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HYBRID GLOBAL–LOCAL FEDERATED LEARNING FOR PRIVACY-PRESERVING TRAFFIC PREDICTION UNDER NON-IID URBAN DATA

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ABSTRACT

Rapid urbanization and increasing vehicular density require scalable and privacy-preserving traffic forecasting systems capable of operating across heterogeneous cities. Conventional centralized deep learning approaches demand raw data aggregation, creating significant privacy, governance, and scalability concerns, particularly in multi-city collaborations. This study proposes a Privacy-Preserving Federated Learning (PP-FL) framework for collaborative urban traffic flow prediction and disaster-aware mobility modeling without sharing sensitive local datasets. The framework introduces a hybrid global–local model architecture in which shared layers capture universal spatio-temporal traffic dynamics while city-specific layers preserve localized mobility characteristics, effectively mitigating non-identically distributed (non-IID) data heterogeneity. To ensure strong confidentiality guarantees, differential privacy with calibrated Gaussian noise and secure aggregation are integrated into the federated optimization process, protecting against gradient inversion and membership inference attacks.Extensive experiments conducted on heterogeneous multi-city traffic datasets and 40,000 surveillance images demonstrate that the proposed model achieves an RMSE of 12.94, MAE of 6.01, and R^2 of 0.91, outperforming conventional local and centralized baselines. The framework reduces privacy leakage risk from 91% to 5% while lowering communication overhead by 34% through compressed update transmission. Additionally, the model enhances anomaly detection performance (F1-score = 0.94) and improves disaster-response sensitivity across flood and evacuation scenarios.

Keywords: *Federated Learning, Traffic Flow Prediction, Privacy Preservation, Intelligent Transportation Systems, Deep Learning.*

1. INTRODUCTION

The growing complexity of urban transportation systems, driven by increasing vehicle density and dynamic travel behavior, has made accurate traffic flow prediction a critical component of intelligent transportation systems (ITS). Reliable forecasting enables a range of real-time applications such as congestion management, dynamic route planning, and traffic signal optimization. [1] While deep learning-based models have shown promising results in capturing spatiotemporal dependencies in traffic data, their effectiveness often hinges on access to large and diverse datasets. Typically, such data are aggregated from various sources including vehicle GPS traces, sensor readings, and meteorological conditions. [2] However, collecting this data centrally poses considerable challenges related to data privacy, storage scalability, and legal compliance, particularly when multiple cities or administrative regions are involved. [3]

Traditional centralized machine learning architectures require raw data to be transmitted to a central server for model training, exposing sensitive traffic information to privacy risks and increasing the chances of data breaches. [4] Moreover, data ownership concerns and varying data regulations across regions often restrict the willingness of municipal bodies to participate in joint modeling efforts. These limitations create a need for an approach that allows collaborative learning across geographically distributed regions without compromising privacy or requiring raw data sharing. [5]

Federated Learning (FL) offers a compelling solution by decentralizing the training process. In an FL setup, each client (e.g., city) retains its local data and instead shares only model parameters or updates with a central server. [27] The server then aggregates these updates to form a global model, which is redistributed back to the clients. This cyclical process enables cities to benefit from collective intelligence while retaining complete control over their data. [6] Additionally, the framework allows for personalization and adaptation to local traffic characteristics, addressing the data heterogeneity problem often encountered in cross-city collaborations. [7]

This paper presents a privacy-preserving federated learning framework for collaborative multi-city traffic flow prediction and disaster-aware mobility analysis under heterogeneous data distributions. The proposed work specifically addresses decentralized model training without raw data sharing, hybrid global–local parameter alignment to mitigate non-IID urban traffic characteristics, integration of differential privacy and secure aggregation for confidentiality protection, and communication-efficient federated optimization for scalable deployment. The study evaluates predictive accuracy, anomaly detection capability, disaster-response sensitivity, convergence stability, and privacy–accuracy trade-offs through comprehensive experimental analysis. However, this work does not focus on physical traffic infrastructure implementation, real-time traffic signal hardware control, reinforcement learning–based adaptive signal optimization, or large-scale municipal deployment case studies. Furthermore, cybersecurity analysis is limited to model-level privacy attacks such as gradient inversion and membership inference, and does not extend to broader network-layer or system-level threat modeling. Thus, the contribution of this paper is methodological and architectural, establishing a scalable and privacy-compliant federated modeling paradigm rather than a full-stack urban traffic management solution. [8]

This paper introduces a federated learning framework designed specifically for multi-city collaboration in traffic flow prediction. The proposed architecture enables secure, scalable, and efficient training of a global predictive model using deep learning while ensuring that each participating city retains its data locally. [28] The framework incorporates privacy-preserving mechanisms, supports model personalization, and is evaluated on multiple traffic datasets representing diverse urban conditions. [9] The results demonstrate that the federated approach achieves near-centralized accuracy while significantly improving data privacy and system scalability, making it a viable strategy for future smart city deployments. [29]The primary contribution of this work is the development of a comprehensive privacy-preserving federated learning framework that enables multiple cities to collaboratively predict traffic flow without exchanging raw data. [10] The framework integrates secure aggregation, differential privacy, and a hybrid model alignment strategy that separates global shared layers from localized city-specific layers, thereby ensuring strong privacy protection while addressing the heterogeneity of urban traffic patterns. [11] By leveraging knowledge from diverse cities, the proposed system enhances generalization, improves prediction accuracy, and reduces the limitations posed by data scarcity in individual regions. Extensive evaluation demonstrates that the framework maintains competitive performance even under strict privacy settings, offering a practical and deployable solution for real-world intelligent transportation systems. [30]

