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Intelligent transportation network-based congestion forecasting with federated learning and a convolutional neural network

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ABSTRACT

The heavy traffic in growing cities hurts the environment, commuters, and economy. Predicting such difficulties early helps increase road network capacity and efficiency and reduce congestion. Many academicians and transportation engineers ignore traffic congestion prediction despite its importance. Insufficient computationally efficient traffic forecast systems and high-quality city-wide traffic data contribute to this. Provide useful information to reduce traffic and construct shorter, more energy-efficient routes. Data storage increases traditional traffic forecasting training, storage costs, and delay. Smarter algorithms can handle today's city expectations because sensors can now communicate with their environment. A vibrant economy requires decent roads. Improving transportation requires uninterrupted highway traffic. To overcome these issues, smart city roadway traffic flow must be monitored in real time using enhanced internet of things (IoT) capabilities. Training data may contain sensitive information, raising privacy problems. This work addresses these issues by training the prediction model near data sources using federated learning (FL). The suggested strategy was tested using Mumbai, Chennai, and Bangalore traffic data. We compared the proposed method to centralized strategies to assess its efficacy. Our experiments confirm the model's traffic jam prediction accuracy. Our approach outperforms auto-encoder and convolutional neural network (CNN) in computer efficiency and prediction.

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1. INTRODUCTION

The rising urbanization in emerging nations such as India has resulted in numerous issues, including pollution, population explosion, and transportation congestion [1]. The significant increase in traffic congestion is a huge problem. Municipal provinces in most rising nations are encountering significant issues in traffic regulation in contemporary times, and India is no exception. It has undergone quick evolution within the economy, resulting in a significant increase in vehicle ownership levels. Traffic congestion has emerged as a significant issue in both industrialized and emerging nations, necessitating the urgent development of an effective predictive model for this phenomenon. The present traffic prediction relies on real-time vehicle tracking and is neither efficient nor accurate as anticipated. This work provides a straightforward and effective traffic prediction algorithm designed to monitor and regulate traffic based on specific forecasts. The projections will rely on historical and real-time data, thereby allowing us to effectively regulate and manage traffic.

Traffic is accurately classified using deep learning [2] and federated learning (FL). One of the world's largest road networks makes traffic in India miserable. Development and economic progress produce many cars, causing traffic congestion. An intelligent infrastructure with internet of things (IoT), predictive models, and public interest applications lowers difficulties. The literature has many neural networks and forecasting model solutions with varied purposes. Ghosh and Lee [3] suggests utilizing convolutional neural network (CNN) and federated averaging (FedAvg) to evaluate two-thirds of the data to predict traffic congestion on a route and inform vehicles planning to travel it [4]-[7]. With accurate traffic control, drivers move fast and safely [8], [9]. Intelligent parking and traffic flow management is enabled by IoT technology in all parking objects. IoT traffic congestion prediction using deep learning algorithms and FL improves human productivity through effective parking management and traffic congestion control [10]. FL and CNN are utilized to manage and regulate traffic following precise traffic congestion estimates from IoT [11]. We will forecast and control traffic using historical and real-time data. Urban organizations have trouble estimating traffic trends [12], [13]. The researchers created a complex algorithm to forecast heavy traffic using historical data. Classifying internet traffic has always attracted networkers. Data is used for intervention detection, network management, and service quality [14]-[16].

The difficulty of traffic congestion prediction arises from numerous non-linear temporal factors and the complexity of long-term forecasting. Traffic congestion at rush hour constitutes the primary patterns. Although most previously proposed strategies concentrate on rush-hour, the impacts on time manner were not addressed in these studies. The findings of this study FedAvg algorithm for traffic congestion prediction. The research in question combines deep learning algorithms with Autoencoder techniques. Traffic congestion is predicted by various performance metrics (precision, recall, and accuracy) based on the road wise traffic.

