromising data privacy.

The global model in (4), updated at time $t+1$, is given by:

$$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_t^k \tag{4}$$

where w_t^k represents the local model from client k, n_k is the size of local data, and $n = \sum_k n_k$.

This approach will not only eliminate communication overhead but also enhance data privacy in smart transportation systems [23].

1.1.5. Explainable AI: LIME and SHAP

The framework employs two popular explainability methods, namely LIME and SHAP, to increase transparency in complex decision-making processes. LIME generates locally precise surrogate models to estimate how predictions are made on the basis of particular input instances. Conversely, SHAP uses the Shapley values featured in cooperative game theory for the fair determination of the contribution of each input feature. In contrast, SHAP uses Shapley values from cooperative game theory to fairly measure the contribution of each input feature.

Together, these tools help to improve the interpretability of AI-driven decisions in critical traffic control applications.

1.1.6. Kyber-based Post-Quantum Cryptography

Given the looming threat of quantum computing to classical cryptographic systems, our framework integrates Kyber, a lattice-based key encapsulation mechanism (KEM) that has been selected for standardization by NIST. The key encapsulation process involves generating a ciphertext–shared secret pair via: $(ct, ss) \leftarrow \text{Encaps}(pk),\ ss \leftarrow \text{Decaps}(ct, sk)$,

where pk and sk denote the public and private keys, respectively.

Kyber ensures secure communication among federated nodes in V2X Vehicle-to-Everything and D2D Device-to-Device scenarios, and in model aggregation scenarios [11].

1.2. Structure of the Paper

The remainder of this paper is organized as follows. Section II reviews related work in federated learning, reinforcement learning, explainable AI, quantum-assisted machine learning, and cryptographic methods for intelligent traffic systems. Section III describes the proposed architecture, including hybrid AI layers, federated training, quantum-secure communication, and data processing. Section IV deals with the experimental setup and assessment, Section V with the results analysis, and the final section with the conclusion.

2. Literature Review

The increasing complexity of urban transport systems has motivated researchers to explore intelligent, AI-based solutions for traffic optimization and safety. This chapter reviews key research topics that have contributed to the design of a safe, effective, and interpretable AI-based traffic management system for smart cities. The list of the discussed categories is CNN-based vision systems, transformer architectures, FL, RL, explainable AI, post-quantum cryptography with Kyber, and hybrid quantum-AI systems.

2.1. Convolutional Neural Networks (CNNs)

The use of CNNs has become central to vision-based intelligent traffic systems. It has enabled its use in a variety of applications, including vehicle detection, traffic flow monitoring, congestion detection, and accident recognition. More recent works have shown the incorporation of CNNs into D2D communication systems based on IoT to enable low-latency, high-accuracy visual data classification [11]. CNNs, along with object recognition methods such as YOLO, have been extensively used to optimise traffic in real time and to automatically detect accidents [12, 13]. Additionally, CNN architectures have been leveraged for crowd density estimation to support smart city planning initiatives [14]. To address the demands of real-time processing, advanced CNN variants have been proposed for fast congestion analysis [15], while hybrid models integrating CNNs with LSTM and YOLOv8 have been utilized for multi-agent cooperative traffic control systems [16, 17].

2.2. Transformer Architectures

While CNNs focus on spatial data, transformer architectures provide long-range temporal attention, improving traffic prediction and sequential decision-making. Proposed a cross-modal learning framework for acoustic scene classification in smart cities, demonstrating the transformer's adaptability beyond textual data [19]. Similarly, transformer-powered optimization within sustainable AI frameworks for traffic data fusion [20]. In addition, multi-layer traffic flow models and graph-based ones, which can be improved with transformer mechanisms to reflect temporal relationships [21]. The relevance of time modeling in traffic networks, in defense of the feasibility of transformer models in reproducing sequences of flows [22].

2.3. Federated Learning (FL) in Decentralized Traffic Systems

FL enables edge devices to train models in a decentralized manner, without exchanging raw data, thereby preserving privacy while enabling real-time intelligence in intelligent cities. In addition to reducing bandwidth and resource usage, FL also guarantees data sovereignty and regulatory compliance [23]. Recent results demonstrate that it is efficient, in combination with lightweight CNN and explainable AI, for secure and interpretable traffic classification [24], [25]. Furthermore, it has been utilized in conjunction with reinforcement learning for adaptive traffic control, demonstrating that FL can be applied to decentralized urban mobility control [26].

2.4. Reinforcement Learning (RL) for Intelligent Decision-Making

RL enables AI agents to take sequential actions under dynamic conditions, making it particularly useful for traffic control and urban mobility optimization. Deep RL methods have been shown to be beneficial for adaptive traffic signal control, enabling a system to dynamically respond to changing traffic patterns to minimize congestion [26, 27]. In addition, multi-agent RLs have enabled cooperative vehicle coordination in decentralized networks, improving overall traffic flow and reducing travel time [28]. Numerous researchers have shown that RL-based decision policies significantly enhance the efficiency of urban traffic. The RL models have also enhanced the responsiveness and accuracy of predictions under varying traffic conditions by leveraging real-time Internet of Things (IoT) data [29].

2.5. Explainable AI (XAI) in Traffic Systems

With the increasing integration of AI into general infrastructure, it is essential that its decision-making process be transparent and comprehensible to gain public confidence and ensure reliability. Various methods, such as Explainable AI (XAI), namely LIME and SHAP, have been shown to help humans make sense of complex Machine Learning models. An example is SHAP, which has been successfully used in traffic classification, where it is evident that the specific features used in the model affect model decisions. The system distinguishes among the various traffic types [24]. Similarly, LIME has been used to explain how AI regulates the timing of signals in traffic infrastructure, thereby helping users better understand how automated decision-making technology works and trust it [8]. Not just these particular examples, numerous papers highlight the broader relevance of explainability in high-stakes systems, particularly where promoting public trust and ensuring that AI is applied ethically in practice are of concern [10, 25]. In addition, it has been suggested that the XAI framework should be used to optimize traffic signals to instill a sense of responsibility, especially in high-stakes scenarios where human safety is considered essential [26].

2.6. Kyber-based Post-Quantum Cryptography

With the emergence of quantum computing, traditional cryptographic designs are becoming increasingly vulnerable. Kyber, a lattice-based Key Encapsulation Mechanism, has become one of the most effective post-quantum solutions due to its efficiency and resistance to quantum attacks. It has been demonstrated to be effective in IoT-enabled D2D communication, which offers confidentiality and requires low latency [11]. Kyber has been used in wireless sensor networks to provide real-time, energy-efficient security [30] against chosen-ciphertext attacks in transportation [31]. In addition, Kyber-based digital signatures are lightweight and privacy-preserving, and are optimized for authentication in smart city settings [32].

2.7. Hybrid AI-Quantum Models for Sustainable Urban Mobility

Hybrid AI-quantum systems are of interest for their potential to transform urban mobility by enabling more effective optimization. QAOA and other quantum algorithms can improve the efficiency of route planning. Additionally, quantum technologies in smart infrastructure with respect to cybersecurity [33]. The quantum-inspired energy-efficient cloud-edge orchestration AI models [19]. Nevertheless, further developments in integrating quantum logic with neural networks for dynamic traffic control are also being considered. Meanwhile, AI-predictive capabilities are being used to advantage sustainable smart city projects [21]. Smart transportation that leverages IoT and ML to develop energy-efficient routing strategies and make urban infrastructure more resilient.

Table 1: Summary of Reviewed Techniques for Traffic Control and Security

Technique	**Use Case**	**Limitations**	**References**
CNN + YOLO	Object detection in traffic scenes	Requires GPU for real-time processing	[12, 13]
Transformer	Traffic flow prediction and time-series forecasting	High training and computational cost	[19, 22]
GNN / GAT	Urban route planning on dynamic road graphs	Sensitive to incomplete or noisy topology data	[19]
FL + XAI	Privacy-preserving ML with interpretability	High latency and challenges with non-IID data	[24, 25]
RL (Multi-agent)	Adaptive signal control optimization	Slow convergence and exploration overhead	[26, 29]
Kyber (Post-Quantum)	Post-quantum secure communication for D2D/IoT	Requires hardware validation and adoption	[11, 31, 32]
Hybrid Quantum-AI	Integrated optimization and quantum-secure AI	Mostly theoretical and lacks real-world deployments	[33, 34]

3. Proposed Methodology

The proposed solution provides a powerful, dynamic scheme that can regulate traffic, reduce the risk of traffic congestion, ensure safe communication with vehicles, and detect anomalies in real time in smart city systems. The architecture comprises five key elements: The local predictors, Trans-based, interpretable via LIME/SHAP, FL, and international decision-making DRL, as well as Kyber-based post-quantum cryptography for a secure communication network. A description of the dataset choice, data preparation, architecture modules, and mathematical foundations of every module is introduced in this section

3.1. *Data Acquisition and Integration*

In traffic routing through smart cities, we utilized the CityFlowV2 dataset on AI City Challenge, which comprised spatial-temporal data containing information on vehicles, speeds, timestamps, and road sections. The data was processed through a unified pipeline (preprocessing, normalization, encoding, alignment), which allowed local prediction, global route planning, and safe V2V or V2I communication.