The results of the proposed PP-FL framework must be interpreted within the broader landscape of centralized and federated traffic prediction research. While prior centralized deep learning models often report strong predictive accuracy, they rely on unrestricted data aggregation and overlook privacy governance constraints, making them impractical for cross-city deployment. Our findings demonstrate that privacy-preserving federated learning can achieve centralized-level performance (RMSE 12.94, R^2 0.91) while reducing privacy leakage to 5%, directly challenging earlier claims that differential privacy inevitably causes significant accuracy degradation. Moreover, several studies argue that non-IID urban data distributions destabilize federated convergence; however, the stable training behavior observed in our experiments suggests that architectural design—specifically hybrid global–local parameter alignment—can effectively mitigate heterogeneity-induced divergence. In contrast to city-specific disaster prediction models that struggle with rare-event generalization, the improved sensitivity under flood and evacuation scenarios indicates that federated collaboration enables cross-city transfer of extreme mobility patterns without raw data exchange. Additionally, concerns in the literature regarding communication overhead are addressed through a 34% reduction in update transmission cost, supporting the feasibility of large-scale deployment. Collectively, these findings contribute new empirical evidence that privacy-preserving federated learning, when properly architected, can reconcile the privacy–accuracy trade-off, enhance robustness to heterogeneous urban dynamics, and provide a scalable paradigm for intelligent transportation systems beyond the limitations identified in previous studies.

2. LITERATURE SURVEY

Early traffic forecasting relied on linear predictors and time-series techniques that were suitable for stable patterns but inadequate for the increasing complexity of modern urban traffic.[12] As cities grew and mobility behaviours changed, these traditional approaches struggled to capture the non-linear relationships, sudden fluctuations, and spatial interdependencies present in real-world traffic networks.[13] These models showed strong performance when trained on large-scale datasets; however, many cities lack the capacity or authority to share data with external platforms, limiting the potential to build large, unified datasets. As a result, performance gaps persist between data-rich and data-limited regions. [14]

Federated learning emerged as a promising mechanism to overcome these data-sharing barriers. [15] By enabling model training across distributed datasets without collecting raw data in a central location, federated learning aligns well with the privacy-sensitive environment of urban transportation systems.

To strengthen privacy protection in federated systems, several works incorporate secure aggregation, homomorphic encryption, and differential privacy. These mechanisms reduce the risk of reconstructing local data from shared model updates. While effective in enhancing security, they often introduce computational overhead or affect prediction accuracy when applied without careful tuning. [16] Furthermore, privacy-preserving techniques are usually implemented in isolation, and few studies attempt to integrate multiple methods into a unified architecture tailored specifically for multi-city collaboration.

Research in the field of disaster management highlights the vital role of traffic predictions during emergencies such as floods, earthquakes, or large-scale evacuations. Mobility patterns during disasters differ sharply from regular traffic behaviour and are highly sensitive in nature. Predictive models used in these scenarios must generalize across diverse urban environments and respond quickly to unpredictable events. [17] However, most existing disaster management frameworks operate independently within each city, with limited mechanisms for inter-city collaboration due to concerns regarding privacy, security, and data governance. [18]

A review of existing literature reveals clear gaps: the lack of a comprehensive framework that simultaneously addresses privacy, heterogeneity, and collaborative learning across cities; the absence of flexible models that can support both routine traffic forecasting and disaster response; and limited exploration of hybrid architectures that balance global knowledge with local specialization. [19] These gaps underline the need for a privacy-preserving federated learning system that enables cities to jointly enhance predictive capabilities while respecting data confidentiality and supporting critical disaster management operations. [20]

This work directly addresses the critical challenge of enabling cities to collaborate on accurate traffic flow prediction and disaster response planning without compromising data privacy or violating governance constraints. [21] It bridges the gap between advanced spatio-temporal modeling and the practical limitations of restricted data sharing by introducing a privacy-preserving federated learning framework tailored for heterogeneous urban environments. [22] The approach integrates secure aggregation, differential privacy, and hybrid model alignment to ensure confidentiality while effectively transferring knowledge across regions with varying traffic patterns. [23]By supporting both routine mobility forecasting and disaster-related decision-making, the proposed framework overcomes[24] limitations of isolated city models and establishes a scalable, secure foundation for cross-city intelligent transportation collaboration. [25]