In section 2, we outline the literature that is relevant to studies on traffic prediction. This section provides an overview of the traffic prediction technique, including the problem formulation, data sources, preprocessing, database design, and the architecture of the FedAvg algorithm for traffic congestion prediction, which is based on FL. In section 4, we detail the model's data description, the metrics used to evaluate the model's performance, how the model was built, and how its results compared to two state-of-the-art prediction models, the Autoencoder and the CNN. The description and comparison of several algorithms for traffic congestion prediction is outlined in section 5. Our study is summarized and the next steps for this inquiry are outlined in section 6.

2. PROPOSED TECHNIQUE

Developing countries have a distinct rural-to-urban transition. In many underdeveloped countries, cities have grown without cars or suburbs. Cars cause congestion on multimodal transportation systems since only a small percentage of the population can afford them [17]. They also increase air pollution, public safety risks, and social inequality. A multimodal system of walking, biking, motorcycling, buses, and trains may manage dense populations.

2.1. Deep neural networks

Because it can extract spatial and temporal information from traffic data, the hybrid neural network [18] outperforms basic neural networks and conventional approaches. Due to a scarcity of high-quality, city-wide congestion data, deep neural network research on traffic congestion prediction is limited [19]. The hybrid model has shown promising results. Recent studies have shown congestion prediction. To assess traffic congestion, the researcher trained the Autoencoder model on artificially compressed traffic pictures from an open-source website [2]. Downsized photographs lack road information, making them unintuitive [1]. A CNN was used to analyze online traffic congestion data and predict route congestion in [12], [20].

2.2. Federated learning

FL averages client device models. This technique protects privacy and reduces transmission costs by saving data on devices. Numerous architectures and non-IID distribution tests have proven the methodology's robustness [3]. Traffic prediction models in intelligent transportation systems are accurate. On-chip memory limits force traditional approaches to balance privacy and performance. A multi-task FL system was created to cut communication costs and protect privacy [14], [21]. FedAvg updates the global model anonymously using secure parameter averaging for traffic flow prediction [15]. When evaluated against CNN and Autoencoder, FedAvg is accurate and private [16]. FL is used to optimize routes using a modified graph-based approach finding the shortest journey times.

While deep learning methods have a number of constraints, the two most significant ones are computational resources and over fitting in machine learning traffic congestion prediction techniques [22]. To circumvent the difficulties associated with training and real-time processing on massive datasets, the authors of this work propose a hybrid approach, the FL algorithms, as a novel contribution [23]. FL the usefulness of this approach, with objective metrics like the precision and the recall used to assess the effectiveness of the traffic congestion prediction for traffic across cities [24].

This effort alerts drivers to traffic risks with 20- and 40-second estimates. According to [10], these traffic congestion studies only evaluated one or a few key major routes; therefore, they can't predict traffic patterns in depth [25]. This hybrid CNN-Autoencoder study estimates high-resolution traffic congestion for the next 20, 40, and 60 minutes utilizing city-wide transportation image data from the Traffic Index website.

3. PROPOSED METHOD

This section starts by outlining the issue with time-series traffic congestion prediction, then moves on to talk about how to gather data from an open-source web platform, and finally describes the parts of the proposed architecture of the traffic congestion prediction network (FedAvg).

3.1. Dataset

For almost every city in India, you may find traffic data on the Traffic Index. Serving the Bay Area in India, the Traffic Index focusses on the traffic conditions of Chennai, Bangalore, and Mumbai. Our study relies on the traffic map supplied from the Traffic Index web service, which provides accurate, real-time congestion levels across the whole city's road network. The raw image of Chennai taken at 08:00 on July 12, 2021, including transportation networks in addition to the backdrop and text.

