Traffic Congestion Monitoring Improvement through Federated Learning Technique

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Abstract: The Internet of Things (IoT) has significantly influenced the management of intelligent traffic systems, mainly by incorporating Machine Learning (ML) for congestion detection. This study underscores the application of Federated Learning (FL) in identifying traffic congestion based on various factors, including stringent delay constraints and real-time speed data obtained from Differential GPS (DGPS). Specifically, the FedAvg (Federated Averaging) model within FL is utilized to forecast traffic speeds, incorporating diverse parameters such as training sets, prediction sets, and road sector data frames. The results are being validated by empowering the Explained Artificial Intelligence (EAI) approach, which employs a dynamic weight factor to detect congestion based on vehicle speeds. In conclusion, the model's outcomes highlight its proficiency, efficiency, and accuracy in managing traffic congestion effectively. The model significantly improves, demonstrating at least 10 to 15% greater efficiency than other approaches.

Keywords: FedAvg (Federated Averaging), Internet of Things (IoT), Federated Learning (FL), Explained Artificial Intelligence (EAI)

1 Introduction

Across the globe, a significant concern persists regarding the escalating traffic congestion that leads to significant traffic challenges, intensifying pollution levels within intelligent cities [1]. The congestion of vehicles in urban areas poses substantial economic setbacks and diminishes the overall well-being of residents. This has spurred a surge in enthusiasm for advancing intelligent transportation systems capable of precise congestion identification and forecasting to address this intricate problem. Recently, the emergence of the Internet of Things (IoT) has brought about significant advancements in the administration of intelligent transportation networks, primarily using Machine Learning (ML) to detect traffic bottlenecks. With urban areas witnessing a surge in population and traffic gridlocks becoming more common, the necessity for sophisticated methodologies to control traffic circulation and mitigate congestion has become crucial [2]. This research underscores the importance of employing Federated Learning (FL) strategies to detect and regulate traffic congestion efficiently. FL, a decentralized machine learning concept, presents promising pathways for traffic control by aggregating data from diverse origins while upholding user confidentiality and data protection. The most crucial aspect of this work is the distinction in calculating validated results through Explained AI, which yields better accuracy than previous approaches. The focal point of this study lies in the meticulous calculation of validated results using Explained AI, which surpasses the accuracy of other conventional approaches utilized in the past. This essential aspect underscores the significance of leveraging advanced techniques for achieving precise outcomes in congestion detection [3]. By employing Explained AI, our research aims to elevate the standards of accuracy and reliability in traffic management systems. Integrating such innovative methodologies marks a paradigm shift in the field, offering enhanced insights into traffic dynamics and congestion patterns. Through rigorous validation and comparative analysis, we aim to elucidate the superiority of Explained AI in deciphering complex traffic data and optimizing congestion detection algorithms. This endeavour represents a notable advancement in intelligent traffic systems, promising more effective strategies for mitigating congestion and enhancing urban mobility. In essence, our study underscores the transformative potential of Explained AI in revolutionizing traffic management practices and fostering sustainable urban development [4].

Urban areas around the globe are confronted with substantial issues due to traffic congestion, particularly in their infrastructure and transportation systems. The conventional means of identifying congestion often lack the scalability and flexibility needed to effectively address the ever-changing traffic behaviours and congestion focal points. Furthermore, incorporating up-to-the-minute data sources, like those derived from Differential GPS (DGPS), offers new possibilities and obstacles in congestion identification and control. This study is driven by the critical necessity for innovative strategies to alleviate traffic congestion and improve traffic fluidity in city settings. Our objective is to create a solid framework for promptly identifying and managing congestion by leveraging the potential of FL and ML methodologies [5].

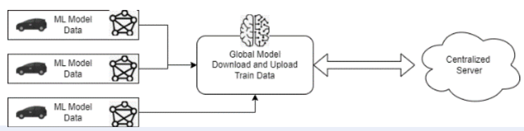


Figure 1. The basic concept of the Federated Learning (FL) Approach.