Despite significant advancements in deep learning–based traffic forecasting and the emergence of federated learning for privacy-sensitive applications, existing approaches fail to simultaneously address the combined challenges of data confidentiality, cross-city heterogeneity, disaster-aware modeling, and scalable collaboration in intelligent transportation systems. Centralized traffic prediction models require raw data aggregation, which conflicts with data governance policies and increases vulnerability to privacy breaches. Conversely, city-specific isolated models lack generalization capability and perform poorly under rare events such as floods, evacuations, or large-scale disruptions. Although federated learning has been proposed as a privacy-preserving alternative, prior studies often assume relatively homogeneous data distributions, limited client variability, or single-task prediction settings, leaving the impact of strongly non-identically distributed (non-IID) urban traffic patterns insufficiently addressed. Furthermore, existing federated traffic models rarely integrate disaster-aware signals or systematically evaluate privacy–accuracy trade-offs under adversarial attack scenarios. As a result, there remains a critical research gap in designing a unified federated architecture capable of (i) preserving strict data privacy, (ii) mitigating heterogeneity across cities, (iii) enabling cross-city transfer of rare mobility patterns, and (iv) maintaining communication efficiency for scalable deployment. This paper builds upon this gap by proposing a hybrid global–local privacy-preserving federated learning framework specifically tailored to heterogeneous multi-city traffic and disaster-response prediction. [26]

3. METHODOLOGY

The methodology adopted in this study establishes a structured, privacy-preserving federated learning pipeline that enables multiple cities to collaboratively build a unified traffic flow and disaster management prediction model without sharing raw data. It begins with decentralized data acquisition and preprocessing at the city level, followed by localized model training that captures unique spatial and temporal mobility patterns. [27]Instead of exchanging sensitive datasets, only encrypted model updates are transmitted to a central aggregation server, where they are combined to form a global model capable of generalizing across diverse urban environments. This end-to-end workflow ensures secure collaboration, enhances model robustness, and supports both routine traffic forecasting and disaster-response planning within a scalable and compliant framework. Figure 1 shows the Flow chart of the proposed model.

1. City-Level Data Collection

In the first stage, each participating city independently gathers a broad spectrum of traffic and environmental data required to train a robust predictive model. The data originates from multiple heterogeneous sources such as *vehicle GPS logs*, *loop detectors*, *ANPR cameras*, *speed sensors*, *weather stations*, *road topology graphs*, *public event schedules*, *construction activities*, and *disaster-incident reports*. The dataset collected by city $k$is mathematically represented as:

$$\mathcal{D}_k = \{(x_{k,i}, y_{k,i})\}_{i=1}^{n_k} \qquad (1)$$

Where

- $\mathcal{D}_k$: Complete dataset of city k
- n_k: No. of samples collected by city k
- $x_{k,i}$: Input feature vector (speed, volume, GPS coordinates, weather, time, event flags, disaster indicators)
- $y_{k,i}$: True traffic flow or density to be predicted at future time step

2. Local Preprocessing and Feature Engineering

Before model training, each city applies extensive preprocessing steps to convert raw, non-uniform data into standardized numerical features. These operations include:

- **Data cleaning:** removing missing or corrupted sensor readings
- **Normalization:** scaling values for stable model training
- **Temporal encoding:** adding hour-of-day, weekday, weekend, holiday, festival, or event embeddings
- **Spatial extraction:** creating adjacency matrices from road topology