3.2. Proposed architecture model

Figure 1 shows how FL explains the communication cycle in one training session. Start with a deep learning neural network to get server input. One will train and initialize a random local client. After starting, the client awaits global server commands and primary model parameters. A random sample of client nodes trains on the local dataset while others await the next federated communication cycle. After planning, the central server randomly selects nodes to train the model with local datasets. Not all nodes centralize server settings. Local models are averaged and sent to the global model via the server. Timeouts handle model updates, node disconnections, and missing nodes. Select client-side nodes to resume federated communication. After the stop criteria are met, the global server averages the new weights to build a global model. Repetition occurs every 20 minutes.

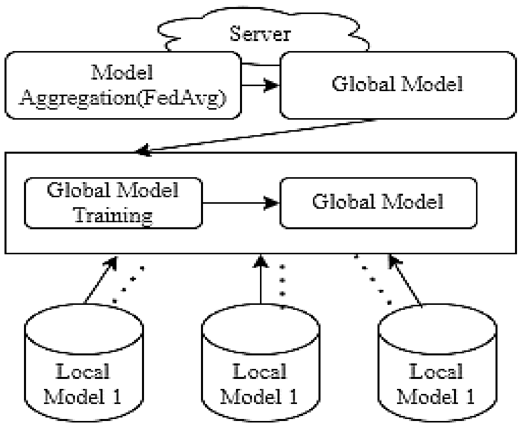


Figure 1. Aggregation model for FedAvg algorithm for traffic congestion prediction

With FL, the FedAvg aggregation method has shown promising results in preserving privacy for traffic flow prediction. This study shows how FL may be applied to real-world traffic data by increasing the number of crossings in the traffic network from 40 to 120. The results show that FL could be a good way to train decentralizedly while protecting users' personal information.

In (1), (2), and (3) delineate precision, recall, and accuracy, respectively, together with the categorical cross-entropy loss function.

$$\text{Recall} = \frac{\text{No of TP}}{\text{No of TP+No of FP}} \tag{1}$$

$$\text{Precision} = \frac{\text{No of TP}}{\text{No of TP+No ofFP}} \tag{2}$$

$$\text{Accuracy} = \frac{\text{True Positive +True Negative}}{\text{Total}} \tag{3}$$

Researchers might apply FL to predict traffic conditions, route planning, and discover the best departure time to decrease travel times. Consider these options to improve traffic management, minimize congestion, and maximize energy use.

4. RESULT AND DISCUSSION

Our proposed model FedAvg, CNN, and Autoencoder's performance metrics on a training dataset at various prediction timelines are shown in Table 1. Twenty, forty, and sixty minutes. To assess the model, it is recommended to utilize a single pixel (or "road-wise value") for every road rather than utilizing the entire image's pixels. The model is truly evaluated by looking at the road-wise prediction performance, as the performance computation does not factor in backdrop pixels or road length. The proposed model, FedAvg, outperforms CNN and Autoencoder by 1 to 10% across the board when it comes to predictions.

Table 2 shows the average road-wise per hour forecast accuracy for all three models from July 12 to October 12, 2021, from 8:00 AM to 11:00 PM. FedAvg performs better at forecasting for 20, 40, and 60 minutes. FedAvg estimates 20-minute interval accuracy at 0.8597-0.8735. CNN's 4-hour projection time is second to least, but FedAvg's 28-hour accuracy is greatest. For the first 23 hours, FedAvg has the best 40-minute forecast window, while CNN has the best last 9 hours. The FedAvg model produces the best 60-minute predictions. FedAvg reported 40-minute and 60-minute forecast accuracy scores of 0.8632 and 0.8523, respectively.

