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Secure and transparent traffic congestion control system for smart city using a federated learning approach

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A B S T R A C T

This study addresses the increasing problems of traffic congestion in smart cities by introducing a Secure and Transparent Traffic Congestion Control System using federated learning. Traffic congestion control systems face key issues such as data privacy, security vulnerabilities, and the necessity for joint decision-making. Federated learning, a type of distributed machine learning, is effective because it allows for training models on decentralized data while maintaining data privacy. Furthermore, incorporating blockchain technology improves the system's security, integrity, and transparency. The proposed system uses federated learning to securely gather and analyze local traffic data from different sources within a smart city without moving sensitive data away from its original location. This method minimizes the risk of data breaches and privacy issues. Blockchain technology creates a permanent, transparent record for monitoring and confirming decisions related to traffic congestion control, thereby promoting trust and accountability. The combination of federated learning's decentralized nature and blockchain's secure, transparent features aids in building a strong traffic management system for smart cities. This research contributes to advancements in smart city technology, potentially improving traffic management and urban living standards. Moreover, tests of the new combined model show a high accuracy rate of 97.78% and a low miss rate of 2.22%, surpassing previous methods. The demonstrated efficiency and adaptability of the model to various smart city environments and its scalability in expanding urban areas are crucial for validating its practical use in real-world settings.

1. Introduction

Traffic congestion has become a significant problem in modern urban environments, leading to increased travel times, fuel consumption, and air pollution. Addressing traffic congestion requires effective management and control systems that can analyze real-time data, make informed decisions, and implement efficient strategies (Jiang et al., 2022). However, there are several challenges in managing traffic congestion that require careful consideration and innovative solutions. Rapid urbanization and population growth have significantly increased the number of vehicles on the roads, leading to issues such as traffic jams, delays, and reduced efficiency of transportation systems. Another challenge is the dynamic nature of traffic patterns. Factors like the time of day, weather conditions, and special events constantly change traffic patterns, making it difficult to predict and manage congestion effectively. Limited infrastructure is also a major obstacle. Building new roads or bridges is often not feasible due to space constraints and high costs. Therefore, alternative approaches are necessary to address traffic congestion effectively. These alternatives may include optimizing existing infrastructure,

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implementing intelligent transportation systems, and promoting alternative modes of transportation such as public transit, cycling, or walking.

Data collection and processing are crucial in managing traffic congestion. Real-time data from sources like sensors, cameras, and GPS devices is essential for understanding traffic conditions and making informed decisions. However, the large volume and variety of this data present technical challenges. Efficient collection, analysis, and processing require robust systems and algorithms capable of handling the complexity and scale of traffic data. Security and transparency are also vital in traffic congestion management. Protecting privacy is crucial because traffic management systems collect sensitive data, such as vehicle locations and travel patterns. Ensuring privacy helps maintain public trust and comply with data protection regulations (Kabir et al., 2022). Maintaining data integrity is essential to prevent tampering or unauthorized modifications, which could lead to inaccurate traffic predictions and ineffective congestion control. Transparent systems that offer clear insight into the decision-making process build public trust and allow stakeholders to hold the system accountable for its actions.

Federated learning, a type of distributed machine learning, offers several benefits for traffic congestion control. One major advantage is improved privacy. By training models on individual devices or edge servers locally, federated learning keeps raw data on the local devices and only shares model updates. This approach preserves data privacy and addresses concerns about sharing sensitive information. Additionally, federated learning supports decentralized data processing. Local processing of traffic data reduces the need for extensive data transfers and allows for real-time decision-making at the edge, enhancing the efficiency and responsiveness of traffic management systems. Another benefit of federated learning is enhanced security. By avoiding centralized data storage, federated learning lowers the risk of data breaches and unauthorized access, thereby protecting sensitive information and improving the overall security of the traffic management system.

1.1. Advanced traffic management systems

As the challenges of traffic congestion continue to grow, there is an increasing need for advanced traffic management systems to tackle the issue effectively. These systems employ innovative technologies and strategies to optimize traffic flow, improve transportation efficiency, and enhance the overall commuting experience (Fadlullah et al., 2017). Here are some key reasons highlighting the necessity of advanced traffic management systems:

- Traffic flow optimization: Advanced traffic management systems utilize real-time data collection and analysis to optimize traffic flow. By integrating sensors, cameras, and other intelligent transportation technologies, these systems can monitor traffic conditions, identify congestion hotspots, and dynamically adjust signal timings to maximize traffic throughput. This proactive approach minimizes delays, reduces travel times, and enhances overall road network efficiency.
- Intelligent routing and navigation: Advanced traffic management systems incorporate intelligent routing and navigation algorithms to provide drivers with real-time, dynamic route guidance. By analyzing traffic conditions, these systems can suggest alternative routes that avoid congested areas, accidents, or roadwork, thereby reducing individual travel times and diverting traffic away from congested routes. This not only benefits individual drivers but also contributes to overall congestion reduction.
- Integration of multi-modal transportation: To address the challenges of traffic congestion comprehensively, advanced traffic management systems aim to integrate various modes of transportation seamlessly (Liu et al., 2021). By incorporating public transit, cycling infrastructure, and pedestrian networks into the overall transportation ecosystem, these systems promote sustainable and efficient travel choices. Integration enables smoother intermodal transfers, encourages mode shifting, and reduces reliance on private vehicles, thus alleviating congestion on roadways.
- Intelligent traffic signal control: Traditional fixed-time traffic signal systems often contribute to congestion by inefficiently allocating green signal times to different directions of traffic. Advanced traffic management systems employ intelligent traffic signal control mechanisms, such as adaptive signal control, to dynamically adjust signal timings based on real-time traffic demand (Guo et al., 2019). This adaptive approach optimizes traffic flow, reduces wait times at intersections, and minimizes the occurrence of gridlock, leading to smoother traffic progression.
- Data-driven decision-making: Advanced traffic management systems heavily rely on data collection and processing to make informed decisions. By integrating data from various sources, such as traffic sensors, GPS devices, and mobile applications, these systems gain a comprehensive understanding of traffic patterns, trends, and congestion factors. This data-driven approach enables transportation authorities to identify bottlenecks, plan infrastructure improvements, and implement targeted congestion mitigation strategies.
- Incident management and emergency response: Advanced traffic management systems play a crucial role in incident management and emergency response. By detecting accidents, breakdowns, or other incidents in real time, these systems can promptly alert authorities, dispatch emergency services, and implement traffic diversions to ensure swift and effective incident resolution. Such proactive measures help minimize