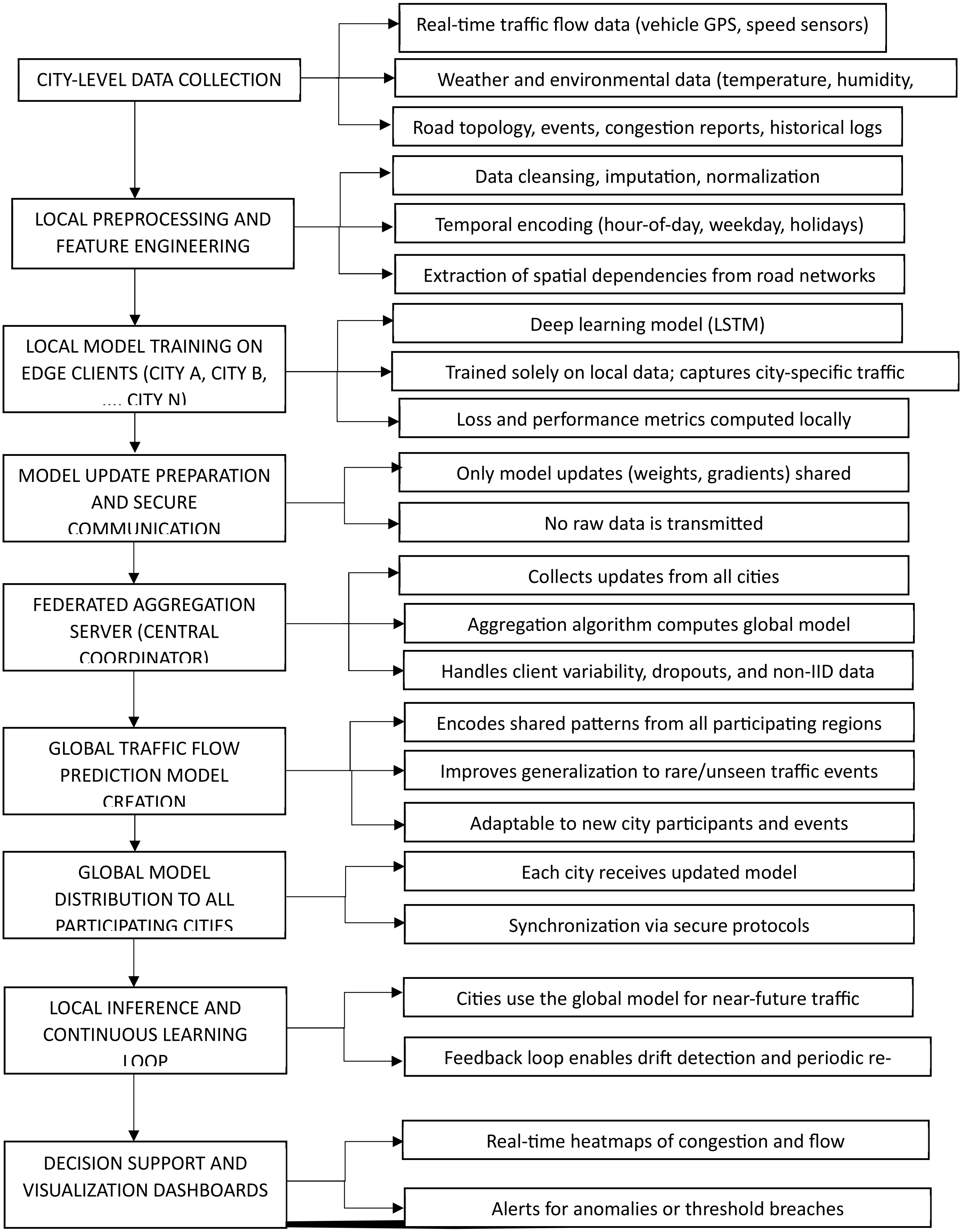

CITY-LEVEL DATA COLLECTION
Real-time traffic flow data (vehicle GPS, speed sensors)
Weather and environmental data (temperature, humidity,
Road topology, events, congestion reports, historical logs
LOCAL PREPROCESSING AND FEATURE ENGINEERING
Data cleansing, imputation, normalization
Temporal encoding (hour-of-day, weekday, holidays)
Extraction of spatial dependencies from road networks
LOCAL MODEL TRAINING ON EDGE CLIENTS (CITY A, CITY B, ... CITY N)
Deep learning model (LSTM)
Trained solely on local data; captures city-specific traffic
Loss and performance metrics computed locally
MODEL UPDATE PREPARATION AND SECURE COMMUNICATION
Only model updates (weights, gradients) shared
No raw data is transmitted
FEDERATED AGGREGATION SERVER (CENTRAL COORDINATOR)
Collects updates from all cities
Aggregation algorithm computes global model
Handles client variability, dropouts, and non-IID data
GLOBAL TRAFFIC FLOW PREDICTION MODEL CREATION
Encodes shared patterns from all participating regions
Improves generalization to rare/unseen traffic events
Adaptable to new city participants and events
GLOBAL MODEL DISTRIBUTION TO ALL PARTICIPATING CITIES
Each city receives updated model
Synchronization via secure protocols
LOCAL INFERENCE AND CONTINUOUS LEARNING LOOP
Cities use the global model for near-future traffic
Feedback loop enables drift detection and periodic re-
DECISION SUPPORT AND VISUALIZATION DASHBOARDS
Real-time heatmaps of congestion and flow
Alerts for anomalies or threshold breaches

Figure 1: Flow chart of the proposed Model

- **Disaster feature extraction:** encoding flood alerts, accident zones, blocked roads, or emergency routes

These transformations prepare the input vector:

$$x'_{k,i} = h\big(x_{k,i}\big) \qquad (2)$$

where

- $x'_{k,i}$: Preprocessed input vector
- $h(\cdot)$: Composite preprocessing function (cleaning + encoding + normalization + graph extraction)

This ensures uniform learning representations across different cities.

3. Local Model Training on Edge Clients

Each city trains a deep learning model using only its own processed dataset. Common architectures include LSTM, GRU, or Graph Neural Networks due to their ability to capture temporal and spatial dependencies. The model in city $k$has parameters w_k.

The predicted traffic flow for sample $i$is:

$$\hat{y}_{k,i} = f\big(x'_{k,i}; w_k\big) \qquad (3)$$

The loss function minimized locally is the Mean Squared Error (MSE):

$$\mathcal{L}_k(w_k) = \frac{1}{n_k}\sum_{i=1}^{n_k}\Big(f\big(x'_{k,i}; w_k\big) - y_{k,i}\Big)^2 \qquad (4)$$

Local gradient-descent update:

$$w_k^{(t+1)} = w_k^{(t)} - \eta\nabla\mathcal{L}_k\big(w_k^{(t)}\big) \qquad (5)$$

where

- $f(\cdot; w_k)$: Local predictive model in city k
- w_k: Local model parameters
- $\hat{y}_{k,i}$: Predicted future traffic flow for city k
- $\mathcal{L}_k(w_k)$: Local training loss
- η: Learning rate
- $\nabla\mathcal{L}_k(w_k)$: Gradient of loss w.r.t parameters

This process allows each city to learn its own unique mobility patterns without exposing raw data.