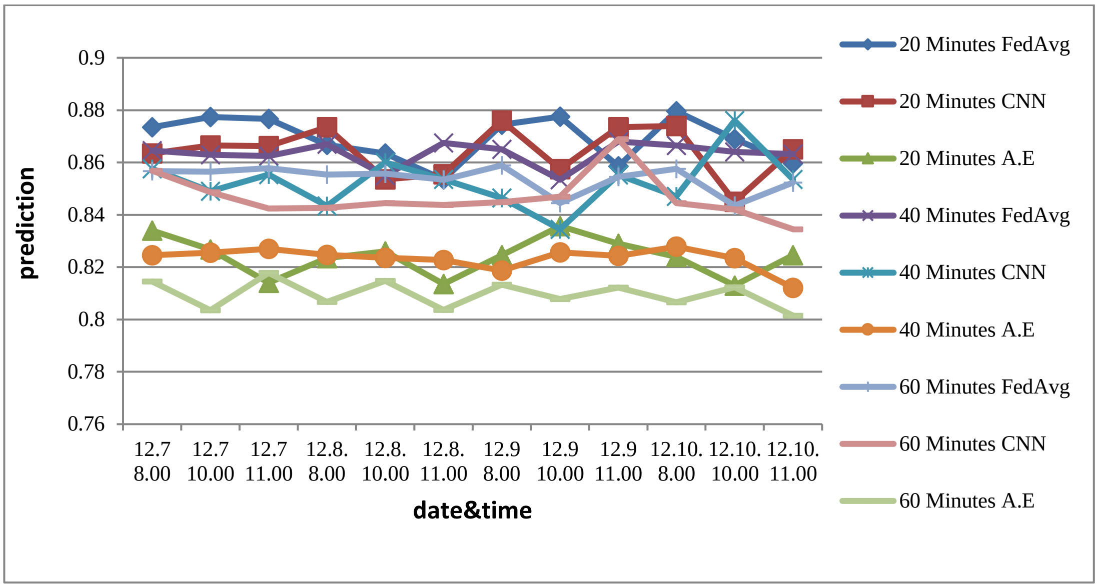
Table 1. The performance comparison on training dataset for the prediction of 20, 40, and 60 minutes. The best result is marked in bold

Prediction	Precision			Recall			Accuracy		
	FedAvg	CNN	Autoencoder	FedAvg	CNN	Autoencoder	FedAvg	CNN	Autoencoder
20	**0.8634**	0.8544	0.8224	**0.8585**	0.8585	0.8132	**0.8825**	0.8715	0.8525
40	**0.8475**	0.8377	0.8215	**0.8525**	0.8525	0.8225	**0.8600**	0.8500	0.8140
60	**0.8425**	0.8410	0.8115	**0.8465**	0.8465	0.8255	**0.8410**	0.8310	0.8110

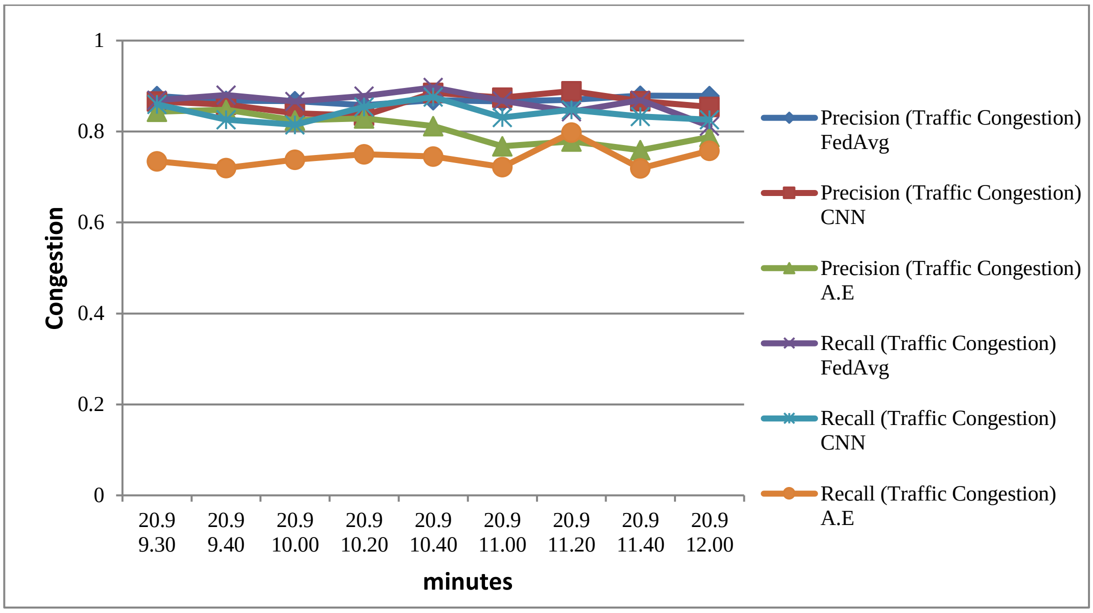
Table 2. Road-wise accuracy comparison for the prediction of 20, 40, and 60 minutes. The best result is marked in bold