the impact of incidents on traffic flow, prevent secondary accidents, and ensure the safety of road users.

1.2. Importance of security and transparency in traffic management

Security and transparency are vital aspects of traffic management systems as they play a crucial role in building public trust, ensuring privacy protection, maintaining data integrity, and promoting accountability (Guo et al., 2019). Here's a detailed explanation of their importance:

- Privacy protection: Traffic management systems collect and process sensitive data, such as vehicle location and travel patterns. It is essential to prioritize privacy protection to safeguard the personal information of individuals and organizations involved in the transportation network. By implementing robust privacy measures, including data anonymization, encryption, and access controls, traffic management systems can ensure that the privacy rights of individuals are respected while still providing effective congestion management.
- Data integrity: Maintaining the integrity of traffic data is critical for accurate traffic predictions, effective congestion control, and informed decision-making. Any unauthorized modification or tampering with traffic data can lead to inaccurate insights and potentially disrupt traffic management operations. Robust security measures, such as data authentication and encryption, help ensure the authenticity and integrity of the data, preventing unauthorized modifications and maintaining the trustworthiness of the system.
- Trust and accountability: Transparent traffic management systems that provide clear visibility into the decision-making process foster public trust. When individuals and communities have confidence in the fairness and effectiveness of traffic management measures, they are more likely to cooperate and adhere to the regulations and recommendations put in place. Transparency also enables stakeholders to understand how decisions are made, raises awareness of the rationale behind congestion management strategies, and allows for constructive feedback and engagement. Furthermore, transparency promotes accountability, as stakeholders can hold the system responsible for its actions and outcomes.
- Security against cyber threats: As traffic management systems become increasingly digitized and connected, the risk of cyber threats and data breaches becomes more pronounced. Safeguarding the system against unauthorized access, data breaches, and cyber-attacks is crucial to ensure the integrity and continuity of traffic management operations. Implementing robust cybersecurity measures, including network monitoring, intrusion detection systems, encryption, and regular security audits, helps mitigate the risk of cyber incidents and protects the system and its users from potential harm.
- Public perception and acceptance: The success of any traffic management system depends on public perception and acceptance. Security and transparency are key factors that influence how the system is perceived by the public. When individuals feel confident that their privacy is protected, their data is handled securely, and the decision-making process is transparent and accountable, they are more likely to embrace and support the system's initiatives. Building public acceptance is crucial for the smooth implementation and long-term effectiveness of traffic management strategies.

1.3. Federated learning

Federated learning revolutionizes the machine learning paradigm by enabling collaborative model training across multiple devices or edge servers (Ibrahim et al., 2024; Saleem et al., 2023). This approach eliminates the need for centralized data aggregation, addressing privacy concerns and ensuring data security. By keeping data local and sharing only model updates or aggregated insights, federated learning safeguards the privacy of sensitive information. This decentralized framework is especially valuable in domains like traffic congestion control, where data privacy is critical. Through collaborative knowledge sharing, federated learning harnesses the collective wisdom of diverse stakeholders, enhancing model accuracy and enabling informed decision-making while upholding data privacy and security.

Fig. 1 shows the federated learning architecture that enables multiple actors to build a common, robust machine learning model (Fatima et al., 2019; Khan et al., 2021) without sharing data, thus addressing critical issues such as data privacy, data security, data access rights and access to heterogeneous data. Its applications engage industries including defense, telecommunications, Internet of Things, traffic management systems, and pharmaceuticals.

1.4. Federated learning for traffic congestion control

Federated learning, a distributed machine learning approach, holds significant potential for addressing traffic congestion control challenges. By leveraging federated learning in traffic management systems, several benefits can be realized. Here's a detailed explanation of how federated learning can be used for traffic congestion control:

- Enhanced privacy: Privacy is a crucial concern when dealing with sensitive data in traffic management systems. Federated learning allows for model training without centralizing the data. Instead, the models are trained locally on individual devices or edge servers, ensuring that the raw data remains on the local devices and only model updates are shared. This preserves data privacy, as the individual user data is not exposed or transmitted while still benefiting from the collective knowledge obtained from all participants.