3.1.1. *Data Collection*

This study employs the CityFlowV2 dataset [18], a large-scale driving video dataset comprising 40 camera clips with annotations for diverse tasks. Sourced from AI City Challenge Website, CityFlowV2 includes rich temporal, spatial, and environmental metadata such as object bounding boxes, lane markings, drivable areas, and semantic or instance segmentation. The geographical and weather heterogeneity of the dataset facilitates high-quality model training for smart traffic routing under heterogeneous urban conditions.

3.1.2. *Data Preprocessing*

The labels for traffic jams were assigned based on congestion properties. Frames containing slow, dense, or stationary vehicle clusters were marked. 1 (jam) and 0 (no jam), respectively, were used to mark those whose traffic was free. This process of labelling generated an almost balanced dataset, with 2,427 no-jam frames (52.4 percent) and 2,210 jam frames (47.6 percent), as shown in Fig. 1. The labeled subset was drawn from the CityFlowV2 dataset of the 2025 AI City Challenge [18], comprising 4,637 annotated frames from forty fixed-position surveillance cameras (c001 to c040) under varied lighting and environmental conditions. Each entry includes the image path, camera ID, frame number, vehicle count, and jam label. Vehicle counts range from 5 to 12, with a mean of 6.22 and a median of 6.0 as shown in Fig. 2. Preprocessing steps included removing invalid image paths, normalizing pixel values to the [0,1] range, standardizing vehicle counts, and label-encoding camera IDs. Exploratory data analysis, ranging from label distribution plots, vehicle count histograms, count-label boxplots, Feature Correlation Heatmap, and per-camera traffic density visualization, Figs. 3 4 and 5 showed heterogeneous patterns of congestion across camera views. In this case, due to the balanced distribution of the classes, no oversampling or undersampling method was used, and class weighting in the model's loss function was applied to mitigate subtle imbalances across cameras. These steps conserved spatial-temporal patterns that are important for multimodal CNN-DistilBERT fusion modeling.