Date and time	20 minutes			40 minutes			60 minutes		
	FedAvg	CNN	Autoencoder	FedAvg	CNN	Autoencoder	FedAvg	CNN	Autoencoder
12.07/08:00	**0.8735**	0.8635	0.8340	**0.8645**	0.8576	0.8245	0.8567	**0.8568**	0.8145
12.07/10:00	**0.8774**	0.8665	0.8267	**0.8630**	0.8490	0.8255	**0.8565**	0.8487	0.8035
12.07/11:00	**0.8767**	0.8663	0.8140	**0.8625**	0.8554	0.8270	**0.8578**	0.8424	0.8178
12.08/08:00	0.8667	**0.8735**	0.8235	**0.8670**	0.8434	0.8247	**0.8554**	0.8426	0.8067
12.08/10:00	**0.8635**	0.8535	0.8260	0.8550	**0.8600**	0.8236	**0.8557**	0.8445	0.8148
12.08/11:00	**0.8535**	0.8555	0.8135	**0.8675**	0.8535	0.8227	**0.8534**	0.8437	0.8036
12.09/08:00	0.8745	**0.8760**	0.8246	**0.8650**	0.8465	0.8187	**0.8589**	0.8448	0.8133
12.09/10:00	**0.8775**	0.8575	0.8357	**0.8534**	0.8345	0.8256	**0.8445**	0.8469	0.8078
12.09/11:00	0.8585	**0.8735**	0.8289	**0.8680**	0.8553	0.8243	0.8545	**0.8689**	0.8122
12.10/08:00	**0.8796**	0.8740	0.8240	**0.8665**	0.8470	0.8278	**0.8576**	0.8445	0.8066
12.10/10:00	**0.8689**	0.8450	0.8130	0.8640	**0.8760**	0.8234	**0.8435**	0.8420	0.8123
12.10/11:00	0.8597	**0.8650**	0.8245	**0.8632**	0.8535	0.8121	**0.8523**	0.8345	0.8015

Figure 2 displays the exact forecast accuracy for the 20-minute and 40-minute prediction scopes from 08:00 to 11:00 on September 20, 2021. The forecast accuracy is shown every five minutes. 20- and 40-minute prediction intervals. The forecast accuracy is shown every five minutes. In thirty of fifty samples, FedAvg's accuracy peaks about 10:00 is seen in Figure 2 a 30 of 50 samples and b imply the FedAvg's 20-minute estimates are correct. CNN is slightly less accurate than FedAvgs, which we recommend.



(a)



(b)

Figure 2. Prediction accuracy of (a) 20 minutes and (b) 40 minutes

However, Autoencoder's poor performance is partly due to its temporal data-only predicting. Table 3 shows all three models' 20 minutes as Table 3(a) and 40 minutes as Table 3(b) traffic congestion estimations using precision and recall. We can measure how well models can show congestion using this indicator. Compares data every five minutes from 8:00 to 11:00 on September 20, 2021. It is believed that FedAvg has very accurate prediction capabilities for all three tiers of management. When it comes to traffic congestion levels, FedAvg achieves accuracy levels between 70% and 96%, with an average value of 85% for 20-minute predictions. This is 12% and 14% better than CNN and Autoencoder, respectively. Like thus, FedAvg gets an accuracy value of 87%. 86% and 81% for a 20-minute estimation, respectively.