- Decentralized data processing: Federated learning enables local data processing, reducing the need for extensive data transfers to a central server. In the context of traffic congestion control, this decentralized data processing approach allows for real-time decision-making at the edge. Traffic data can be processed locally on devices or edge servers, analyzing local traffic conditions and making localized predictions and control decisions. This reduces the latency associated with data transfer and enables faster response times to traffic conditions.
- Improved security: Federated learning reduces the risk of data breaches and unauthorized access by avoiding the need for centralized data storage. With federated learning, sensitive traffic data remains on local devices, minimizing the potential attack surface for malicious actors. By distributing the learning process, federated learning enhances the overall security of the traffic management system, ensuring the integrity and confidentiality of the data.
- Collaborative knowledge sharing: Federated learning facilitates the collaborative sharing of knowledge and expertise among multiple stakeholders. In the context of traffic congestion control, this means that traffic authorities, transportation companies, and individual drivers can contribute their local knowledge and insights to improve the overall traffic congestion control models. This collaborative approach leverages the collective intelligence and experience of various stakeholders, leading to more accurate congestion predictions and better decision-making.
- Adaptability to dynamic traffic patterns: Traffic congestion is highly dynamic and influenced by various factors such as time of day, weather conditions, and special events. Federated learning can adapt to these dynamic patterns by continuously updating the models based on the latest local data. As traffic conditions change over time, federated learning enables the models to learn and adapt, providing more accurate predictions and control strategies for managing congestion.
- Scalability and flexibility: Federated learning is highly scalable, as it allows for the simultaneous training of models on a large number of devices or edge servers. This scalability is particularly valuable in traffic management systems, where a vast amount of data is generated from numerous sources. Additionally, federated learning is flexible and can accommodate heterogeneous data sources and varying computational resources, making it suitable for the diverse and distributed nature of traffic congestion control.

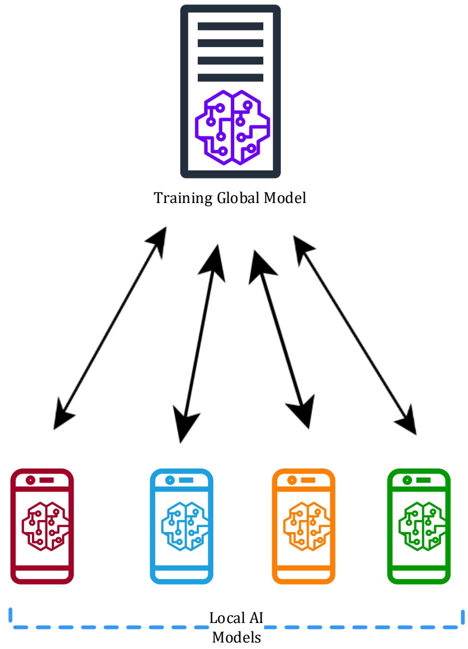

Fig. 1: Federated learning architecture

1.5. Blockchain technology

Blockchain technology is a decentralized and transparent system that utilizes a distributed ledger to securely record and verify transactions (Yaga et al., 2018). It operates on a peer-to-peer network, eliminating the need for a central authority and ensuring resilience to single points of failure. Each transaction is added to a block, which is then linked to previous blocks, forming an immutable chain of transaction history. Through consensus mechanisms like Proof of Work or Proof of Stake, participants validate transactions, ensuring the integrity and security of the blockchain. This technology has applications beyond cryptocurrencies, offering benefits such as increased transparency, enhanced security, and decentralized record-keeping in various industries, including finance, supply chain management, healthcare, and more.

1.6. Blockchain for traffic congestion control

Using blockchain technology for traffic congestion control could significantly change how transportation systems are managed. Blockchain, a decentralized and transparent ledger system, offers multiple benefits that can help overcome challenges associated with traffic congestion. Here is a detailed explanation of how blockchain can be utilized for this purpose:

- Data integrity and security: Blockchain provides a tamper-proof and immutable record, ensuring the integrity and security of traffic data (Malik and Saleem, 2023). Traffic information, such as real-time conditions, congestion levels, and management decisions, can be securely stored and verified on the blockchain. This prevents data manipulation, unauthorized changes, and fraud, thereby enhancing the reliability of information and improving decision-making.

- Decentralized data sharing: Blockchain enables decentralized sharing of data among various stakeholders like traffic authorities, transportation companies, and drivers. Using smart contracts and permissioned networks, parties can securely access and share data, such as traffic flow, incident reports, and road conditions. This supports collaborative analysis and planning, leading to more effective traffic management.
- Smart contracts for automated decision-making: Smart contracts on blockchain can automate certain traffic management tasks. For example, they can adjust traffic signal timings, reroute traffic, or allocate resources to manage congestion based on predefined rules and conditions. This reduces the need for manual intervention, cuts response times, and ensures consistent application of congestion control measures.
- Micropayments and incentive mechanisms: Blockchain-based systems can implement micropayments and incentives to encourage behaviors that reduce congestion. Drivers who opt for alternative routes, carpooling, or public transport might receive tokens or incentives, promoting efficient use of transport resources.
- Transparent and accountable systems: Blockchain enhances transparency and accountability in traffic management. Its decentralized nature ensures all recorded transactions and actions are visible to relevant stakeholders, increasing trust and allowing public oversight of decision-making processes. Furthermore, blockchain's ability to provide an audit trail helps in tracing actions, resolving disputes, and identifying responsible parties.
- Infrastructure management and planning: Blockchain can also aid in managing and planning infrastructure by transparently tracking investments, maintenance, and upgrades. Blockchain-based asset management systems can record and monitor the lifecycle of infrastructure components such as roads and bridges, ensuring timely maintenance, minimizing downtime, and optimizing resource allocation.

2. Literature review

Enhanced traffic control systems are being developed using a range of strategies. Over the past decade, the Internet of Things (IoT) and Information and Communication Technology (ICT) have significantly impacted how organizations approach innovation and leverage opportunities in their day-to-day operations. The concept of Smart Cities has emerged from the integration of IoT and ICT, aiming to provide valuable services to individuals while offering businesses the potential for transformative advancements through the adoption of state-of-the-art technologies. This convergence presents numerous possibilities for both improving urban traffic management and revolutionizing various aspects of urban life.

In their research, the scientists employed security cameras to monitor traffic and utilized Optical Character Recognition (OCR) to classify vehicles based on number plate recognition, a straightforward identification technique. However, it is important to note that implementing this system in Pakistan may present challenges due to the diverse types of traffic, including cycles and donkey carts, which do not bear number plates (Jain et al., 2017).