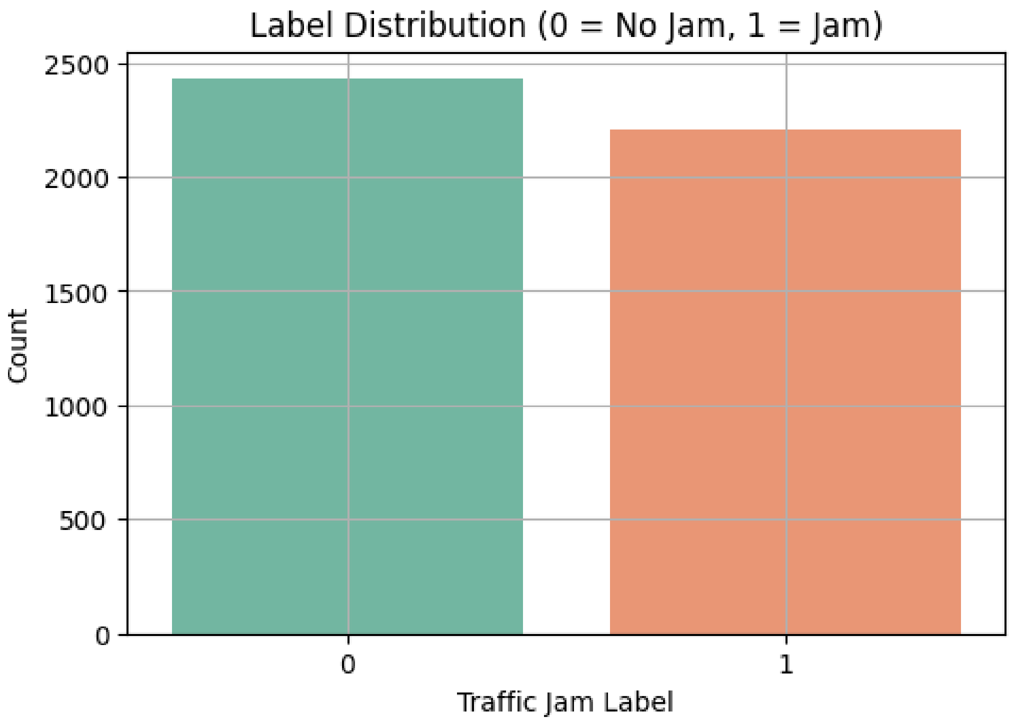

Figure 1: Label Distribution

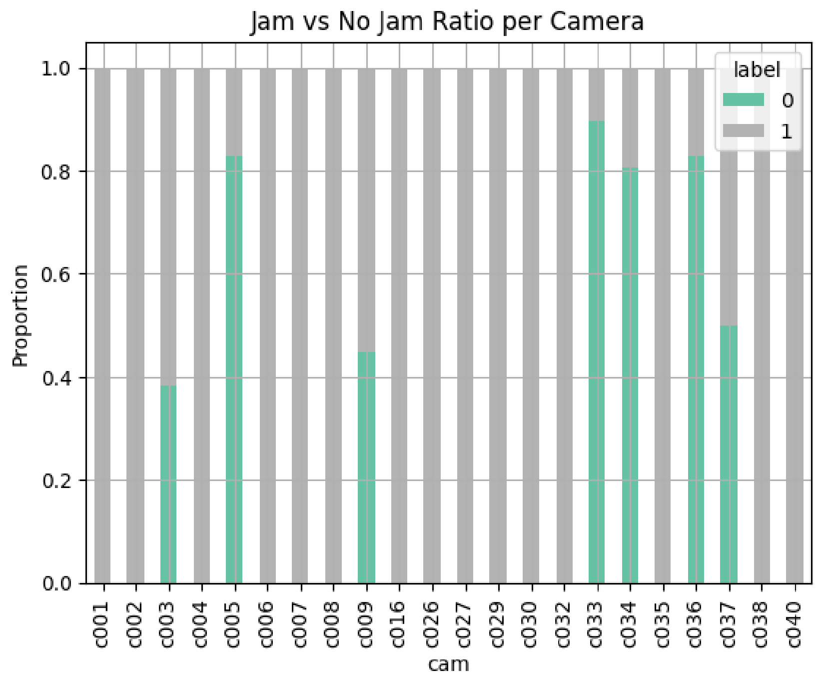

Figure 2: Jam vs No Jam Ratio per Camera

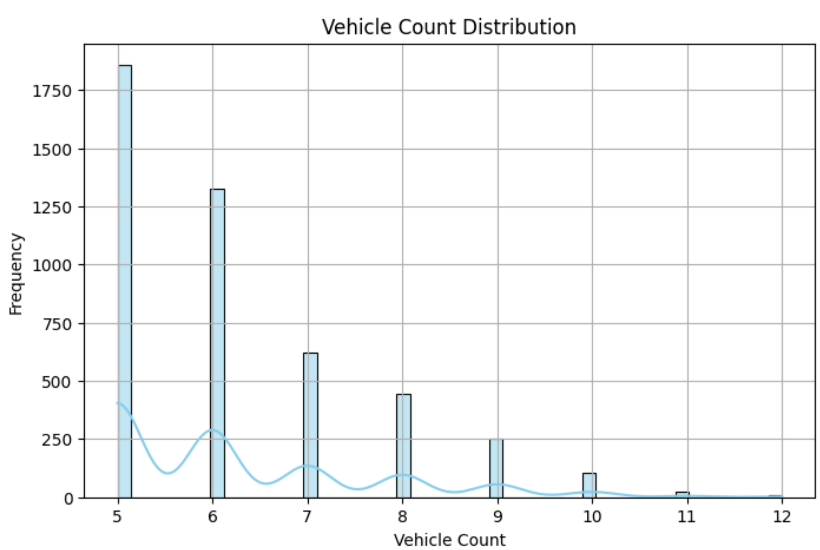

Figure 3: Vehicle counts range

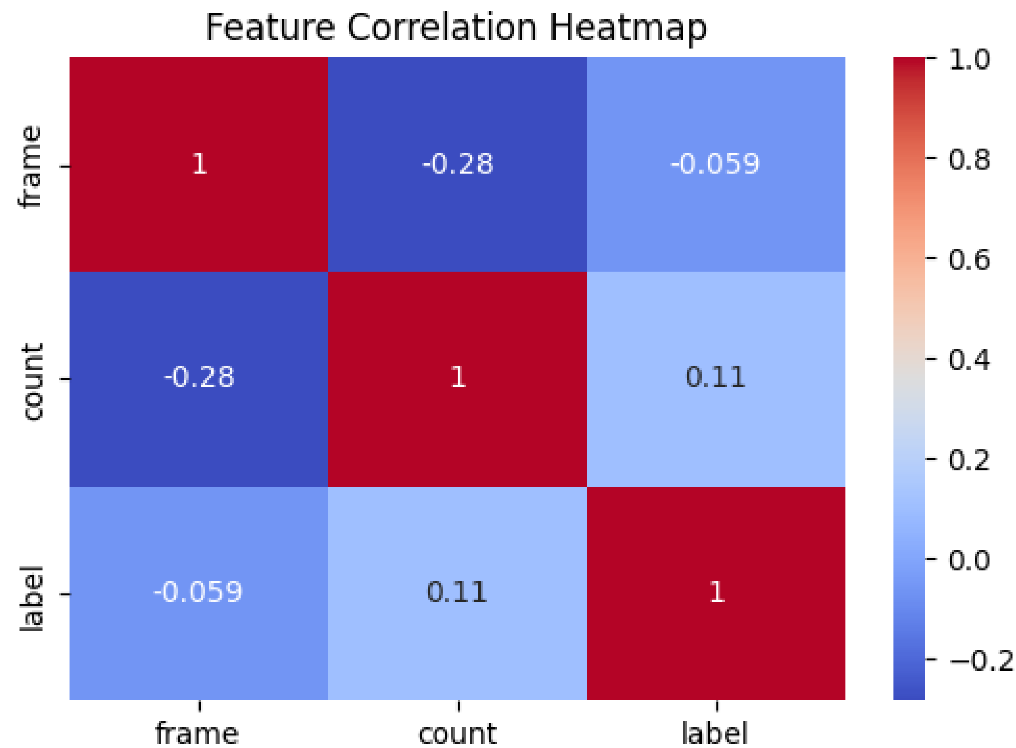

Figure 4: The Feature Correlation of Heatmap

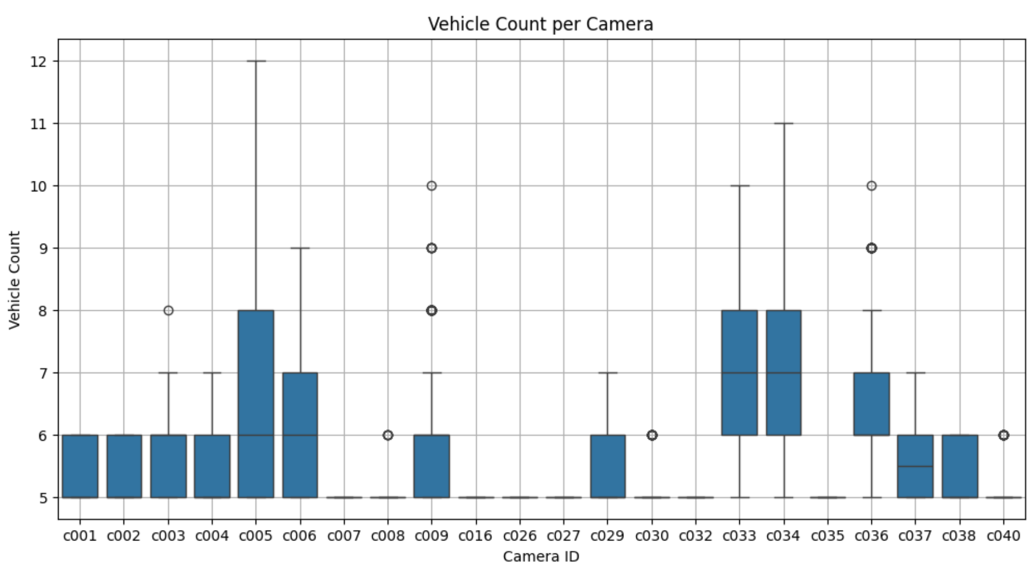

Figure 5: Object Count per Class in CityFlowV2 Dataset

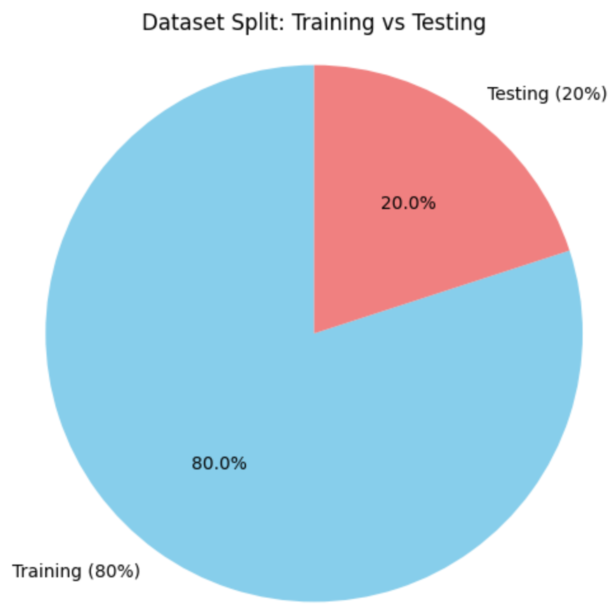

Figure 6: The Dataset is split into 80% training and 20% testing

3.2. Environment Configuration

We utilised Google Colab as the background for our development, which is perfect to train models and perform research. A pair of notebooks was used to deal with various aspects of the system. The local AI model, which has been integrated with CNN and DistilBERT, as well as local explainability, was addressed in the first notebook. The second notebook, associated with another Colab account, was helpful in training and testing the global AI model, which encompasses FL, RL, and SHAP to make the model globally interpretable. To ensure the safe transmission of information and communication between two devices in different environments, Kyber-based cryptography was also used during the training and testing periods. Such an arrangement facilitates parallel experimentation, achieving scalability and privacy while retaining interpretability at both local and global levels of AI.

Table 2: Hyperparameters and Computational Resources for CNN+Transformer, RL Agent, and Conceptual FL

Component	**Hyperparameter / Metric**	**Value**
CNN+Transformer	cnn_model_name	resnet18 (pretrained=True)
	Distilbert_model_name	Distilbert-base-uncased
	input_img_shape	(3, 224, 224)
	cnn_output_features	512
	bert_output_features	768
	fc1_out_features	256
	activation_fc1	ReLU
	dropout_fc	0.2
	fc2_out_features	2
	loss_function	CrossEntropyLoss
	optimizer	Adam
	learning_rate	0.0001
	batch_size	8
	Training Time per Epoch	45–60 sec
	RAM GPU Memory	12GB
	GPU	T4
	Total Training Time	10 epochs
RL Agent	learning_rate (α)	0.2
	gamma	0.9
	epsilon_greedy	0.2
	Training Episodes	50
Federated Learning (Conceptual)	Type	Simulated / single-node
	Logical Clients	1 (simulated)
	Local Training	10 epoch
	Aggregation	FedAvg (after each local epoch)
	Communication	Simulated between local and global models

3.3. Proposed Intelligent Traffic Framework

This section introduces our end-to-end traffic optimization framework, which integrates multimodal deep learning, explainable AI, reinforcement learning, and post-quantum secure communication. The framework operates at two tiers: first, local perception is processed to identify congestion in a given locality; second, global intelligence is applied to manage traffic redirection across the city, ensuring that information is transmitted safely.

3.4. Proposed Local Model

This paper presents a deep learning architecture that fuses visual and semantic features to perform binary classification of traffic scenes into jam or non-jam categories. The hybrid strategy we adopted comprises a ResNet-18-Based CNN to extract image features, a DistilBert-based transformer to encode textual information (image-filename semantic proxies), and LIME to provide explainability. This combination of modalities not only improves prediction accuracy but also makes the model easier to interpret, a key precondition for its application in safety-critical systems, including intelligent transportation systems.