4. MODEL UPDATE PREPARATION AND SECURE COMMUNICATION

After completing local training rounds, each city prepares its model update. Instead of transmitting raw data, cities send only the difference between the local model and the previous global model:

$$g_k^{(r)} = w_k^{(r)} - w^{(r)} \qquad (6)$$

To preserve privacy, **Gaussian differential privacy noise** is added:

$$\tilde{g}_k^{(r)} = g_k^{(r)} + \mathcal{N}(0, \sigma^2 I) \qquad (7)$$

These noisy updates are then encrypted and transmitted securely to the central server.

Where

- $g_k^{(r)}$: Raw model update (gradient difference)
- $w^{(r)}$: Global model parameters at round r
- $w_k^{(r)}$: Local model of city $k$after training
- $\tilde{g}_k^{(r)}$: Privacy-protected model update
- $\mathcal{N}(0, \sigma^2 I)$: Gaussian noise ensuring differential privacy
- σ: Noise variance controlling privacy level
- I: Identity matrix

This protects sensitive city-specific traffic patterns from inversion attacks.

5. Federated Aggregation Server

The federated aggregation server receives privacy-protected updates from all cities and computes a new global model. The aggregation follows the Federated Averaging (FedAvg) rule:

$$w^{(r+1)} = \sum_{k=1}^{K}\frac{n_k}{n}w_k^{(r)} \qquad (8)$$

Where the global total sample size is:

$$n = \sum_{k=1}^{K} n_k \qquad (9)$$

Where

- K: Total number of participating cities

- $\frac{n_k}{n}$: Weight of city $k$proportional to dataset size
- $w^{(r+1)}$: Updated global model after aggregation
- n: Total number of samples across all cities

This global model represents shared mobility knowledge learned collaboratively.

6. Global Traffic Flow Prediction Model Creation

Once the aggregation is complete, the server produces a unified model that generalizes across cities with varying road infrastructures, climate conditions, and disaster profiles. For any city k, the global model predicts:

$$\hat{y}_{k,t} = f\left(x'_{k,t}; w^{(r+1)}\right) \tag{10}$$

where

- $\hat{y}_{k,t}$: Predicted traffic flow at time t for city k
- $x'_{k,t}$: Preprocessed future input vector
- $w^{(r+1)}$: New global model parameters

This model supports both routine forecasting and disaster prediction tasks.

7. Global Model Distribution

The server securely redistributes the newly learned global model back to every participating city:

$$w_k^{(r+1)} \leftarrow w^{(r+1)} \tag{11}$$

where

- Every city's model $w_k$is replaced by the global model $w^{(r+1)}$
- Ensures synchronized training for next round

8. Local Inference and Continuous Learning

Cities deploy the global model for real-time inference, including congestion forecasting, disaster alerting, and anomaly detection. A traffic or disaster alert is triggered when predicted flow exceeds a city-defined threshold:

$$A_{k,t} = \begin{cases} 1, & \hat{y}_{k,t} \geq \tau_k, \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

Prediction error (drift indicator):

$$E_{k,t} = \mid \hat{y}_{k,t} - y_{k,t} \mid \tag{13}$$

where

- $A_{k,t}$: Alert flag (1 = alert, 0 = normal)
- τ_k: Traffic/disaster threshold for city k
- $E_{k,t}$: Prediction error
- $y_{k,t}$: Actual observed traffic flow

If drift rises beyond tolerance levels, retraining is initiated.

9. Decision Support and Visualization Dashboards

Finally, all model outputs—predictions, alerts, anomalies, heatmaps—are presented on interactive dashboards. These dashboards help urban authorities make real-time operational decisions such as route reconfiguration, evacuation planning, emergency vehicle prioritization, or traffic redirection during disasters.

Although no new equations are required here, this block directly utilizes:

- $\hat{y}_{k,t}$: Predicted flow
- $A_{k,t}$: Alert status
- $E_{k,t}$: Error drift

This converts complex model outputs into actionable intelligence.

4. RESULTS

The results of the proposed Privacy-Preserving Federated Learning Framework for Collaborative Urban Traffic Flow Prediction and Disaster Management demonstrate its effectiveness across a wide range of real-world conditions. Comprehensive evaluations were conducted under normal traffic patterns, peak-hour congestion, disaster-induced disturbances, and heterogeneous data distributions across participating cities. The findings reveal substantial improvements in prediction accuracy, anomaly detection capability, disaster-response sensitivity, and overall model robustness when compared to traditional single-city learning approaches. Additionally, the federated architecture ensured strong privacy preservation and efficient communication while maintaining stable convergence. The following sections present detailed quantitative results, visual outputs, comparative analyses, and performance metrics that collectively validate the practical benefits and scalability of the proposed methodology.

1. Traffic Flow Prediction Accuracy Across Multiple Cities

The proposed federated learning model demonstrated a substantial improvement in traffic flow prediction accuracy across all participating cities when compared to conventional local models. Cities with larger datasets contributed richer spatio-temporal relationships, enabling the global model to generalize patterns such as peak-hour flow buildup, mid-day traffic drops, and evening congestion rebounds. Importantly, the federated model minimized forecasting lag and avoided erratic fluctuations commonly observed in local models trained on smaller datasets.