In a study, Osman et al. (2017) proposed a methodology that involved the utilization of installed cameras to classify traffic volume. They employed MATLAB as a traffic manager and employed a wireless transmitter to transmit captured photos to a server. The server then analyzed the images from different sections to determine traffic density based on predefined criteria, primarily focusing on the number of vehicles on the route. An algorithm was employed to calculate the distance based on traffic density on the road to regulate the duration of the red light for a specific lane at the junction. This information was transmitted to both the microcontroller and the server (Osman et al., 2017).

In their research, Jadhav et al. (2016) utilized surveillance cameras, MATLAB, and KEIL to address the issue of traffic congestion. Their study focused on implementing priority-based traffic management and a red signal broker system. However, it is important to note that this approach presents challenges in terms of complexity and cost compared to alternative methods that rely on heavy equipment (Jadhav et al., 2016).

In a research work, Bui et al. (2017) examined a dynamic approach based on real-time procedure synchronization to efficiently manage traffic flow. The researchers employed sensors to detect and monitor traffic while utilizing wireless communication devices to establish connectivity between vehicles and infrastructure. The central controller, situated at the junction, received and processed information and requests from both vehicles and pedestrians, following a first come, first served approach to manage the traffic efficiently (Bui et al., 2017).

Swathi et al. (2016) presented a smart traffic routing framework that utilizes the most direct and least congested path for efficient navigation. The framework incorporates sensors powered by both solar energy and batteries to collect data on traffic density. These sensors continuously emit infrared light and analyze the reflectivity from vehicles to determine traffic congestion levels. It is important to note that certain environmental factors, such as temperature and humidity, can affect the accuracy of these measurements (Swathi et al., 2016).

Al-Sakran (2015) developed a system with the primary objectives of car classification and location control, utilizing sensors and RFIDs. The collected data was then transmitted via a wireless link to a centralized supervisory center for further processing. The researchers incorporated various contemporary tools and technologies such as cloud computing, RFIDs, GPS, WSN, and agents to effectively gather, store, monitor, and manage traffic data (Al-Sakran, 2015).

Shekar et al. (2012) have introduced a novel navigation approach in their research for ambulances based on Vehicular Ad-hoc Network (VANET). The primary objective of this approach was to efficiently guide ambulances to their destinations, considering the challenge of avoiding unexpected traffic congestion. To achieve this, the researchers utilized a combination of real-time traffic data updates and historical data. By integrating these sources with the Global Positioning System (GPS), they proposed a dynamic routing framework. This framework also incorporated the integration of a metro rail system and road transportation network to facilitate real-time guidance for emergency vehicles in various scenarios (Shekar et al., 2012).

Djahel et al. (2013) have presented an innovative approach that offers an adaptive context for efficient traffic management of emergency vehicles. This approach not only dynamically adjusts traffic signals but also provides recommendations for necessary changes in driver behavior, driving regulations, and the implementation of appropriate security measures. By considering these aspects, the proposed system aims to enhance the overall effectiveness of traffic management for emergency vehicles.

Sundar et al. (2014) proposed a novel approach for intelligent traffic control that addresses multiple objectives, including clearing the way for ambulances, detecting stolen vehicles, and managing traffic congestion. The method utilizes Radio Frequency Identification (RFID) tags installed on vehicles, enabling the system to monitor the number of vehicles traveling on specific routes, identify stolen vehicles, and transmit relevant information to the police control room. Additionally, the system communicates with traffic controllers through ZigBee modules to coordinate the prioritized movement of ambulances.

Addressing the challenging task of accurately predicting traffic flow, a recent research paper introduces a novel deep architecture that surpasses the limitations of traditional statistical models. The proposed architecture utilizes a deep belief network as its foundation, effectively extracting crucial high-level features from the input data. At the top layer, a multitask regression component enables simultaneous prediction of multiple traffic flow-related parameters, significantly enhancing prediction accuracy. To further optimize multitask learning for traffic flow density prediction, the authors propose a group method based on their deep architecture. This method intelligently groups correlated and dependent traffic flow-related parameters, reducing the complexity of the multitask learning problem. By harnessing the capabilities of deep learning, this innovative approach demonstrates the potential to develop more efficient and sustainable transportation systems (Huang et al., 2014).

Sivaraman and Trivedi (2010) presented a comprehensive active learning framework that robustly identifies and tracks vehicles on the road. To further enhance this system, they incorporate particle filter tracking and conduct evaluations using real-world datasets. In the realm of traffic signal control, particularly in multi-intersection vehicular networks, reinforcement learning plays a significant role. To devise an efficient traffic signal control strategy, the authors propose a unique approach employing a multi-agent intelligent system (Arel et al., 2010). They suggest leveraging a deep neural network to learn the Q-function of reinforcement learning, using traffic system inputs and outputs to determine suitable signal timing policies (Li et al., 2016). The existing approach to edge storage for computing offloading solutions primarily relies on conventional storage architectures. However, a recent advancement introduces a new approximation algorithm that prioritizes caching load balance and fairness metrics. This algorithm, based on integer linear programming, effectively optimizes edge storage performance (Huang et al., 2017). Furthermore, a novel multiplier cooperative storage algorithm utilizing alternating directions aims to minimize task latency and operation costs while maximizing the utilization of local information and improving system trustworthiness (Wu et al., 2017). To address the information asymmetry between users and service providers, an optimal auction mechanism has been proposed, favoring service providers and promoting fair and efficient transactions (Cao et al., 2018). Additionally, a computationally efficient approach has been developed to assess user payments and optimize cache allocation, ensuring both optimal cache performance and equitable compensation for user transactions.

