Federated Learning and Blockchain-Enabled Framework for Traffic Rerouting and Task Offloading in the Internet of Vehicles (IoV)

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***Abstract*—The Internet of Vehicles (IoV) presents significant opportunities for enhancing traffic management and vehicle coordination, but it also faces challenges related to traffic congestion, data privacy, and efficient computational resource allocation. Traffic congestion remains a critical problem, impacting travel time, fuel consumption, and emissions. Additionally, task offloading in the edge-cloud environment demands efficient strategies to balance latency, resource usage, and computational load. Our proposed system, Joint Federated Learning and Blockchain-Enabled Traffic Rerouting with Efficient Task Offloading of Consumer IoV in the Edge-Cloud Environment, addresses these issues by integrating federated learning and blockchain technologies. Federated learning allows vehicles to collaboratively train a global model without sharing raw data, preserving privacy and reducing bandwidth usage. Blockchain ensures the security and integrity of the model updates, fostering trust among participants. Efficient task offloading strategies optimize the use of edge and cloud resources, minimizing latency and energy consumption. Our approach is validated using a comprehensive dataset, and the results demonstrate significant improvements in traffic prediction accuracy, security, and overall system performance, highlighting the effectiveness of the integrated solution in addressing the challenges of Consumer Internet of Vehicles (CIoV).**

***Index Terms*—Blockchain Network, Task Offloading, IoV, Traffic Rerouting, Federated Learning.**

I. Introduction

THE rapid advancement of vehicular networks and Internet of Things (IoT) technologies has led to the emergence of the Internet of Vehicles (IoV). IoV represents an interconnected ecosystem where vehicles communicate with each other and with surrounding infrastructure, enhancing traffic management, safety, and the overall driving experience. This ecosystem is poised to transform urban mobility by enabling advanced traffic coordination, real-time communication, and data-driven decision-making [1], [2]. However, as IoV expands, it faces several challenges, including traffic congestion, data privacy concerns, and the need for efficient computational resource allocation in edge-cloud environments.

Traffic congestion remains a significant issue in urban areas, negatively affecting travel time, fuel consumption, and environmental sustainability. The proliferation of connected vehicles within IoV networks offers new possibilities for dynamic traffic management and rerouting strategies. However, the success of these strategies depends on effective data processing and real-time decision-making capabilities [3], [4].

In this context, efficient task offloading strategies in edge-cloud environments are critical for managing computational load, minimizing latency, and optimizing resource usage [5]. Additionally, the integration of IoV introduces privacy and security challenges due to the vast amounts of sensitive data generated and exchanged among vehicles and infrastructure. Traditional centralized data management approaches are insufficient to address these issues, as they increase the risk of data breaches and latency [6], [7]. Federated learning, a decentralized machine learning approach, offers a promising solution by allowing vehicles to collaboratively train global models without transmitting raw data, preserving privacy and reducing bandwidth usage [8].

Blockchain's decentralized ledger further enhances data integrity and immutability, fostering trust among participants and strengthening the security of model updates in federated learning [9], [10]. By integrating federated learning and blockchain technology with efficient task offloading strategies, this research proposes a comprehensive solution to the challenges facing IoV. The objective of this paper is to present a novel system: Joint Federated Learning and Blockchain-Enabled Traffic Rerouting with Efficient Task Offloading for the Internet of Vehicles in Edge-Cloud Environments. This proposed system aims to improve traffic management, enhance data privacy and security, and optimize computational resources [11].

This paper contributes to the existing body of knowledge by offering an integrated approach that addresses IoV's multifaceted challenges through the convergence of federated learning, blockchain technology, and efficient task offloading.

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The remainder of this paper is organized as follows: Section 2 reviews relevant literature; Section 3 details the methodology; Section 8 presents the results analysis; and Section 9 discussed conclusions and future research directions.

II. Literature Review

The Internet of Vehicles (IoV) signifies a transformative shift in vehicle interactions with their environment and with each other, leveraging advanced communication technologies to enhance traffic management and safety. Despite its potential benefits, IoV faces critical challenges that must be addressed to fully realize its potential. This literature review examines current research on federated learning, blockchain technology, and task offloading in edge-cloud environments, which are core components of the proposed system.

Traffic congestion is a pervasive issue in urban areas, impacting economic productivity, environmental sustainability, and quality of life. Traditional approaches to traffic management, such as static signal control and fixed routing, are inadequate for handling growing vehicle numbers and the pressures of urbanization. Intelligent Transportation Systems (ITS) aim to address this by using advanced communication technologies to optimize traffic flow and reduce congestion [12].