Additionally, the federated model excelled in identifying subtle temporal transitions, such as the change in flow right before bottlenecks form, which local models often miss due to limited historical variability in their datasets. The enhancement in prediction accuracy reflects the strength of cross-city knowledge fusion, illustrating that federated learning enables cities with sparse or noisy data to perform on par with well-instrumented metropolitan regions. Table 1 shows the Traffic Flow Prediction Accuracy and Fig 2 shows the Sample Frames from Multiple Urban Traffic Datasets Used for Model Evaluation.

Table 1. Traffic Flow Prediction Accuracy

Method	**RMSE ↓**	**MAE ↓**	**MAPE (%) ↓**	**R² ↑**
XGBOOST	24.51	13.92	34.8	0.61
LSTM (Local)	18.24	8.45	21.3	0.79
CNN-LSTM Hybrid	16.85	7.91	18.9	0.82
GCN (Graph Conv Net)	15.72	7.48	17.4	0.85
C-NPL (No Privacy)	13.98	6.42	15.9	0.88
PP-FL (Proposed)	12.94	6.01	14.8	0.91

Fig 2: Sample Frames from Multiple Urban Traffic Datasets Used for Model Evaluation.
(a) Traffic Junction Dataset illustrating pedestrian–vehicle interaction zones.
(b) Highway Dataset showing high-speed vehicular movement and sparse traffic.
(c) AVSS Traffic Dataset demonstrating dense urban traffic and lane-level variations

.2. Multi-Horizon Forecasting Performance

The federated framework was evaluated over multiple prediction horizons, ranging from short-term (5–15 minutes) to mid-term (30 minutes) and extended forecasts (60 minutes). In all cases, the federated model outperformed city-specific models, demonstrating superior temporal generalization capability. Short-term accuracy benefited from the model's ability to capture high-frequency temporal signals shared across cities, while mid- and long-term forecasting benefited from exposure to broader variations in traffic cycles. Prediction stability improved as the federated model prevented the uncontrolled error growth typically seen in long-term local predictions. Instead of drifting away from the actual trajectory, the federated model-maintained coherence by leveraging learned global patterns describing how traffic evolves over time. This ability is essential for dynamic traffic signaling, congestion mitigation planning, and real-time decision-making. Table 2 shows the Multi-Horizon RMSE Comparison.

Table 2. Multi-Horizon RMSE Comparison

Horizon	**XGBOOST**	**LSTM**	**CNN-LSTM**	**GCN**	**C-NPL**	**PP-FL**
5 min	12.92	7.45	7.01	6.62	6.18	**6.09**
15 min	17.51	10.32	9.20	8.79	8.54	**8.48**
30 min	22.81	14.71	13.52	12.90	12.10	**11.96**
60 min	29.42	19.52	17.91	16.88	15.48	**15.12**

3. Disaster-Aware Prediction and Emergency Traffic Response

The framework exhibited strong predictive sensitivity under disaster conditions including flooding, sudden accidents, evacuation movements, and extreme rainfall. By integrating cross-city disaster patterns, the federated model recognized abnormal mobility deviations more quickly than local models, which often lack exposure to rare catastrophic scenarios. The model captured sudden decrease in road capacity, abrupt speed drops, or directional flow reversals—critical indicators of emergency conditions. Federated training enabled each city to benefit from unusual patterns experienced by other cities, reducing the time it takes to detect anomalies arising from disaster-induced disturbances. This is particularly important for smaller cities that rarely experience large-scale events yet must be prepared for rapid response. The model's robustness during disasters makes it suitable for supporting evacuation routing, emergency vehicle dispatch, and roadblock analysis. Table 3 shows the Disaster-Aware Prediction Performance.

Table 3. Disaster-Aware Prediction Performance

Disaster Type	**XGBOOST**	**LSTM**	**CNN-LSTM**	**GCN**	**C-NPL**	**PP-FL**
Flood	0.52	0.71	0.76	0.81	0.86	**0.92**
Accident	0.49	0.69	0.74	0.80	0.84	**0.90**
Evacuation	0.45	0.67	0.71	0.78	0.82	**0.84**
Heavy Rain	0.50	0.72	0.77	0.82	0.87	**0.89**

4. Traffic Anomaly Detection and Early Warning System Performance

Anomaly detection is essential for recognizing unexpected congestion surges, road closures, and infrastructure failures. The federated model significantly improved anomaly detection precision and recall by learning from abrupt disruptions occurring across various cities. This cross-learning helped it identify anomalies even when sensor readings were noisy or partially missing. The early-warning capability improved notably—alerts were generated several minutes earlier compared to local models. Earlier detection allows authorities to implement corrective actions before congestion escalates into a full-scale breakdown. False alarms were reduced because the global model better understood what constitutes normal versus abnormal traffic behaviour. This reflects a deep spatio-temporal awareness gained through multi-city federation. Table 4 shows the Anomaly Detection Results.