3. Proposed methodology

This research work is designed to address the challenges of the traffic congestion prediction model in smart cities by leveraging the combined benefits of blockchain technology and Federated Learning (FL). The model ensures the security, transparency, and privacy of traffic data by utilizing blockchain's decentralized and immutable nature for data storage and integrity. With FL, local devices can collaboratively train congestion control models without sharing raw data, preserving privacy. The blockchain-based approach enhances transparency by providing a clear audit trail of model updates and decision-making processes. By combining these technologies, the system enables efficient traffic congestion control while ensuring data security, transparency, and privacy in smart cities. The proposed model is shown in Fig. 1.

Fig. 2 shows the proposed model for predicting traffic congestion, which has both the training and validation phases. The training phase consists of the 'n' number of traffic management systems in which data is sensed from the traffic data input layer and proceeded to the blockchain layer. The training phase consists of the 'n' number of traffic management systems in which data is sensed from the traffic data input layer and processed for the blockchain layer. In the blockchain layer, the traffic data is stored in a decentralized and immutable manner using blockchain technology. This layer ensures data integrity and security by storing the traffic information as blocks in a transparent and tamper-resistant ledger. With transparency and audibility, stakeholders can access and verify the data, while smart contracts enable automation and enforce predefined rules. This layer also facilitates secure data sharing and collaboration among different entities, leveraging decentralization and fault tolerance to enhance the efficiency and effectiveness of the traffic management system. After the blockchain layer, in the preprocessing layer, the traffic data is further refined and transformed to prepare it for analysis and modeling, including tasks such as data cleaning, normalization, and other preprocessing techniques.

In the application layer, various machine learning algorithms are used to train models using the preprocessed traffic data. These algorithms may include (decision trees, random forests, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and others), aiming to optimize the models' performance and accuracy for traffic management tasks. Then, the trained models are uploaded to the local server. The trained model is uploaded to a local server for further refinement using machine learning algorithms. This technique combines with aggregation to improve accuracy and efficiency. Federated learning is particularly useful for decentralized systems, such as traffic applications, where data may be distributed across multiple locations. After the aggregation process, the aggregated model is updated to the 'n' number of traffic management systems to predict traffic congestion. The mathematical representation of fused federated learning is given in Tables 1 and 2.

In the validation phase, the input values are collected from the traffic data layer in real time. After collecting input values, the developed model is imported from the cloud after aggregation to predict traffic congestion, and it is checked to see if it is found or not. The process will be discarded if the response is No, and if the answer is Yes, a message will be displayed stating that traffic congestion has been found.

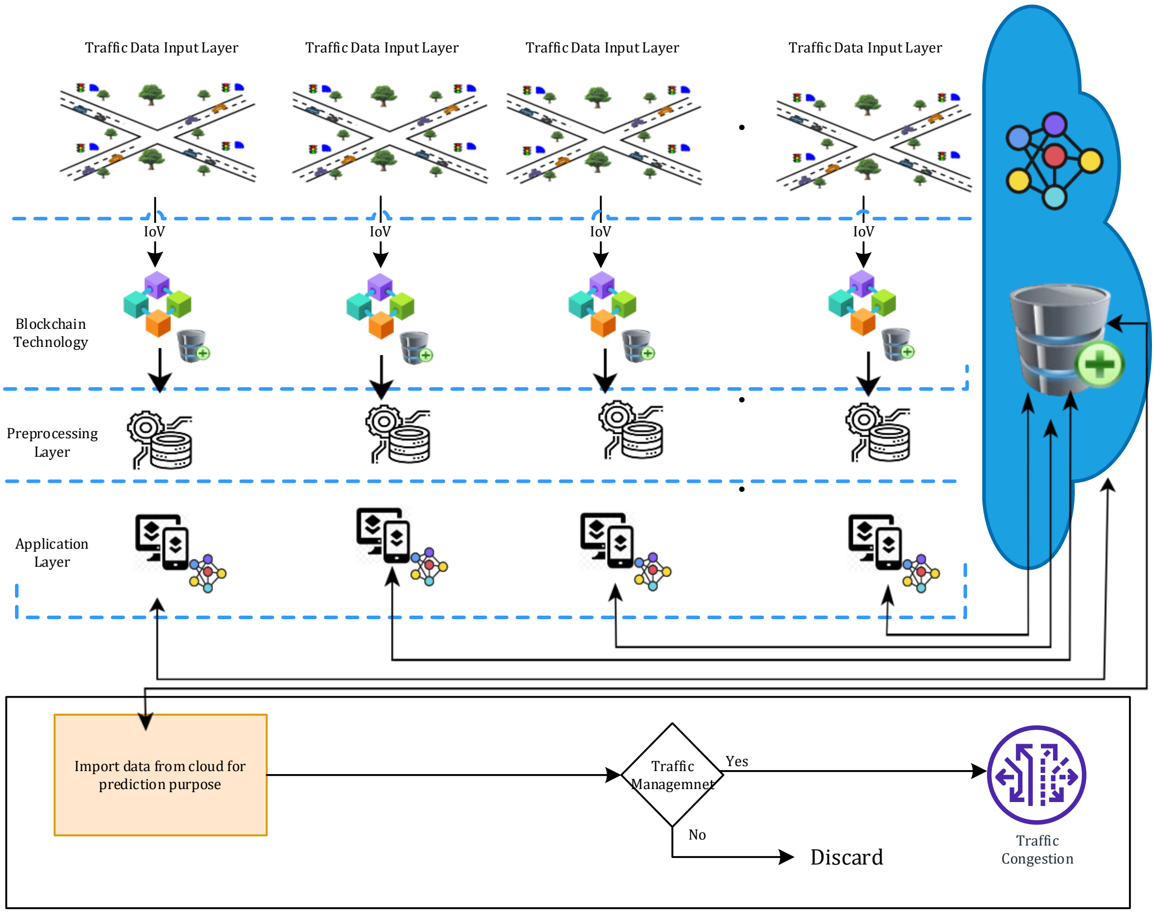

Fig. 2: Proposed model

4. Simulation results

In this research, the federated learning approach is used on a dataset that is divided into 70% for training (1155 samples) and 30% for validation (495 samples). The dataset is utilized to predict traffic congestion by using a combined federated learning method to identify positive and negative congestion events. This combined approach shows potential for improving traffic management systems by offering more accurate congestion predictions, which can lead to more efficient urban transportation. The effectiveness of the algorithm is confirmed through a detailed analysis of various numerical metrics and performance measures.