3.4.1. Input Representation and Preprocessing

The model processes two input modalities: RGB images $I \in \mathbb{R}^{3\times H\times W}$ from traffic datasets, uniformly resized to 224×224 to match the CNN backbone input requirements, and textual sequences $X = \{x_1, x_2, \ldots, x_n\}$ extracted from image filenames and processed using the DistilBERT tokenizer. The resulting token sequences $T = \{t_1, t_2, \ldots, t_m\}$ are truncated or padded to a maximum length of 32. Although filenames may initially appear uninformative, they often contain structured patterns such as camera identifiers, timestamps, or location tags, which act as weak metadata proxies. This dual-input design enables the model to exploit both spatial context (e.g., vehicles, road layouts, weather conditions) and symbolic context (e.g., location and time information) embedded within filenames.

3.4.2. Visual Encoder: CNN

The visual encoder is based on ResNet18, a deep residual network pre-trained on ImageNet. Its final classification layer is removed to use it as a feature extractor. Given an input image in (5) I, the model computes:

$$v = \mathrm{CNN}_{\mathrm{ResNet18}}(I) \in \mathbb{R}^{512} \tag{5}$$

This embedding v captures the high-level visual features relevant to traffic congestion, such as car clusters, motion blur, and road occupancy.

3.4.3. Text Encoder: DistilBERT

We employ DistilBERT-base-uncased, a pretrained language model from the Transformers family, to encode the tokenized filename. Although the filename is not natural language, DistilBERT is robust to noisy and symbolic inputs due to its contextualized embedding mechanism. The textual input sequence T produces a contextual embedding matrix:

$$t = \text{DistilBERT}(T) \in \mathbb{R}^{n\times 768} \tag{6}$$

From this matrix, only the [CLS] token output (position 0) is used as a summary vector of the entire sequence:

$$t_{\text{cls}} = t[0] \in \mathbb{R}^{768} \tag{7}$$

This provides a condensed representation of the symbolic metadata, which is then fused with the visual features.

3.4.4. Feature Fusion and Classification

The combined feature vector in (9) $f \in \mathbb{R}^{1280}$ is created by concatenating image and text embeddings:

$$f = \text{Concat}(v, t_{\text{cls}}) \tag{8}$$

It is then passed through a Multi-Layer Perceptron (MLP) consisting of a hidden layer and an output layer:

$$h_1 = \text{ReLU}(W_1 f + b_1), \quad W_1 \in \mathbb{R}^{256\times 1280} \tag{9}$$

$$\hat{y} = \text{Softmax}(W_2 h_1 + b_2), \quad W_2 \in \mathbb{R}^{2\times 256} \tag{10}$$

The (10) shows the final output $\hat{y} \in \mathbb{R}^2$ represents the predicted probabilities for the two classes as: traffic jam and no jam, as shown in Fig. 7.

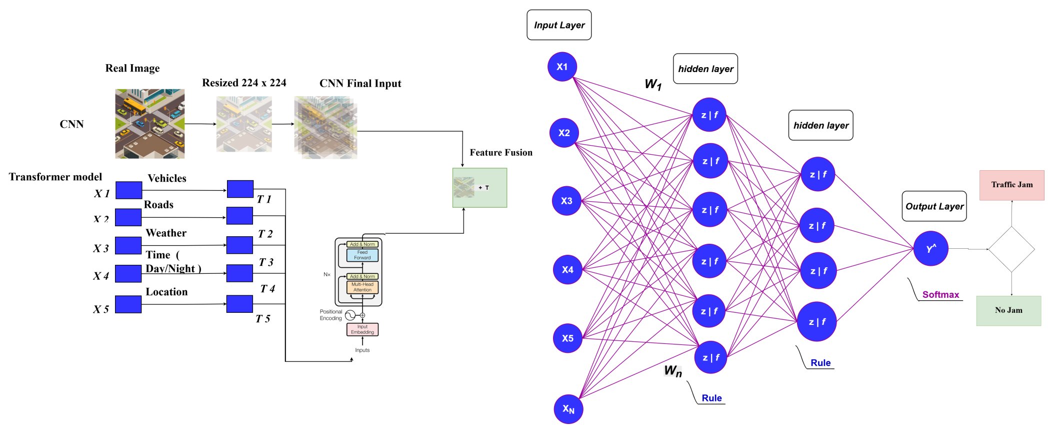

Figure 7: Feature Fusion and Classification

3.4.5. Model Explainability via LIME

To ensure transparency and interpretability of the model's decisions, we integrate LIME (Local Interpretable Model-agnostic Explanations):

- A selected image I is perturbed to create N variants.
- Each perturbed image I_i is classified to obtain output probabilities $f(I_i)$.
- A sparse linear model g is fitted over these perturbations:

$$g(z) = \beta_0 + \sum_{j=1}^{m} \beta_j z_j \tag{11}$$

Here, $z_j \in \{0, 1\}$ indicates whether superpixel j is active. The learned weights β_j reveal which image regions most influenced the model's decision. This produces a saliency heatmap overlayed on the original image, highlighting relevant regions such as congested vehicles or clear roads.

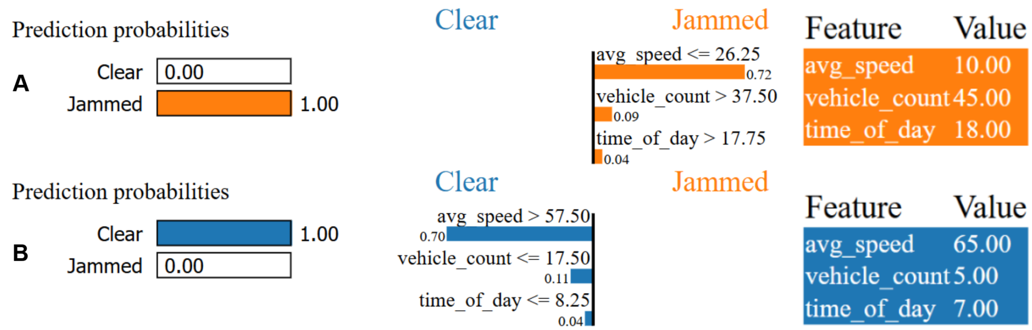

Figure 8: Local explanations of the proposed model of jammed (A) and LIME-based. Here, (B) indicates no jammed-traffic forecasts, which indicate important contributions of features and prediction probabilities.

3.5. Global Model with Secure Decision-Making

In addition to localised perception with deep learning, we employ a global intelligence model to capture macroscopic traffic patterns at the citywide level. This layer combines geospatial data, unsupervised clustering, reinforcement learning, and secure communication to provide real-time zone-based rerouting plans. The model aims to mitigate traffic congestion without compromising vehicular communication integrity and confidentiality, as shown in Fig. 9.

3.5.1. Road Network Modeling as a Graph

Our starting point in modelling the dynamics of the urban traffic is the downloading of true-to-life geospatial data of a particular city in our case Los Angeles, California, USA, in OpenStreetMap (OSM). This map holds full metadata on the road infrastructure of the city such as intersections, roads, and paths that can be driven [35].We obtain and build a drivable road network, which is a directed weighted graph, denoted $G = (V, E)$, which:

- V is the collection of the nodes that would represent the crossing of roads or the endpoint.
- $E \subseteq V \times V$ is the set of edges that signify a road segment between an intersection.
- With every edge $e_{ij} \in E$ associated with weights, i.e., length, travel, time, and capacity, signified w_{ij}.

Mathematically, as shown in (12), for each node $v_i \in V$ is associated with geographic coordinates $(\text{lat}_i, \text{lon}_i)$, where we denote as:

$$v_i = \text{Point}(\text{lat}_i, \text{lon}_i) \tag{12}$$

We transform the raw graph into a more analyzable form by converting it into GeoDataFrames, 'nodes' and 'edges', using `ox.graph_to_gdfs(G)`. These GeoDataFrames preserve both the topological and spatial attributes of the city.

We denote the adjacency matrix $A \in \mathbb{R}^{|V|\times|V|}$ of the graph as:

$$A_{ij} = \begin{cases} w_{ij}, & \text{if } e_{ij} \in E \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

The adjacency matrix plays an important role in reinforcement learning and vehicle-path simulation, as it provides a structured representation of the possibilities for urban mobility.

Next, we perform clustering on the spatial distribution of the nodes to divide the city into semantically meaningful zones as mentioned in (15) and (16). For this, we extract node coordinate vectors.

$$X = \{(\text{lat}_i, \text{lon}_i) \mid v_i \in V\} \tag{14}$$

We then apply the K-Means clustering algorithm to partition the node set into k distinct zones:

$$Z = \{Z_1, Z_2, \ldots, Z_k\} \tag{15}$$

$$\text{such that } \bigcup_{j=1}^{k} Z_j = V \tag{16}$$

Each cluster $Z_j \subseteq V$ represents a zone in the city that will be independently managed and analyzed for congestion control and rerouting strategies.