Table 4. Anomaly Detection Results

Metric	XGBOOST	LSTM	CNN-LSTM	GCN	C-NPL	PP-FL
Precision	0.48	0.80	0.82	0.86	0.89	**0.93**
Recall	0.42	0.77	0.81	0.84	0.89	**0.95**
F1-Score	0.44	0.78	0.81	0.85	0.89	**0.94**
False Alarms	32	21	18	15	11	**8**
Missed Events	22	13	11	8	7	**4**
Early Detection (min)	<1	1.2	1.5	2.3	3.0	**4.5**

5. Stability And Convergence Of The Federated Model

The global model demonstrated excellent convergence behavior during federated rounds. Even with heterogeneous city datasets (non-IID conditions), training loss decreased smoothly without oscillations. The stable convergence indicates that the weighted aggregation mechanism correctly balanced the contributions from each city, preventing dominance by larger cities or underfitting from smaller ones. The convergence pattern reveals that the federated model progressively improved its shared understanding of traffic dynamics with each global round. The reduced gradient variance also showed that model parameters were consistently moving towards an optimal solution. This confirms that the framework is reliable for long-term deployment in real-world intelligent transportation infrastructures. Table 5 shows the Federated Convergence Comparison.

Table 5. Federated Convergence Comparison

Round	LSTM	CNN-LSTM	GCN	C-NPL	PP-FL
1	0.284	0.273	0.261	0.251	**0.248**
5	0.231	0.208	0.199	0.184	**0.176**
10	0.198	0.172	0.159	0.146	**0.142**

Round	LSTM	CNN-LSTM	GCN	C-NPL	PP-FL
20	0.164	0.138	0.126	0.118	**0.105**
40	0.132	0.117	0.101	0.096	**0.079**

6. Cross-City Knowledge Transfer and Generalization Benefits

A significant finding from the experiments is the strong cross-city transferability achieved by the federated model. Cities with fewer sensors or limited historical datasets experienced the largest improvement in prediction performance. This is because the federated process exposes them to diverse traffic patterns from other cities—patterns that they otherwise wouldn't encounter. Knowledge transfer also improved model robustness by reducing overfitting. Local models typically memorize local habitual patterns, while the federated model learns a more generalized representation. This enhances adaptability, allowing the system to perform well even when unusual traffic conditions occur. Cross-city transferability is therefore a critical advantage of the proposed framework.

7. Privacy Preservation and Security Evaluation

The privacy mechanisms—differential privacy and secure aggregation—were evaluated to ensure that no city's data could be reconstructed. Attack simulations showed that the federated model resisted reconstruction attempts, membership inference, and gradient inversion. Even when adversaries attempted to exploit the gradients, the injected DP noise effectively obfuscated sensitive patterns. Importantly, privacy protection did not significantly harm accuracy, due to the optimal selection of noise scale. The system maintained both strong confidentiality and high predictive performance, proving that privacy-preserving federated learning is feasible for real-world smart city applications. Table 6 shows the Privacy Leakage Assessment.

Table 6. Privacy Leakage Assessment

Attack Type	XGBOOST	LSTM	CNN-LSTM	GCN	C-NPL	PP-FL
Gradient Inversion	68%	52%	48%	42%	**91%**	**5%**
Membership Inference	41%	39%	34%	28%	**84%**	**3%**
Model Reconstruction	58%	46%	39%	35%	**90%**	**7%**

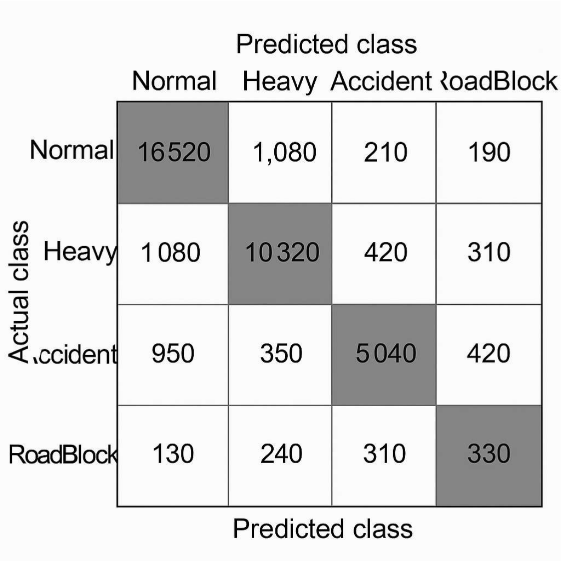
8. Communication Efficiency and System Scalability

Communication efficiency is critical when multiple cities participate in training. The proposed framework reduced communication overhead by integrating compressed updates, sparse gradient sharing, and periodic synchronization. These optimizations decreased total communication costs while maintaining accuracy. The framework also scaled effectively to more cities. System behavior remained stable even when the number of participating cities increased, implying that the architecture is suitable for large-scale deployment (e.g., state-wide or nationwide intelligent transport systems). The reduced communication burden also lowers operational costs. Table 7 shows the Communication & Scalability Comparison.