In IoV contexts, dynamic traffic management strategies are enabled by real-time data exchange between vehicles and infrastructure, requiring robust data processing and predictive models to anticipate traffic patterns and optimize routing decisions. However, this data sharing introduces privacy and security challenges, as sensitive information, such as vehicle location and driving behavior, can be vulnerable to data breaches and unauthorized access [13]. Effective traffic management in IoV must, therefore, balance the need for data sharing with privacy and security protections.

Federated learning offers a promising approach to address data privacy concerns in distributed machine learning applications. Unlike traditional centralized learning models, federated learning allows multiple devices to collaboratively train a global model without transmitting raw data to a central server. This decentralized approach is particularly suitable for IoV, where data privacy is paramount.

Recent studies have explored federated learning in vehicular networks. For instance, researchers have proposed a federated learning framework for traffic prediction in IoV, showing its effectiveness in preserving privacy while achieving high prediction accuracy. Another study applied federated learning to distributed vehicle routing, reducing communication overhead and improving model performance [14]. However, federated learning in IoV still faces challenges related to data heterogeneity, model convergence, and communication efficiency. Data generated by vehicles in IoV networks varies widely in terms of volume, quality, and distribution, which can impact model convergence and performance. To address these challenges, researchers have proposed various techniques, such as model aggregation and communication optimization [15].

Blockchain technology provides a decentralized and secure framework for managing data within IoV networks. By offering an immutable ledger for recording transactions, blockchain ensures data integrity and transparency, making it an ideal solution for enhancing trust and security in federated learning applications [16]. Recent studies have integrated blockchain with federated learning in vehicular networks, demonstrating its potential to prevent data tampering and unauthorized access to model updates [17].

In addition to enhancing security, blockchain can facilitate efficient task offloading in edge-cloud environments. Blockchain's transparent resource allocation mechanism enables dynamic and fair distribution of computational resources, improving IoV systems' overall efficiency [18]. However, the computational overhead associated with blockchain operations remains a challenge, especially in resource-constrained environments like IoV [19]. Researchers are exploring solutions such as lightweight consensus algorithms and off-chain approaches to mitigate this overhead [20].

Task offloading is crucial in IoV systems to efficiently manage computational resources in edge-cloud environments. Effective task offloading strategies balance latency, resource usage, and computational load to ensure system responsiveness and reliability. Recently, there has been a focus on developing adaptive task offloading models for edge-cloud environments, with reinforcement learning emerging as a promising approach. Reinforcement learning-based models learn optimal offloading strategies from real-time feedback, dynamically adjusting to changing system conditions [21]. For example, a reinforcement learning-based model for vehicular edge computing significantly improved resource utilization and reduced latency [22].

Some recent works from Yadav et al., [23], [24] were addressed the challenges lack of resource allocation mechanism for energy efficiency and energy-latency trade-off using Energy-efficient dynamic Computation Offloading and resources allocation Scheme (ECOS). Furthermore, in their second paper, they proposed Computation Offloading using Reinforcement Learning (CORL) scheme for minimizing energy consumption and latency. Also, Ling et al., [25] introduced vehicular MEC architecture to analyze the time of arrival for predicting vehicles driving state and used dynamic programming algorithm for optimizing response fairness and QoS for decreasing computation offloading problem.

III. Proposed Work

The rapid expansion of CIoV introduces both opportunities and challenges in traffic management, data security, and computational resource optimization. Traditional centralized systems face significant limitations, such as:

- Scalability challenges in handling large-scale data and computational loads.
- Data privacy concerns are due to the transmission of sensitive raw data to centralized servers.
- Inefficiency in task management, resulting in sub-optimal resource utilization and higher latency.
- Traffic congestion issues, which require advanced routing mechanisms to adapt to dynamic traffic conditions.

A. Motivation

Our work is motivated by the need to address the above challenges. Specifically, we aim to:

- Preserve privacy while leveraging large-scale data for traffic prediction in the IoV ecosystem.
- Enhance the scalability and security of collaborative learning processes using blockchain technology.
- Improve the efficiency of computational resource utilization through optimized task offloading.
- Dynamically reroute vehicles to reduce congestion and improve travel times using advanced hybrid algorithms.

B. Contributions

To achieve these goals, we propose a novel system that integrates Federated Learning, Blockchain, Traffic Rerouting, and Task Offloading strategies within an edge-cloud architecture. The key contributions of our work are as follows:

1) Federated Learning Module: Enables collaborative training of a global traffic prediction model without sharing raw data, ensuring privacy preservation and reducing network bandwidth usage.
2) Blockchain Module: Secures the federated learning process by recording model updates as immutable transactions on a distributed ledger. This ensures integrity, transparency, and trust among IoV participants.
3) Efficient Task Offloading Module: Optimizes computational task distribution between edge and cloud resources, achieving a balance among latency, resource utilization, and energy consumption.
4) Hybrid Traffic Rerouting Algorithm (HTR): Combines a Modified Ant Colony Optimization (ACO) technique with Deep Reinforcement Learning (DRL) to dynamically adjust vehicle routes based on real-time traffic data. This approach minimizes congestion and reduces travel time by leveraging bio-inspired optimization and predictive machine learning.