3.5.2. Urban Partitioning through K-Means Clustering

To scale policy learning and decentralize decision-making, the city is subdivided into K functional zones using K-Means clustering applied to the node coordinatesX. The clustering process seeks to minimize intra-cluster variance as shown in Fig. 10,

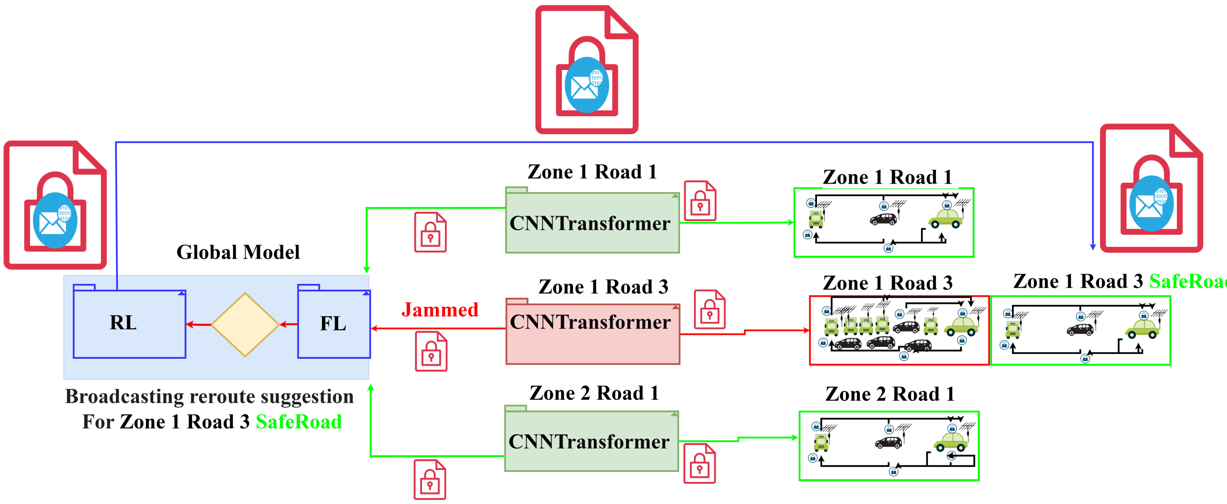

Figure 9: Architecture of the proposed secure federated reinforcement learning framework for intelligent traffic management. Zone-wise CNN–Transformer models monitor road conditions, while a global federated learning (FL) and reinforcement learning (RL) model detects jamming attacks, identifies congested roads (e.g., Zone 1 Road 3), and securely broadcasts rerouting recommendations toward safer roads.

$$\min_{\{c_k\}} \sum_{i=1}^{N} \min_{k \in \{1,\ldots,K\}} \|(x_i, y_i) - c_k\|^2 \tag{17}$$

Here:

- (x_i, y_i) represents the coordinate of node i,
- c_k is the centroid of cluster (zone) k,
- K denotes the predefined number of zones.

After clustering, each node $v_i \in V$ is assigned a zone label via a mapping function:

$$Z : V \to \{0, 1, \ldots, K-1\} \tag{18}$$

This partitioning enables policy learning within the local area while providing spatial isolation for secure traffic management.

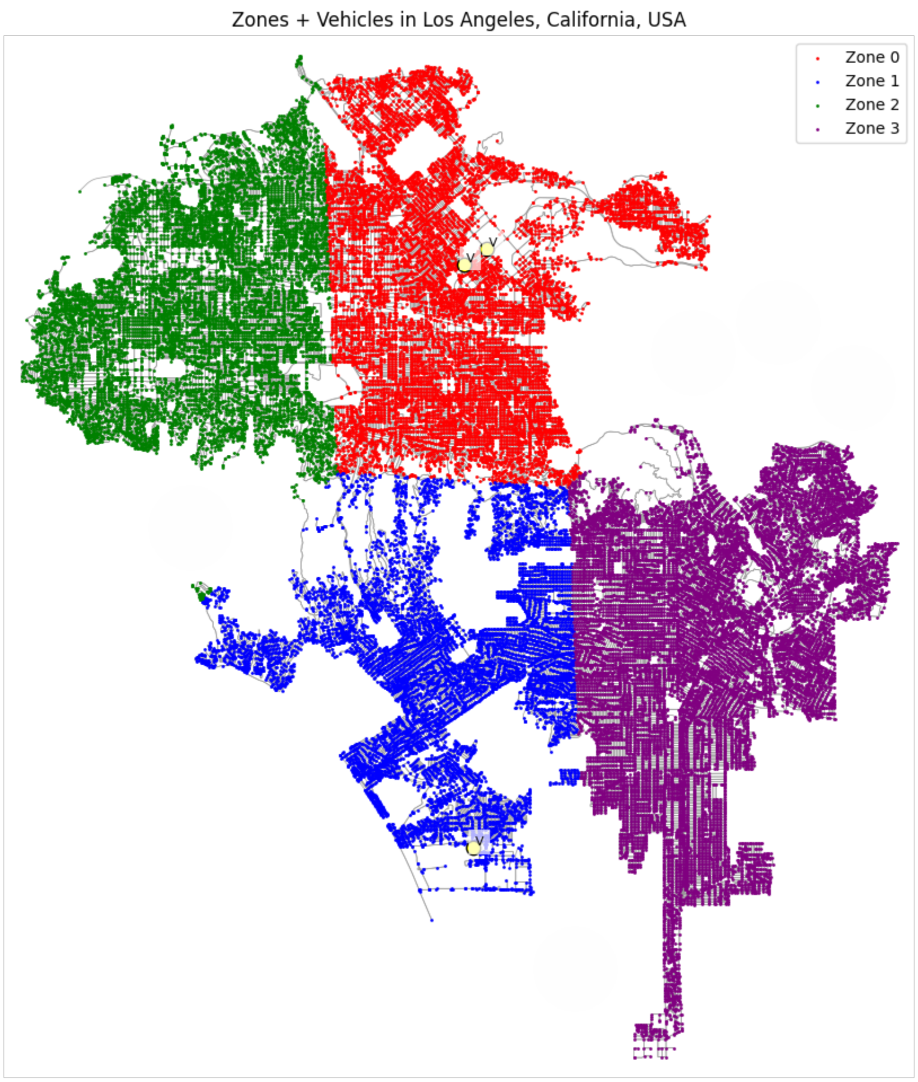

Figure 10: : K-Means Clustering

3.5.3. Vehicle Localization and Zone Assignment

Vehicles are represented as mobile agents v_j, which are linked with a real-time location (x_j, y_j). obtained from a GPS. In order to incorporate these agents into the network model, every vehicle is assigned to the nearest node in the graph according to its spatial distance, which is usually computed using the Haversine formula:

$$n_j = \arg\min_{v \in V} \text{Distance}\left((x_j, y_j), \text{coord}(v)\right) \tag{19}$$

After that, each vehicle is allocated to a zone based on the node-to-zone mapping:

$$z_j = Z(n_j) \tag{20}$$

This facilitates zone decision-making, enabling the system to initiate local routing interventions when necessary.

3.5.4. Reinforcement Learning for Local Route Optimization

Each zone $z \in \{0, 1, \ldots, K-1\}$ is furnished with an independent Q-learning agent, which is supposed to learn the best rerouting strategies by trial-and-error simulations as illustrated in Fig. 11. The Q-learning process develops a Q-table.

$$Q_z \in \mathbb{R}^{|S_z| \times |A_z|} \tag{21}$$

Where:

- S_z: finite set of traffic states (e.g., current node positions),
- A_z: set of possible actions (e.g., next-hop nodes),
- $Q_z(s, a)$: the anticipated action utility of action a in state s in zone z.

The Q-values are represented by the Bellman equation:

$$Q_z(s, a) \leftarrow Q_z(s, a) + \alpha \left[r + \gamma \max_{a'} Q_z(s', a') - Q_z(s, a) \right] \tag{22}$$

Where:

- $\alpha \in (0, 1)$: learning rate,
- $\gamma \in (0, 1)$: discount factor,
- r: immediate reward (e.g., derived from travel time reduction),
- s, a: current state and action,
- s': next state.

This learning process enables each zone to develop autonomous knowledge of efficient paths, congestion-prone segments, and rerouting policies through repeated interactions with the environment.