FL trains AI models collaboratively across decentralized edge devices while preserving data privacy. It allows the ML model to learn from distributed data sources without directly accessing raw data, thus ensuring privacy and data sovereignty.

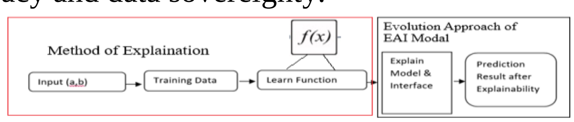


Figure 2. The basic concept of the Federated Learning (FL) Approach.

Explaining their decisions allows AI systems to establish trust with users and ensures that their choices adhere to ethical and legal standards. EAI further enhances the reliability and robustness of AI systems by empowering users to identify and rectify errors or biases in the system, as illustrated in Figure 2. EAI aims to address any problem by developing AI systems that are transparent and explainable [6]. There are several approaches to EAI, including rule-based systems, symbolic AI, and machine-learning techniques designed to explain their decisions. These explanations can take other forms, such as textual or visual explanations, and can be tailored to the needs of different users, such as clinicians, regulators, or consumers. The primary objective of this research is to investigate the efficacy of FL in identifying traffic congestion based on a comprehensive set of parameters, including stringent delay constraints and real-time speed data from DGPS [7].

2 Research Methods

Vehicle congestion is a significant issue in city areas close to stadiums, inflicting inconvenience, environmental problems, and economic costs. Various solutions were proposed, inclusive of the usage of the device getting-to-know and sensor networks to screen and expect visitors. This work entails a systematic approach consisting of a few steps. Initially, we embark on data collection and pre-processing, acquiring real-time traffic data encompassing speed measurements from DGPS. The pre-processing phase ensures the consistency and accuracy of the data, laying a robust foundation for subsequent analyses. Subsequently, we delve into implementing the Federated Learning (FL) framework, where the FedAvg model is deployed to train and update the congestion detection model across distributed devices, all while safeguarding data privacy. Incorporating the FL framework underscores our commitment to harnessing collaborative intelligence for effective traffic management [8].

Following the FL framework, our methodology includes Explained Artificial Intelligence (EAI) validation, where we scrutinize the model's performance and interpretability in identifying traffic congestion based on vehicle speeds. This validation step enhances our confidence in the model's reliability and accuracy, crucial for its real-world applicability. Finally, we conduct a comprehensive performance evaluation, scrutinizing the proficiency, efficiency, and accuracy of the FL-based congestion detection model. Through rigorous evaluation and comparative analysis with existing approaches, we aim to ascertain the efficacy of our methodology in addressing the complexities of traffic congestion management [9]. The results of the study should be written clearly and concisely. The discussion should describe the importance of the results of the study, not repeat it.

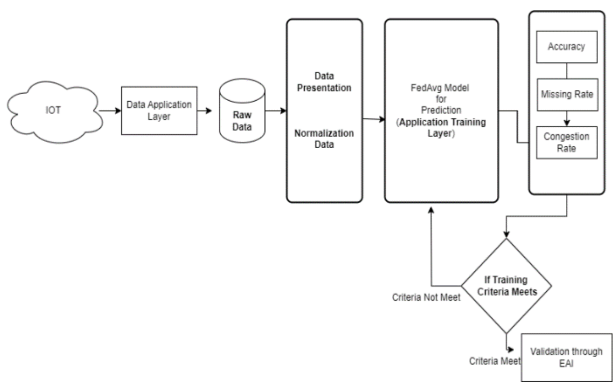


Figure 3. FedAvg model by using FL approach for prediction of Congestion Rate.