As seen in Table 3, the FedAvg has the highest average recall value among all models when it comes to predicting all levels of traffic congestion for all predictions. The FedAvg's maximum recall values for traffic congestion levels are 0.893 for 20 minutes and 0.888 for 40 minutes. The corresponding values for the other two time periods are 0.765 and 0.893, respectively. In terms of recall, FedAvg beats CNN by about 8-12% and Autoencoder by about 12-16% when it comes to predicting the level of traffic congestion.

Traffic congestion prediction is a huge area, and many people have made key contributions to it over the years. In addition to the previous researchers and methodologies, there are countless others who have made significant contributions to the field of IoT and deep learning algorithm. The primary result of this research is a FL and CNN method, road wise prediction performance (precision, recall, accuracy), which has been implemented and tested. To overcome the difficulties associated with traffic congestion in every 20, 40 and 60 minutes; this technique combines road wise prediction performance and road wise accuracy comparison.

Table 3. Precision and recall metrics of all the models at different prediction of (a) 20 minutes and (b) 40 minutes. Best performance values are marked in bold

(a)

	20 minutes					
Date and time	Precision (traffic congestion)			Recall (traffic congestion)		
20.09 09:00	FedAvg	CNN	Autoencoder	FedAvg	CNN	Autoencoder
20.09 09:10	**0.887**	0.876	0.840	**0.868**	0.850	0.740
20.09 09:20	**0.890**	0.856	0.843	**0.879**	0.846	0.743
20.09 09:30	0.876	**0.888**	0.824	**0.856**	0.835	0.734
20.09 09:40	**0.875**	0.870	0.860	**0.874**	0.864	0.760
20.09 09:50	**0.879**	0.869	0.862	**0.893**	0.866	0.765
20.09 10:00	**0.886**	0.865	0.762	0.878	**0.891**	0.752
20.09 10:10	0.880	**0.898**	0.788	0.834	**0.888**	0.758
20.09 10:20	**0.867**	0.850	0.789	**0.864**	0.823	0.729
20.09 10:30	**0.856**	0.840	0.768	0.832	**0.856**	0.768
Average	0.877	0.868	0.815	0.864	0.857	0.749

(b)

	40 minutes					
Date and time	Precision (traffic congestion)			Recall (traffic congestion)		
20.09 09.10	FedAvg	CNN	Autoencoder	FedAvg	CNN	Autoencoder
20.09 09.30	**0.878**	0.866	0.844	**0.869**	0.860	0.735
20.09 09.40	**0.868**	0.859	0.848	**0.880**	0.826	0.720
20.09 10.00	**0.867**	0.840	0.825	**0.866**	0.815	0.738
20.09 10.20	**0.858**	0.835	0.829	**0.878**	0.854	0.750
20.09 10.40	0.869	**0.885**	0.812	**0.897**	0.876	0.745
20.09 11.00	0.866	**0.875**	0.768	**0.868**	0.831	0.722
20.09 11.20	0.870	**0.889**	0.778	0.844	**0.848**	0.798
20.09 11.40	**0.879**	0.867	0.759	**0.869**	0.833	0.719
20.09 12.00	**0.878**	0.854	0.788	0.812	**0.826**	0.758
Average	0.870	0.863	0.805	0.864	0.841	0.742

5. DISCUSSION

The algorithm predicts transportation network congestion at 20, 40, and 60 minutes using traffic photos in chronological order. We examined FedAvg, CNN, and Autoencoder accuracy, precision, and recall using a training dataset and prediction intervals of 20, 40, and 60 minutes. Instead of using all image pixels, we randomly select one pixel for each road (the road-wise value) to test the model. Road-wise prediction performance accurately evaluates the model because performance measurements are unaffected by background pixels and road length. The FedAvg model outperforms CNN and Autoencoder by 2–12% across all forecasts.