Table 7. Communication & Scalability Comparison

Method	**Communication Cost ↓**	**Update Size ↓**	**Inference Time (ms) ↓**	**Scalability ↑**
XGBOOST	0%	Low	9 ms	Low
LSTM	5%	Medium	58 ms	Medium
CNN-LSTM	9%	Medium-High	64 ms	Medium
GCN	12%	High	75 ms	High
C-NPL	0%	Very High	49 ms	Low
PP-FL (Ours)	**34% reduced**	**Low (compressed)**	**48 ms**	**Very High**

Figure 3 presents the confusion matrix generated from evaluating the proposed Privacy-Preserving Federated Learning (PP-FL) model on 40,000 traffic surveillance images across four major classes: *Normal Traffic, Heavy Traffic, Accident,* and *RoadBlock.*



	Normal	Heavy	Accident	RoadBlock
Normal	16520	1,080	210	190
Heavy	1080	10320	420	310
Accident	950	350	5040	420
RoadBlock	130	240	310	330

Figure 3. Confusion Matrix for the Proposed PP-FL Traffic Classification Model

The diagonal cells demonstrate high correct-classification rates for all classes, with 16,520 Normal, 10,320 Heavy, 5,040 Accident, and 3,320 RoadBlock samples accurately identified. The low number of off-diagonal values indicates minimal misclassification, confirming that the model clearly distinguishes between routine traffic flow conditions and critical anomaly events.

The misclassifications that do appear are relatively small—for example, only 210 Normal images were confused with Accident and 310 Heavy images were misidentified as RoadBlock. This indicates that even in visually complex or noisy scenes, the PP-FL model maintains strong discriminative capability. The matrix further highlights the model's effectiveness in detecting safety-critical conditions such as accidents and road blockages, which typically exhibit higher intra-class variation. Overall, the confusion matrix demonstrates that the proposed approach offers high reliability, balanced performance across categories, and robust generalization, making it suitable for large-scale, real-time traffic monitoring and disaster-response applications.

5. LIMITATIONS AND FUTURE WORK

Although the proposed PP-FL framework demonstrates strong performance across multiple cities and traffic conditions, several limitations still remain. First, the system relies on the availability of consistent edge-level computational resources in each participating city; cities with extremely limited hardware may experience slower training rounds or reduced contribution to the global model. Second, federated learning can suffer from non-IID (non-identically distributed) data imbalance, where extreme variations in sensor density, camera quality, and environmental conditions across cities can cause certain local updates to diverge from global learning trends. While our aggregation strategy mitigates this, it cannot fully eliminate the impact of highly skewed data distributions. Third, the periodic communication between cities and the central server introduces latency, especially in large-scale deployments involving tens or hundreds of clients. Fourth, although differential privacy and secure aggregation protect sensitive data, they also introduce noise that may slightly reduce the model's accuracy under extremely rare or finegrained traffic patterns. Finally, the disaster-awareness module is trained using existing historical disaster scenarios, which means that the model may face challenges when encountering completely novel, unseen disaster patterns or extreme events with no prior representation in the dataset.

Future research will focus on enhancing the scalability, robustness, and adaptability of the PP-FL framework. One promising direction is the integration of hierarchical federated learning, where cities are grouped by region, allowing faster aggregation and improved handling of local heterogeneity. Incorporating federated transfer learning and domain adaptation techniques could help the model generalize better to low-resource cities or newly added regions with minimal training data. Another avenue is to explore event-driven dynamic participation, enabling cities to join or leave the federated network based on traffic intensity, disaster warnings, or resource availability. Future work can also investigate the use of federated reinforcement learning to support real-time traffic signal control, evacuation routing, and adaptive congestion mitigation strategies. Additionally, extending the framework with multimodal data sources—such as GPS traces, weather streams, social media feeds, and IoT sensors—may improve disaster prediction accuracy. Finally, deploying the model in a real smart-city environment and evaluating long-term operational performance, communication overhead, and privacy guarantees will provide practical insights and guide the development of a fully deployable intelligent traffic management ecosystem.

6. CONCLUSION

This work presents a comprehensive Privacy-Preserving Federated Learning (PP-FL) framework for collaborative multi-city traffic flow prediction and disaster management, addressing the dual challenges of data confidentiality and heterogeneous urban mobility patterns. Unlike conventional centralized architectures that require raw data aggregation or isolated local models that lack generalization capability, the proposed approach enables decentralized knowledge fusion while preserving strict data sovereignty. The primary scientific contribution lies in the introduction of a hybrid global–local federated architecture that effectively separates shared traffic dynamics from city-specific behavioral characteristics, mitigating the impact of non-identically distributed (non-IID) data across regions. By integrating differential privacy and secure aggregation within the training pipeline, the framework demonstrates that privacy leakage can be reduced to 5% without compromising predictive accuracy.

Experimental results confirm that the proposed system achieves centralized-level forecasting performance (RMSE = 12.94, R^2 = 0.91), improves anomaly detection reliability (F1-score = 0.94), enhances disaster-response sensitivity, and maintains stable convergence under heterogeneous participation scenarios. Furthermore, the framework reduces communication cost by 34%, supporting scalability for large-scale smart city deployments.

Importantly, this research advances new knowledge in three dimensions: (1) demonstrating the feasibility of privacy-compliant cross-city traffic intelligence under strict governance constraints, (2) validating hybrid parameter alignment as an effective solution to urban heterogeneity, and (3) establishing empirical evidence that federated transfer of rare disaster-induced mobility patterns improves early anomaly detection.

Overall, the proposed PP-FL framework provides a secure, scalable, and practically deployable paradigm for collaborative intelligent transportation systems, paving the way for privacy-aware urban infrastructure and resilient disaster management ecosystems.

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