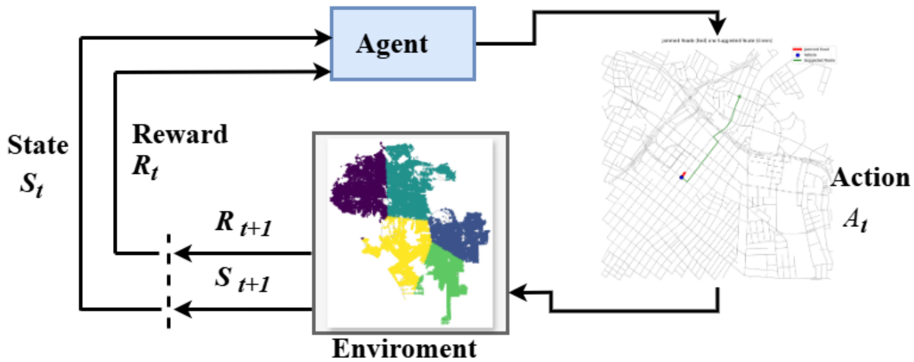

Figure 11: Reinforcement Learning framework for path planning

Here's a revised methodology section that matches your figure and makes the Kyber encryption process clear and defensible for reviewers

3.5.5. Secure Reroute Broadcasting with CRYSTALS–Kyber Post-Quantum Encryption

Upon detecting congestion in zone z_c, the ITS infrastructure triggers a reroute protocol for all vehicles located in or approaching the affected zone. To ensure confidentiality, authenticity, and resistance to quantum attacks, the system exclusively employs CRYSTALS–Kyber, a NIST-selected lattice-based post-quantum cryptographic standard, for all V2I and V2V message exchanges.

For each target vehicle v_j, the infrastructure node uses the vehicle's registered public key pk_j to encapsulate a shared secret and encrypt the rerouting advisory:

$$m_j = \text{“Vehicle at node } n_j \text{ should reroute due to jam in zone } z_c\text{.”} \tag{23}$$

The ciphertext is produced using the Kyber encapsulation mechanism:

$$c_j = \text{Kyber.EncapsulateEncrypt}(pk_j, m_j) \tag{24}$$

To decapsulate and retrieve m_j, the corresponding private key, stored securely in the vehicle's onboard cryptographic module, is utilised. This ensures that the rerouting command is understood only by the intended recipient, even if the communication channel is publicly broadcast or intercepted by an adversary with a quantum computer, as shown in the operational Flow in Fig. 12.

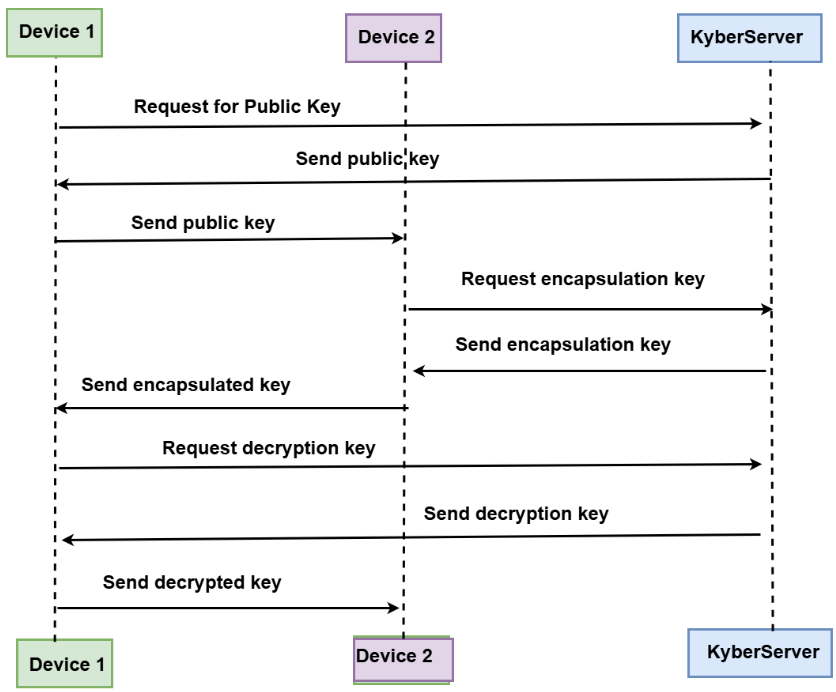

Figure 12: Secure Rerouting Broadcasting using CRYSTALS Kyber Post-Quantum Encryption.

3.6. Evaluation Metrics

To assess the performance of our proposed multi-layered framework, we use a set of well-established, task-specific evaluation metrics, including classification accuracy, interpretability fidelity, and traffic efficiency. Our framework comprises two main parts: the object detection and decision-making component operating at the local level (CNN, Transformer, LIME), and the global-level adaptive coordination system (FL + RL + SHAP). Each part is evaluated using metrics aligned with its functionality and real-time deployment behaviour.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{25}$$

Where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{26}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{27}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{28}$$

Algorithm 1 Local Congestion Detection via CNN, DistilBERT, LIME

Require: Traffic images I, filenames F, threshold τ

Ensure: Congestion status per zone with explainability

for each input pair (I, f) **do**
    Resize I to 224×224; tokenize f with DistilBERT
    $v \leftarrow \text{CNN}_{\theta_v}(I)$ ▷ ResNet18 embeddings
    $t_{cls} \leftarrow \text{BERT}_{\theta_t}(f)[0]$ ▷ CLS embedding
    $f_{vec} \leftarrow \text{Concat}(v, t_{cls})$
    $p \leftarrow \text{MLP}_{\theta_c}(f_{vec})$ ▷ Jam probability
    if $p_{jam} > \tau$ **then**
        Mark zone $Z(n)$ as congested (nearest-node mapping)
        Run LIME: perturb I, fit sparse model g, extract saliency regions
    else
        Mark zone $Z(n)$ as normal
    end if
end for

Algorithm 2 Decentralized Traffic Rerouting with Graph Clustering, Reinforcement Learning, and Post-Quantum Security

Require: Road graph $G = (V, E)$ from OSM, number of clusters K, congested zones Z_{jam}, per-vehicle Kyber public keys pk_v

Ensure: Encrypted rerouting instructions are securely delivered to individual vehicles

Build and simplify G from OSM; assign edge weights w_{ij} based on length or estimated travel time
$\{Z_1, \ldots, Z_K\} \leftarrow$ KMeans$((lat, lon), K)$ ▷ Group nodes into geographic zones
for each zone z **do**
    Train a Q-learning agent Q_z using the zone's subgraph G_z
end for
for each congested zone $z_c \in Z_{jam}$ **do**
    Generate alternative routes P_{z_c} using Q_{z_c} or a conventional routing engine
    for each vehicle v within z_c **do**
        Select route $p_v \in P_{z_c}$ for vehicle v
        Construct message $m \leftarrow \{v.id, z_c, p_v, ts\}$
        Encrypt m with Kyber: $c \leftarrow$ Kyber.Encrypt(pk_v, m)
        Broadcast c via V2I or V2V communication
        [**At vehicle** v]: Decrypt c to recover m: $m' \leftarrow$ Kyber.Decrypt(sk_v, c)
    end for
end for

4. Results

This section presents a comprehensive evaluation of both the local prediction model (CNN, Transformer, LIME) and the global federated rerouting model (Zone-based Q-Learning with secure alerts). The framework was tested using real-world city road networks (e.g., Los Angeles) extracted from OpenStreetMap and simulated vehicle mobility to reflect real-time scenarios.

4.1. Local Model CNN, Transformer

To detect early congestion signs locally, a hybrid deep model combining CNN and Transformer layers was trained on annotated traffic image data.