C. System Overview

Figure 1 illustrates the system architecture designed for traffic management in the CIoV. Vehicles act as data producers and consumers, generating local data (e.g., location, speed, traffic density) for federated learning. Local models are aggregated into a global model at edge servers, integrated into a blockchain to ensure security and transparency. The system employs hybrid algorithms for traffic rerouting and optimizes task distribution between edge and cloud resources.

IV. Federated Learning for Traffic Prediction

Federated Learning (FL) enables vehicles to collaboratively train a global model without sharing raw data, preserving privacy and reducing bandwidth consumption. The goal is to create a predictive model for traffic conditions based on decentralized data.

Let D_i the local dataset for vehicle i containing input-output pairs (x_{ij}, y_{ij}), where x_{ij} represents features as such as location, speed, and time, and y_{ij} is the target traffic condition.

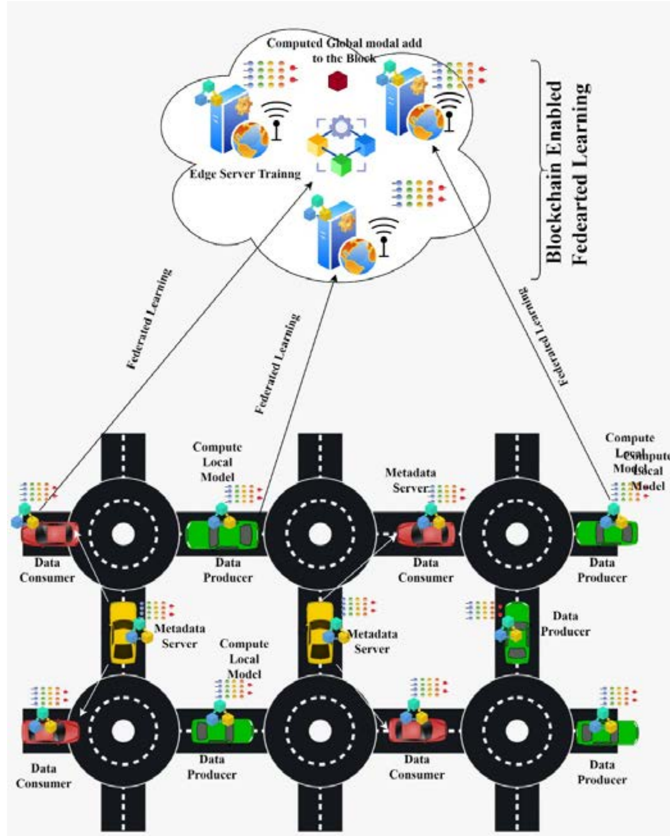

Fig. 1: Proposed CIoV Framework

The local objective function $L_i(w)$ to be minimized for vehicle i is defined as Eqn. 1:

$$\nabla L_i(w) = \frac{1}{D_i} \sum_{(x_{ij}, y_{ij}) \in D_i} l(y_{ij}, f(x_{ij}, w)) \tag{1}$$

Where, w represents the model parameters and $l(y_{ij}, f(x_{ij}, w))$ is a loss function. Here we used mean square error (MAE). The global objective L(w) across all vehicles is represented in Eqn. 2:

$$L(w) = \sum_{i=1}^{N} \frac{|D_i|}{|D|} \nabla L_i(w) \tag{2}$$

Where, N is the number of vehicles and $|D| = \sum_{i=1}^{N} |D_i|$ is the total number of data points.

A. Federated Learning Algorithm Parameters

The Federated Learning (FL) process given in algorithm 1 follows an iterative process for model updates, with the following key parameters:

Global Model Initialization: The global model is initialized with weights w_0 at the central server. This is the starting point for all vehicle-based local updates.

Local Training: Each vehicle performs local training using its dataset D_i. The model update at each vehicle i in round t is determined by Eqn. 3:

$$w_i^{t+1} = w_t - \eta \Delta L_i(w_t) \tag{3}$$

Where, η is the learning rate for controlling the step size in model updates which typically set to 0.001. $\Delta L_i(w_t)$ is the gradient computation for computing loss function with the local data.