FL models can process diverse data sources, including traffic volume, vehicle speed, weather conditions, and road incidents, to predict congestion that recommends real-time adaptive traffic control strategies [10]. By real-time past observations and continuously updating their models, FL systems can adapt to changing traffic conditions and improve the overall efficiency of transportation networks. This objective is based on two parts of the topic [11]. This objective encompasses two critical aspects of the topic. Firstly, it uses FedAvg, to calculate the congestion rate effectively. ML algorithms play a crucial role in analyzing traffic and precisely identifying areas of congestion. Secondly, the objective also delves into the empire of pure Federated Learning (FL), a sophisticated approach employed in this research. FL facilitates collaborative learning across decentralized devices while preserving data privacy, making it a promising avenue for enhancing traffic management systems. By integrating with FL techniques, this objective seeks to devise a comprehensive solution for addressing traffic congestion challenges in smart cities.

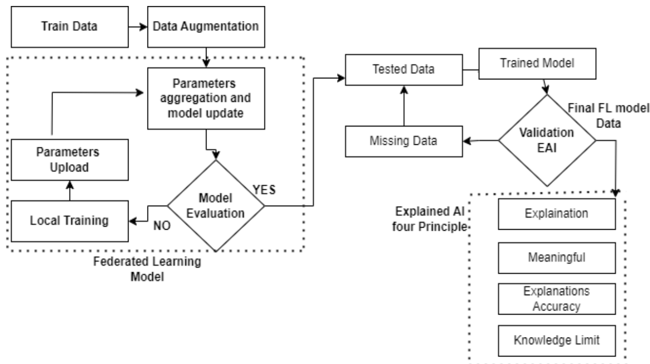


Figure 4: Explained AI techniques validate the accuracy of congestion rate

Figure 4 represents the model training; congestion rate predictions undergo validation against predetermined criteria using Explained AI techniques, providing interpretability and transparency into the model's predictions. By using this validation process, get insights into the factors influencing congestion rates and assess the model's effectiveness in managing traffic congestion. Further evaluation is integral, ensuring that predicted congestion rates align with predefined criteria. If discrepancies arise, the model iterates predictions until desired results are attained, facilitating accurate and reliable congestion management strategies.

3 Result and Analysis

The Federated Averaging (FedAvg) algorithm is primarily used for federated learning scenarios, where multiple devices or clients train a global model collaboratively while keeping their data decentralized. The algorithm operates in several steps, including local training on each device, aggregation of model updates, and updating the global model. However, the mathematical equations involved in FedAvg may not directly calculate traffic congestion missing rates, as its primary purpose is to facilitate model training in a distributed environment.

To calculate traffic congestion missing rates, one would typically employ statistical methods or models specific to traffic analysis and congestion detection. Aggregate the local model updates from all clients

$$\omega_{t+1} = \frac{1}{K}\sum_{K=1}^{K}\omega_t^k \qquad (1)$$

Here, ω_{t+1} represents the model parameters at the Kth client at the tth iteration. K is the total number of clients (IoT devices). This equation represents Receive the global model parameters train the local model using client's data to minimize the loss function.

$$\omega_{t+1} = \omega_{t+1} - \eta\nabla f(\omega_{t+1}) \qquad (2)$$

Where $\eta\nabla f(\omega_{t+1})$ is the gradient of the loss function at ω_{t+1} that is using for Update the global model parameters with the aggregated model updates represent in equation 2.

These equations primarily deal with model parameter updates and aggregation across multiple clients. To calculate traffic congestion missing rates, you must incorporate traffic data, congestion metrics, and appropriate statistical or machine learning models specific to traffic analysis and congestion detection.

$$A(w) = d(w)/|w| \qquad (3)$$

Where A(w) denotes the flow of rate of traffic with road segments in Eq 3.

$$B(w) = t(w)/|w| \qquad (4)$$

Eq 4 represents a measure of bias per unit weight, often used in the context of neural networks or machine learning models. The bias is an additional parameter in machine learning models that allows them to fit data better. It helps shift the activation function of a neuron to the left or right, aiding in better predictions.

$$C(w) = d(w)/t(w) \tag{5}$$

Eq. 5 calculates the bias per unit weight by dividing the magnitude of the weights. It essentially measures how much bias is exerted by the model per unit of weight. This can be useful in understanding the relative impact of bias in the model's decision-making process, particularly in the context of neural networks where bias terms can affect the activation of neurons and, consequently, the model's predictions.