These performance parameters are as follows:

$$Sensitivity = \frac{\sum True\ Positive}{\sum Condition\ Positive} \tag{3}$$

$$Specificity = \frac{\sum True\ Negative}{\sum Condition\ Negative} \tag{4}$$

$$Accuracy = \frac{\sum True\ Positive + \sum True\ Positive}{\sum Total\ Population} \tag{5}$$

$$Miss-Rate = \frac{\sum False\ Negative}{\sum Condition\ Positive} \tag{6}$$

$$Fallout = \frac{\sum False\ Positive}{\sum Condition\ Negative} \tag{7}$$

$$Likelihood\ Positive\ Ratio = \frac{\sum True\ Positive\ Ratio}{\sum False\ Positive\ Ratio} \tag{8}$$

$$Likelihood\ Negative\ Ratio = \frac{\sum True\ Positive\ Ratio}{\sum False\ Positive\ Ratio} \tag{9}$$

$$Positive\ Predictive\ Value = \frac{\sum True\ Positive}{\sum\ Predicted\ Condition\ Positive} \tag{10}$$

$$Negative\ Predictive\ Value = \frac{\sum True\ Negative}{\sum\ Predicted\ Condition\ Negative} \tag{11}$$

Table 1: Proposed federated learning pseudo code (server side)

No.	Steps
1	Start
2	Initialize $w^k_{G,fml}$ & $v^k_{G,fml}$
3	For each cycle k from I to K do
4	S_k(Random set of clients from η)
5	a. For each client $l \in S_k$ parallelly do $[w^n_{k+1}, v^n_{k+1}]$= Client Training (n, w_k, v_k) End for
6	$w^k_{G,fml} = \frac{1}{\sum n \varepsilon \eta} \sum_{n=1}^{N} \frac{S_n}{S} w^n_{k+1}$ (Avg aggregation) $v^k_{G,fml} = \frac{1}{\sum n \varepsilon \eta} \sum_{n=1}^{N} \frac{S_n}{S} v^n_{k+1}$
7	End for
8	Stop

[Table 3](#) demonstrates that the proposed model uses a total of 1155 training samples, which are divided into 515 positive and 640 negative samples. Out of these, 508 samples are correctly predicted as positive, indicating no traffic congestion, while 7 samples are incorrectly predicted as negative, indicating traffic congestion. Similarly, out of 640 negative samples indicating traffic congestion, 630 are correctly recognized, and 10 samples are incorrectly predicted as positive, indicating no traffic congestion despite its presence. Table 4 shows that the proposed model uses 495 validation samples divided into 251 positive and 244 negative samples. Out of these, 241 samples are correctly predicted as positive, indicating no traffic congestion, while 10 samples are incorrectly predicted as negative, indicating traffic congestion. Similarly, out of 244 negative samples indicating traffic congestion, 243 are correctly recognized, and 1 sample is incorrectly predicted as positive, indicating no traffic congestion despite its presence. Table 5 (Fused Federated) is representing that within the training, the proposed model accuracy, TPR, TNR, FNR, and precision are 98.53, 98.07, 98.90, 1.47, and 98.64, respectfully, but within validation, the proposed model is 97.78, 99.59, 96.05, 2.22, and 96.02. Furthermore, the proposed framework produces 89.15, 1.48, and 98.44 during training and 25.21, 2.31, and 99.59 during validation in aspects of likelihood positive ratio, likelihood negative ratio, and NPV, correspondingly.

Table 2: Proposed federated learning pseudo code (Client Side)

No.	Steps
1	Start
2	Split local data to mini batches of size S
3	Initialization of both layer weights ($\boldsymbol{w}_{ij}$ & $\boldsymbol{v}_{jk}$), Error (E)= 0 and the number of epochs, £ = 0
4	For each training pattern p
5	a. do the feedforward phase to i) calculate φ_j ii) calculate φ_k
6	b. Calculate the output of errors for signals and hidden layer signals
7	c. Then update weights $\boldsymbol{v}_{jk}$ and $\boldsymbol{w}_{ij}$ (error of backpropagation)
8	£ = £ + 1
9	Test the ending conditions: If no ending conditions are satisfied, go to step 4
10	Return optimum local trained model weights $\boldsymbol{v}_{jk}$ and $\boldsymbol{w}_{ij}$ to Server
11	Stop

Table 3: Proposed training model for traffic prediction (Fused federated)

Proposed model training			
	Total samples (1155)	Result (output)	
Input	Expected output	Predicted Positive (PP)	PN
		True positive (TP)	False positive (FP)
	515 positive	508	7
		False negative (FN)	True negative (TN)
	640 negative	10	630

Table 4: Proposed validation model for traffic prediction (Fused federated)

Proposed model validation			
	Total samples (495)	Result (output)	
Input	Expected output	PP	PN
		TP	FP
	251 positive	241	10
		FN	TN
	244 negative	1	243

Table 6 provides a comprehensive comparison of the performance of the proposed fused federated model with previously published machine learning models. The results clearly demonstrate that the model achieves a notable accuracy rate of 97.78%. The proposed model integration into existing traffic management using federated learning and blockchain enhanced the effectiveness of control centers and signal systems. This seamless integration ensures practicality in smart cities, supporting both authorities and citizens with enhanced efficiency.