The CNN and Autoencoder are two cutting-edge deep learning neural networks we used to evaluate FedAvg’s efficacy and superiority. CNNs use convolution operations instead of internal matrix multiplication to extract spatial and temporal information from input image sequences. In a deep Autoencoder neural network, the encoding layer learns an encoding from a dataset, and the decoding layer reduces the encoding to the minimum needed to reconstruct the original input as precisely as possible. Traffic congestion estimates for 20, 40, and 60 minutes were used to compare and examine the indicated FedAvg. The study shows traffic prediction model recall, accuracy, and precision. Architecture for a model using deep learning and FL to forecast traffic congestion across a city using image data obtained from a web-based traffic portal. Using the input data to successfully learn spatial and temporal correlations, predicts city-wide traffic congestion. Three different prediction intervals-20, 40, and 60 minutes-were used to train the model. The accuracy of road-wise forecasts, precision in predicting congestion levels, and recall are all measured in this study, and we compare the results with two current state-of-the-art algorithms, CNN and Autoencoder. Analyses and findings show that our proposed model achieves the best overall accuracy across all three predictions, with FedAvg showing better recall and precision values for each forecast regardless of congestion level. On top of that, our proposed FedAvg is more efficient than the CNN and can train on high-resolution picture data using less resources than the Autoencoder.

Many individuals have made significant contributions to the vast field of traffic congestion prediction. In addition to the aforementioned scholars and approaches, innumerable others have also made substantial contributions to the domain of deep learning algorithm and the IoT. A system called road wise prediction performance (precision, recall, and accuracy) that combines FL and CNN has been developed and evaluated as the main outcome of this research. Combining road wise prediction performance with road wise accuracy comparison, this technique overcomes the issues associated with traffic congestion every 20, 40, and 60 minutes.

6. CONCLUSION AND FUTURE SCOPE

The FedAvg technique is utilized for traffic congestion prediction to consolidate local models based on regional traffic data while preserving sensitive information. This decentralized methodology is particularly advantageous for short-term congestion forecasting, including the prediction of traffic conditions at 20, 40, and 60-minute intervals. Local models utilize previous traffic data (speed, volume, incidents) to forecast congestion during these intervals. FedAvg facilitates the integration of localized forecasts into a comprehensive model, enhancing accuracy across areas while maintaining anonymity. The model emphasizes short-term traffic variations for 20-minute projections, providing near real-time updates. Forty-minute forecasts facilitate enhanced traffic management by offering insights into impending congestion. Sixty-minute forecasts provide extensive projections, beneficial for scheduling and planning. FedAvg's potential applications include smart traffic systems, navigation systems, and regional planning. Enhance FedAvg to provide tailored congestion forecasts based on individual commuting behaviours, utilize real-time sensor data for more precise 20, 40, and 60-minute congestion predictions, and implement transfer learning to refine predictions for areas with sparse historical data. In future FedAvg to examine historical traffic patterns within the framework of urban expansion, and creating standardized benchmark datasets to promote additional research. Researchers may investigate the application of multi-agent FL for cooperative traffic management among cities and incorporate environmental variables to enhance sustainability in forthcoming traffic prediction models.

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AUTHOR CONTRIBUTIONS STATEMENT

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Kamaleswari Pandurangan	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Krishnaraj Nagappan	✓	✓			✓	✓		✓		✓	✓	✓		
B. Galeebathullah	✓			✓			✓			✓	✓			
N. Shunmuga Karpagam		✓			✓	✓			✓			✓		
N. Kumaran					✓		✓			✓		✓		
S. Navaneethan	✓			✓		✓		✓		✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

No conflict of interest.

DATA AVAILABILITY

Open-source web platform like Kaggle and GitHub.

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