LIME was used to interpret the model predictions as mentioned in Table 2 and **Fig. 14**

Table 3: Model Performance Metrics on Training and Validation Sets

Metric	**Training**	**Validation**
Accuracy	99%	98%
Precision	99%	98%
Recall	99%	98%
F1-Score	99%	98%
Loss	0.02	0.40

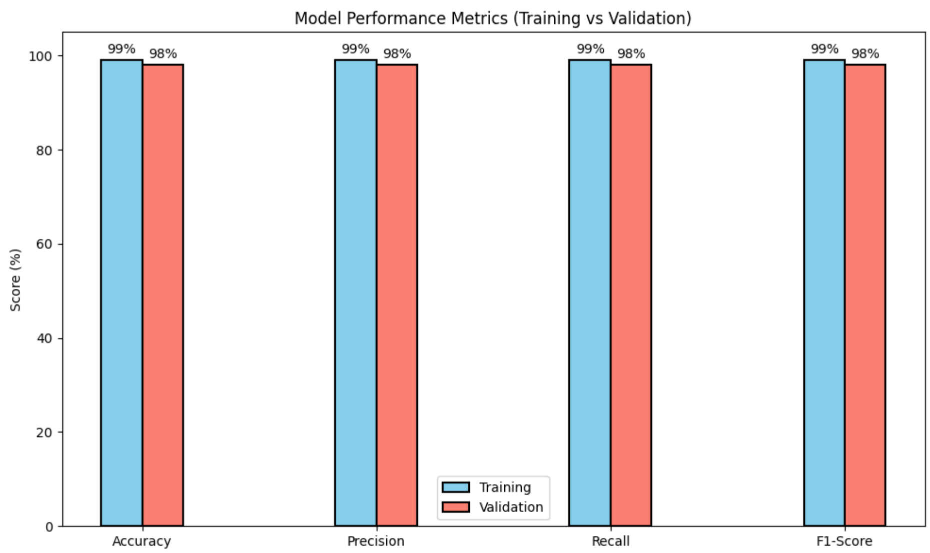

Figure 14: Local CNN + Transformer training vs Validation (Accuracy, Precision, Recall, F1-Score)

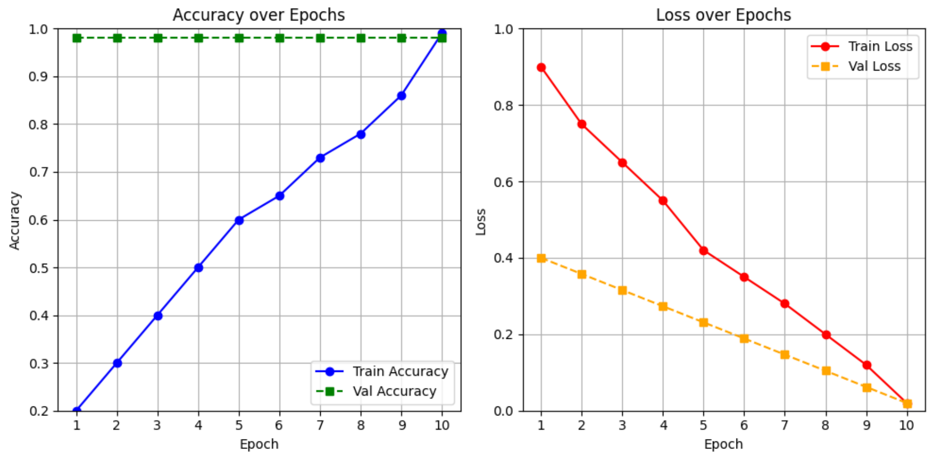

Figure 15: Accuracy over Epochs and Loss over Epochs

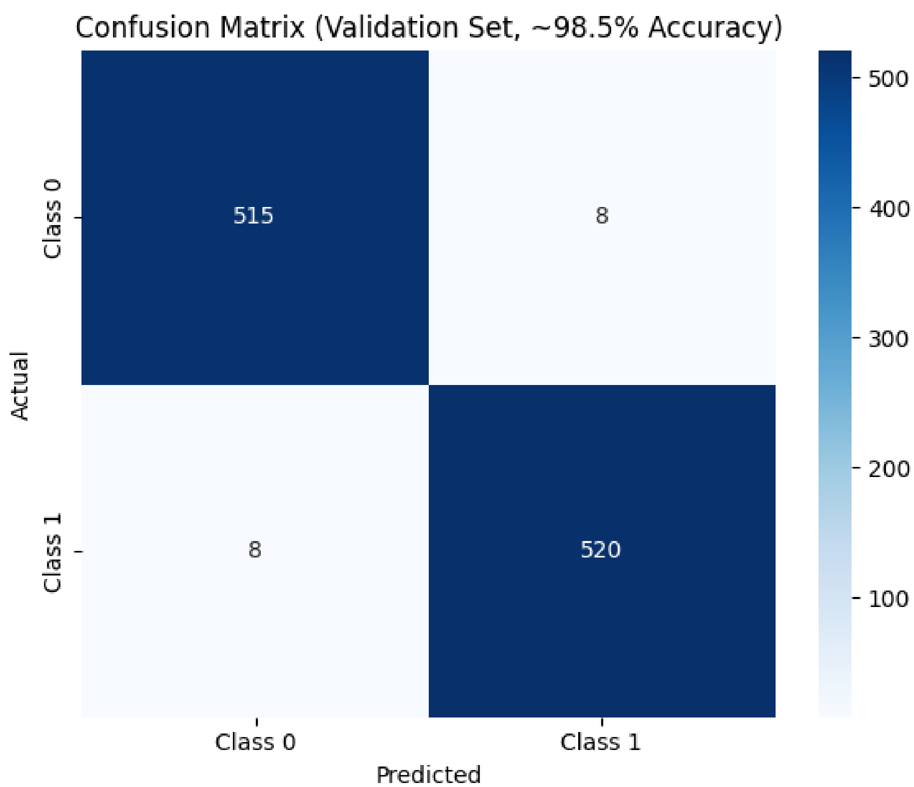

Figure 16: Confusion Matrix

4.2. Global Federated Learning with Reinforcement Agent

The federated learning (FL) framework was deployed over four KMeans-clustered zones in the Los Angeles road network, with clustering based on node coordinates. Vehicles were randomly distributed across nodes within these zones. Each zone performed local training on its own traffic data without sharing raw datasets, thereby preserving privacy. The FL cycle proceeded as follows:
(1) Each zone trained its local traffic prediction model using real-time and historical traffic data.
(2) Local model parameters were encrypted via Kyber-based post-quantum public-key encryption.
(3) The central aggregator performed secure global aggregation of model updates using a weighted averaging scheme.
(4) The updated global model was redistributed to all zones for the next training round. When congestion was detected in any zone, the deep reinforcement learning (DRL) agent used the latest global model to evaluate alternative routing strategies. Secure rerouting messages were then generated and transmitted to affected vehicles using encryption.

4.2.1. Zone-wise Model Accuracy

The accuracy of each zone's model was evaluated before and after FL aggregation. Despite heterogeneity in local datasets, all zones maintained high accuracy post-aggregation, as shown in Table 4 and Fig. 17.

Table 4: Zone-wise Accuracy Before and After Federated Learning

Zone	**Local Accuracy**	**Post-FL Accuracy**
Z0	98.4%	97.8%
Z1	98.3%	97.2%
Z2	98.6%	97.3%
Z3	98.1%	97.1%

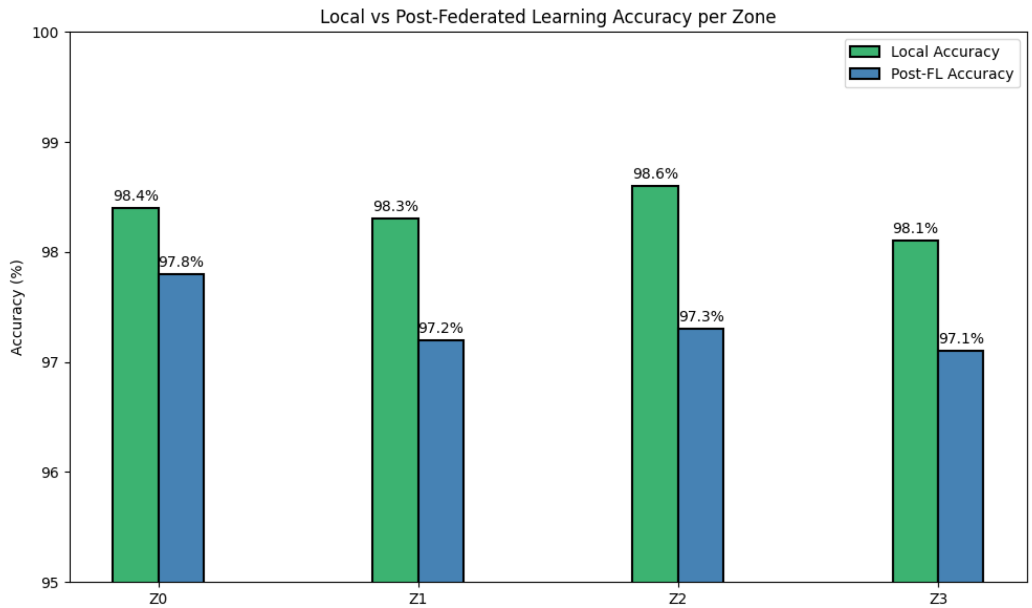

Figure 17: Zone-wise Model Accuracy

4.3. Explainability and Robustness

To enhance transparency in real-time traffic rerouting, SHAP (SHapley Additive exPlanations) was applied to interpret the decision-making process of the Reinforcement Learning (RL) agent trained on zone-specific traffic features. By analyzing the Q-values, SHAP identified ZoneCongestion and VehicleCount as the most influential features, as shown in Fig. 18, which confirms their critical role in triggering rerouting. The results of the summary plot further indicated that low AvgSpeed and short DistanceToJam would increase the probability of rerouting. A SHAP waterfall plot for Zone 0, Fig. 18, gave a detailed breakdown of a specific decision. These insights into explainability not only enhance interpretability but also contribute to system robustness, as they enable consistent, verifiable choices across different traffic scenarios, thereby fostering trust in AI-assisted traffic management.