Table 5: Performance of proposed model in training and validation with fused federated

		Accuracy	Sensitivity TPR	Specificity TNR	Miss-rate (%) FNR	Fall-out FPR	LR+	LR-	PPV (Precision)	NPV
CNN	Training	98.53	98.07	98.90	1.47	0.0110	89.15	1.48	98.64	98.44
	Validation	97.78	99.59	96.05	2.22	0.0395	25.21	2.31	96.02	99.59

Table 6: Comparison of the proposed model for traffic congestion with previous machine learning algorithms

Method	Accuracy	Miss-rate
YOLO (Chakraborty et al., 2018)	91.4%	8.6%
DCNN (Chakraborty et al., 2018)	90.2%	9.8%
SVM (Chakraborty et al., 2018)	85.7%	14.3%
AlexNet (Lee et al., 2019)	96.33%	3.67%
MLP (Awan et al., 2020)	72.07%	27.93%
KNN (Awan et al., 2020)	78.38%	21.62%
RF (Awan et al., 2020)	83.15%	16.85%
Proposed model	97.78%	2.22%

This research highlights the real-world applicability and scalability of the proposed traffic congestion control system, focusing on seamless integration with existing infrastructures and manageable computational demands to ensure practicality and adaptability across diverse urban settings.

5. Conclusion

In modern smart cities, traffic congestion creates significant challenges for efficient and sustainable transportation. Rapid urbanization and the increasing number of vehicles have led to more traffic, causing longer commute times, environmental pollution, and economic inefficiencies. Current traffic control systems face problems with security and transparency, as centralized methods raise privacy concerns and lack clear decision-making processes. To solve these issues, a secure and transparent traffic congestion control system is necessary. This research proposes a system based on blockchain technology and federated learning. Blockchain technology ensures secure, immutable, and transparent records of congestion control activities and data exchanges, building trust among stakeholders. Federated learning allows collaborative model training without compromising data privacy by using data from multiple sources while protecting individual privacy. The proposed system has the potential to improve traffic management, reduce congestion, enhance mobility, and support the sustainable development of smart cities by addressing security and transparency issues in traffic congestion control. Additionally, simulations of the proposed fused federated model show an impressive 97.78% accuracy and a low 2.22% miss rate, outperforming previous methods. This model could be implemented in urban areas with local partners, ensuring scalability and integration based on initial success.

5.1. Limitations and future work

Computational resources or scalability across diverse urban environments and computational resource demands pose challenges. In the future, these limitations could be addressed by focusing on adaptive algorithms and optimized computational processes to address these limitations.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Al-Sakran HO (2015). Intelligent traffic information system based on integration of Internet of Things and agent technology. International Journal of Advanced Computer Science and Applications, 6(2): 37-43. https://doi.org/10.14569/IJACSA.2015.060206

Arel I, Liu C, Urbanik T, and Kohls AG (2010). Reinforcement learning-based multi-agent system for network traffic signal control. IET Intelligent Transport Systems, 4(2): 128-135. https://doi.org/10.1049/iet-its.2009.0070

Awan FM, Saleem Y, Minerva R, and Crespi N (2020). A comparative analysis of machine/deep learning models for parking space availability prediction. Sensors, 20(1): 322. https://doi.org/10.3390/s20010322 **PMid:31935953 PMCid:PMC6983166**

Bui KH N, Camacho D, and Jung JE (2017). Real-time traffic flow management based on inter-object communication: A case study at intersection. Mobile Networks and Applications, 22: 613-624. https://doi.org/10.1007/s11036-016-0800-y

Cao X, Zhang J, and Poor HV (2018). An optimal auction mechanism for mobile edge caching. In the 38th International Conference on Distributed Computing Systems, IEEE, Vienna, Austria: 388-399. https://doi.org/10.1109/ICDCS.2018.00046

Chakraborty P, Adu-Gyamfi YO, Poddar S, Ahsani V, Sharma A, and Sarkar S (2018). Traffic congestion detection from camera images using deep convolution neural networks. Transportation Research Record, 2672(45): 222-231. https://doi.org/10.1177/0361198118777631

Djahel S, Salehie M, Tal I, and Jamshidi P (2013). Adaptive traffic management for secure and efficient emergency services in smart cities. In the International Conference on Pervasive Computing and Communications Workshops, IEEE, San Diego, USA: 340-343. https://doi.org/10.1109/PerComW.2013.6529511

Fadlullah ZM, Tang F, Mao B, Kato N, Akashi O, Inoue T, and Mizutani K (2017). State-of-the-art deep learning: Evolving machine intelligence toward tomorrow's intelligent network traffic control systems. IEEE Communications Surveys and Tutorials, 19(4): 2432-2455. https://doi.org/10.1109/COMST.2017.2707140

Fatima A, Khan MA, Abbas S, Waqas M, Anum L, and Asif M (2019). Evaluation of planet factors of smart city through multi-layer fuzzy logic (MFL). The ISC International Journal of Information Security (ISeCure), 11(3): 51-58. https://doi.org/10.22042/isecure.2019.11.0.7

Guo M, Wang P, Chan CY, and Askary S (2019). A reinforcement learning approach for intelligent traffic signal control at urban intersections. In the Intelligent Transportation Systems Conference, IEEE, Auckland, New Zealand: 4242-4247. https://doi.org/10.1109/ITSC.2019.8917268 **PMid:30900705**