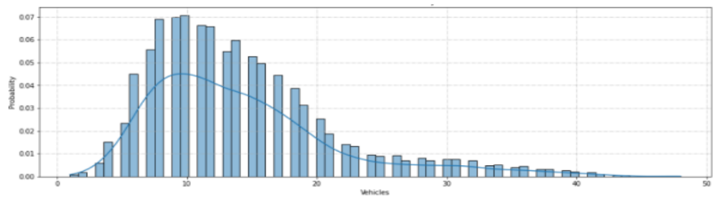
3.1 VALIDATION OF RESULT WITH EXPLAINED AI

Validating the congestion rate calculated from Federated Learning (FL) machine learning models through explanation forms entails thoroughly assessing the model's behaviour and the rationale behind its predictions. One crucial validation aspect involves conducting feature importance analysis, where we delve into the significance of various input features on the predicted congestion rates. By determining which variables, such as traffic volume, road conditions, or time of day, exert the most substantial influence on the model's predictions, we can align the model's outputs with domain knowledge and validate its efficacy.

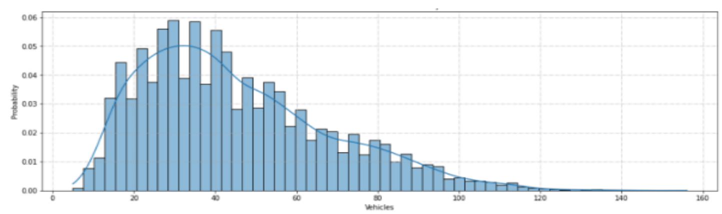
Table2: Congestion rate calculated in different time span with different speed of vehicle

Time Date	**Congestion Rate**	**Vehicle Speed rate (%)**
3/3/2024 12.12	1.2	48.98
3/3/2024 01.10	0.3	87.3
3/3/2024 02.32	1.1	67.23
3/3/2024 04.21	2.9	23.66

Explanation AI techniques, conducting consistency checks, and cross-validation procedures is paramount to validating the FL machine learning model's predictions comprehensively. By scrutinizing the model's performance across different subsets of data and ensuring its outputs align with known patterns and domain expertise, we can ascertain its reliability and generalization capabilities. Through a meticulous validation process encompassing explanation forms and consistency checks, we can build trust and confidence in the FL machine learning model's ability to accurately calculate congestion rates and provide actionable insights for traffic management.



(A)



(B)

Figure 5. Traffic congestion detection and prediction accuracy after evaluation results of EAI

Figure 5 illustrates the traffic congestion detection and prediction process, which comprises several sequential stages, each leveraging specific algorithms to facilitate effective traffic management. Real-time traffic data is initially sourced from channels like loop detectors and GPS devices. Subsequently, feature extraction is conducted to isolate crucial traffic flow parameters. Traffic state estimation is then undertaken, employing algorithms like Fedavg, while congestion detection relies on machine learning techniques such as FL. Time-series forecasting methods are used within the FL framework to anticipate future congestion levels for congestion prediction. Finally, traffic management strategies, informed by algorithms like adaptive traffic congestion calculation and forecasting, are implemented to regulate traffic flow and mitigate congestion in real time, ensuring streamlined traffic management and enhanced overall road network performance.

4 Conclusion

In conclusion, this research endeavours to address the critical challenges associated with traffic congestion by integrating Federated Learning techniques [12]. The objective is to construct a robust framework capable of efficiently and accurately detecting and managing congestion through Explained Artificial Intelligence (EAI), which involves evaluating real-time data streams and employing innovative modelling approaches. The anticipated outcomes of this study have the potential to substantially enhance traffic management practices and elevate the overall quality of urban life. By harnessing the power of Federated Learning and EAI, we aspire to pave the way for more effective and sustainable solutions to mitigate the adverse effects of traffic congestion in urban areas [13].

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