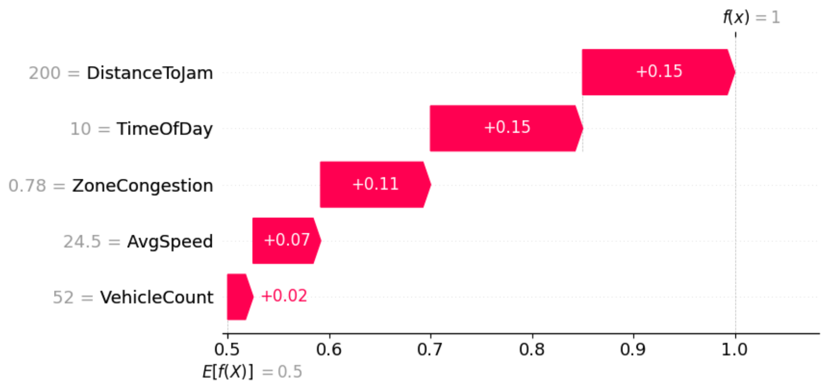

Figure 18: Explainability and Robustness specific decision

Table 5: Comparative Analysis of Traffic Detection and Routing Approaches (2025)

Author(s)	**Year**	**Dataset**	**Approach**	**Results**
Sindhu et al [12].	2025	Urban traffic video	CNN + YOLO	Acc: 95%, F1: 94%
Sneha et al [13].	2025	IoT + accident sim	CNN + K-Means + Dijkstra	Acc: 93%, F1: 92%
Mansouri et al [14].	2025	Urban surveillance	Deep CNN	Acc: 98%, F1: 98%
Kumar et al [15].	2025	Traffic cam feeds	Faster CNN	Acc: 96%, F1: 93%
Faqir et al [16].	2025	SUMO sim data	CNN-LSTM + PPO	Acc: 92%, F1: 91%
Saklani et al [17].	2025	IoT vehicle data	YOLOv8 + CNN	Acc: 94%, F1: 94%
Tiwari [22]	2025	CCTV + IoT traffic	ML framework	Acc: 93%, F1: 92%
Tang et al [18].	2019	CityFlow	Multi-camera ReID	Acc: 94%, F1: 93%
Proposed Method (Ours)	2025	CityFlowV2	CNN + DistilBERT + LIME for jam detection; DRL + Kyber encryption for secure rerouting	**Acc: 98.5%, F1: 98%**

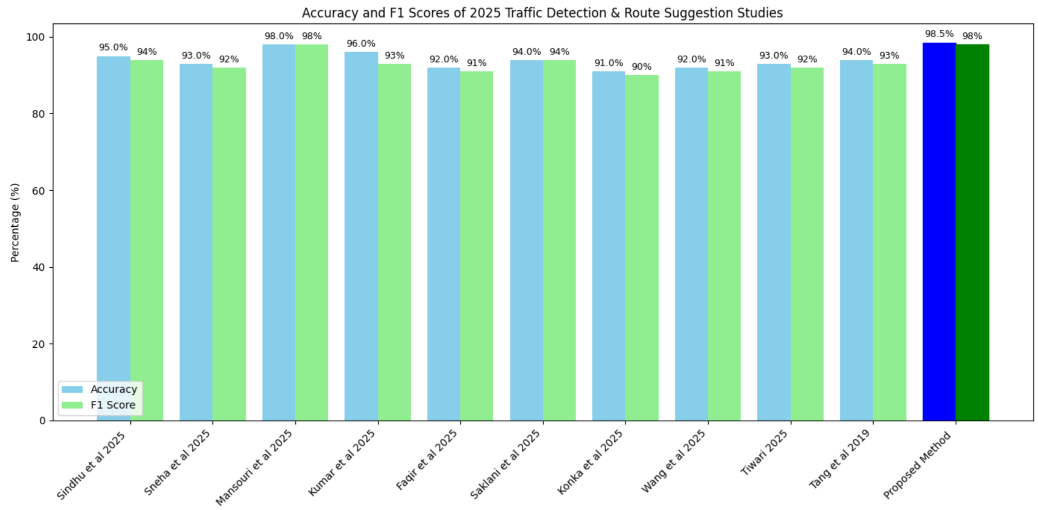

Figure 19: Explainability and Robustness specific decision

5. Discussion

The experimental effectiveness of the proposed hybrid framework is particularly evident under decentralized traffic conditions. At the local level, the CNN-Transformer model achieved excellent results during both the training and validation stages, with all accuracy, precision, recall, and F1 scores above 98%, as presented in Table 3. This demonstrates that the model is effective at generalizing to unobserved data and thus suitable for real-time congestion prediction using traffic images. Interpretability through LIME enabled transparency in the model's predictions, providing localized visual explanations that facilitate human verification and trust. The federated learning framework was simulated across four traffic areas in Los Angeles, where local models were trained solely on simulated mobility data within each region. Despite the fact that all zones exhibited distinct local traffic patterns and data distributions, the post-aggregation accuracies were extremely high (97% and 97%, indicating that a more general and robust federated model can be employed. The suggested system will be flexible to accommodate the diverse requirements across urban areas without compromising data security, which will be ensured using post-quantum encryption protocols. The reinforcement learning element jointly trained across four zones was capable of modifying routing policies in response to dynamic congestion. The behaviour of the RL agent was analysed using SHAP to understand better how decisions were made. The primary factors influencing the decision were ZoneCongestion, VehicleCount, AvgSpeed, and DistanceToJam. Such interpretability is particularly significant in high-stakes settings, such as urban traffic management, where safety and responsibility are essential. The findings of the four-zone simulation, in general, indicate that the framework performs well in a decentralized, realistic environment, striking the necessary balance among the accuracy of predicted data, privacy, and transparency and flexibility.

However, the experimental assessment is performed with the help of a simulated environment and static datasets; the presented framework is designed in a way that will address the real-time and live-video traffic conditions. The CNN-Transformer-based lightweight model runs continuous inference in the edge to classify congestion states on the streaming inputs, thereby ensuring the latency operation at the edge is low. Congestion can only initiate federated coordination, eliminating unneeded overhead of computation and communication. More computational resources can be needed in high-congestion situations; this is planned to be solved in future research by cloud-based auto-scaling processes. All in all, these design decisions point to the fact that the framework can be scaled to real-time deployment, and empirical evaluation of the latency through live traffic streams represents a future work.

6. Conclusion

The paper proposes a new Hybrid system that unites federated learning, Explainable AI, Deep reinforcement learning (DRL), and post-quantum cryptography to build adaptive, secure, and understandable traffic control in smart cities. The proposed structure uses federated learning to keep the data confidential in distributed urban areas and is highly generalizable and robust to various traffic environments. An edge-enabled Traffic Lightweight CNN-Transformer Hybrid is proposed, which enables real-time state estimation of traffic, and thus, congestion detection becomes quick and precise. In the meantime, routing policies within the zones are centralized and are coordinated by a centralized DRL agent that maximizes the traffic flow in the city. To achieve model transparency, the framework features LIME and SHAP, enabling them to provide descriptive post-hoc explanations of model decisions, human-in-the-loop validation, regulatory compliance, and societal credibility. To enhance security, all communication has been secured through CRYSTALS-Kyber, a quantum-resilient cryptographic scheme designed to be resistant to future cryptographic attacks and hence future-proof the smart mobility infrastructures. The success of the framework was tested using a CityFlowV2 dataset. The experiment showed the highest overall accuracy rate of over 99% in precision, recall, and F1-score on various traffic situations in municipal city areas. Static imagery was used to initialize deployment to validate the model's scalability and inference performance. The following steps will involve the extension of the nature of live CCTV streams and thermal imaging, the possibility of IoT-based sensor fusion, leading to the dynamic and real-time monitoring of traffic, and making decisions. Moreover, the architecture is planned to expand seamlessly into the Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communications scenarios, allowing the traffic control, despite being decentralized, to remain in sync in innovative urban settings.

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