Huang W, Song G, Hong H, and Xie K (2014). Deep architecture for traffic flow prediction: Deep belief networks with multitask learning. IEEE Transactions on Intelligent Transportation Systems, 15(5): 2191-2201. https://doi.org/10.1109/TITS.2014.2311123

Huang Y, Song X, Ye F, Yang Y, and Li X (2017). Fair caching algorithms for peer data sharing in pervasive edge computing environments. In the 37th International Conference on Distributed Computing Systems, IEEE, Atlanta, USA: 605-614. https://doi.org/10.1109/ICDCS.2017.151

Ibrahim M, Abbas S, Fatima A, Ghazal TM, Saleem M, Alharbi M, and Elmitwally N (2024). Fuzzy-based fusion model for β-thalassemia carriers prediction using machine learning technique. Advances in Fuzzy Systems, 2024: 4468842. https://doi.org/10.1155/2024/4468842

Jadhav P, Kelkar P, Patil K, and Thorat S (2016). Smart traffic control system using image processing. International Research Journal of Engineering and Technology, 3(3): 2395-0056.

Jain K, Choudhury T, and Kashyap N (2017). Smart vehicle identification system using OCR. In the 3rd International Conference on Computational Intelligence and Communication Technology, IEEE, Ghaziabad, India: 1-6. https://doi.org/10.1109/CIACT.2017.7977297

Jiang P, Liu Z, Zhang L, and Wang J (2022). Advanced traffic congestion early warning system based on traffic flow forecasting and extenics evaluation. Applied Soft Computing, 118: 108544. https://doi.org/10.1016/j.asoc.2022.108544

Kabir MH, Hasan KF, Hasan MK, and Ansari K (2022). Explainable artificial intelligence for smart city application: A secure and trusted platform. In: Ahmed M, Islam SR, Anwar A, Moustafa N, and Pathan ASK (Eds.), Explainable artificial intelligence for cyber security: Next generation artificial intelligence: 241-263. Springer International Publishing, Cham, Switzerland. https://doi.org/10.1007/978-3-030-96630-0_11

Khan AH, Khan MA, Abbas S, Siddiqui SY, Saeed MA, Alfayad M, and Elmitwally NS (2021). Simulation, modeling, and optimization of intelligent kidney disease predication empowered with computational intelligence approaches. Computers, Materials and Continua, 67(2): 1399-1412. https://doi.org/10.32604/cmc.2021.012737

Lee HJ, Ullah I, Wan W, Gao Y, and Fang Z (2019). Real-time vehicle make and model recognition with the residual SqueezeNet architecture. Sensors, 19(5): 982. https://doi.org/10.3390/s19050982 **PMid:30813512 PMCid:PMC6427723**

Li L, Lv Y, and Wang FY (2016). Traffic signal timing via deep reinforcement learning. IEEE/CAA Journal of Automatica Sinica, 3(3): 247-254. https://doi.org/10.1109/JAS.2016.7508798

Liu Y, Lyu C, Liu Z, and Cao J (2021). Exploring a large-scale multi-modal transportation recommendation system. Transportation Research Part C: Emerging Technologies, 126: 103070. https://doi.org/10.1016/j.trc.2021.103070

Malik JA and Saleem M (2023). Blockchain and cyber-physical system for security engineering in the smart industry. In: Motahhir S and Maleh Y (Eds.), Security engineering for embedded and cyber-physical systems: 51-70. 1st Edition, CRC Press, Boca Raton, USA.

Osman T, Psyche SS, Ferdous JS, and Zaman HU (2017). Intelligent traffic management system for cross section of roads using computer vision. In the 7th Annual Computing and Communication Workshop and Conference, IEEE, Las Vegas, USA: 1-7. https://doi.org/10.1109/CCWC.2017.7868350

Saleem M, Khan MS, Issa GF, Khadim A, Asif M, Akram AS, and Nair HK (2023). Smart spaces: Occupancy detection using adaptive back-propagation neural network. In the International Conference on Business Analytics for Technology and Security, IEEE, Dubai, UAE: 1-6. https://doi.org/10.1109/ICBATS57792.2023.10111286

Shekar BS, Divyashree C, George G, Rani HU, Murali A, and Kumar GN (2012). GPS based shortest path for ambulances using VANETs. In the International Conference on Wireless Networks (ICWN 2012), IACSIT Press, Singapore, Singapore, 49: 190-196.

Sivaraman S and Trivedi MM (2010). A general active-learning framework for on-road vehicle recognition and tracking. IEEE Transactions on Intelligent Transportation Systems, 11(2): 267-276. https://doi.org/10.1109/TITS.2010.2040177

Sundar R, Hebbar S, and Golla V (2014). Implementing intelligent traffic control system for congestion control, ambulance clearance, and stolen vehicle detection. IEEE Sensors Journal, 15(2): 1109-1113. https://doi.org/10.1109/JSEN.2014.2360288

Swathi K, Sivanagaraju V, Manikanta AKS, and Kumar SD (2016). Traffic density control and accident indicator using WSN. Traffic, 2(4): 18-21.

Wu G, Chen J, Bao W, Zhu X, Xiao W, Wang J, and Liu L (2017). MECCAS: Collaborative storage algorithm based on alternating direction method of multipliers on mobile edge cloud. In the International Conference on Edge Computing, IEEE, Honolulu, USA: 40-46. https://doi.org/10.1109/IEEE.EDGE.2017.14

Yaga D, Mell P, Roby N, and Scarfone K (2018). Blockchain technology overview. NISTIR 8202, National Institute of Standards and Technology, Gaithersburg, USA. https://doi.org/10.6028/NIST.IR.8202