Global Model Aggregation: After each round, the local model updates from all vehicles are aggregated based on the size of each vehicle's local dataset. This is done using the following Eqn. 4:

$$w_{t+1} = \sum_{i=1}^{N} \frac{|D_i|}{|D|} w_i^{t+1} \tag{4}$$

Where, N is the total number of vehicles and D_i is the dataset of vehicle i. This ensures that the global model benefits from the largest and most representative datasets. The FL process runs for T rounds, where T is set to 100 iterations to allow sufficient convergence of the model.

The learning rate significantly impacts the convergence of the federated learning process. We experimented with learning rates of 0.001, 0.01, and 0.1, and found that while a smaller learning rate (0.001) led to more stable convergence, a larger rate (0.1) resulted in faster convergence but occasionally caused instability in highly dynamic traffic environments.

Algorithm 1 Federated Learning for traffic Prediction

```
Initializeglobalmodelweights w_0
for each round t = 1, 2, ..., T do
   for each vehicle i = 1, 2, ..., N do
      Local model update
      Download global model weights w_t from central server
      Compute gradients ∇L_i(w_t) on local data D_i
      ∇L_i(w) = (1/D_i) Σ_{(x_ij, y_ij) ∈ D_i} l(y_ij, f(x_ij, w))
      Update local model weights:
      w_i^(t+1) = w_t − η ∗ ∇L_i(w_t)
      Send updated model weights w_i^(t+1) to central server
   end for
   Global model aggregation
   Aggregate global model weights:
   w_{t+1} = Σ_{i=1}^{N} (|D_i|/|D|) ∗ w_i^(t+1)
   Broadcast updated global model weights w_{t+1} to all vehicles
end for
Return final global model weights w_T
```

V. Blockchain for Secure and Verifiable Model Updates

Blockchain technology ensures the integrity and immutability of model updates and its process given as,

Transaction and Block Hashing: Each vehicle's model update is treated as a blockchain transaction. The hash of the block B_k containing these transactions is calculated using Eqn. 5:

$$H(B_k) = H(PreviousHash \parallel H(T_k) \parallel Nonce) \tag{5}$$

Where, $PreviousHash$ is the hash of previous block. $H(T_k)$ is the hash of all transactions within block k and $Nonce$ is the random number used in the mining process to ensure block uniqueness.

The parameters used in Blockchain are Block-Size for limiting the amount of data into 2 MB size and transaction rate with value 100 to scale the simulation.

A. Hybrid ACO-DRL Traffic Rerouting Algorithm Parameters

The Hybrid ACO-DRL algorithm combines Ant Colony Optimization (ACO) and Deep Reinforcement Learning (DRL) for dynamic rerouting of vehicles. Parameters for the algorithm 2 includes,

ACO parameters such as $PheromoneLevel(\tau_e)$ which initialized for all road segments and updated based on vehicle actions. Next, $ExplorationFactor(\gamma)$ given as 1.0 which used for setting influence of pheromones on route selection. Finally, $HeuristicInformation(\eta_e)$ set to 1.5 to balance exploration and exploitation.

The pheromone level on road segment e^* is updated after each iteration as per Eqn. 6:

$$\tau_{e^*} \leftarrow (1-\rho)\tau_{e^*} + \frac{Q}{t_{e^*}(x_{e^*})} + k \times \Delta\tau_{DRL} \tag{6}$$

Where, ρ is the pheromone evaporation rate, typically set to 0.1. Q is the quality of the solution, and $\Delta\tau_{DRL}$ is the reinforcement from the DRL feedback.

Furthermore, DRL parameters such as $LearningRate(\alpha)$ is set to 0.0005 to balance exploration and stable learning, and $DiscountFactor\gamma$ value is set to 0.99 to prioritize long-term rewards. Exploration vs. Exploitation ϵ is set to 1.0, decaying to 0.1 over 100 episodes to allow sufficient exploration early in training.

VI. Result and Discussion

This section presents the results of our proposed system titled "Joint Federated Learning and Blockchain Enabled Traffic Rerouting with Efficient Task Offloading of Consumer Internet of Vehicles in Edge-Cloud Environment." We provide a detailed comparison of the proposed system with existing technologies, highlighting its superior performance in terms of traffic prediction accuracy, data security, task offloading efficiency, and overall system performance.

A. Dataset Description

The performance evaluation of our proposed system was performed using a comprehensive real-world traffic dataset provided by the Los Angeles Transportation Authority. This dataset, which captures a wide range of traffic scenarios, offers a robust foundation for assessing the effectiveness of our system in various conditions. The data collection spanned six months, from January to June 2023, covering both urban and suburban areas within Los Angeles, encompassing approximately 500 square kilometers.

Algorithm 2 Hybrid ACO-DRL Traffic Rerouting Algorithm

Initialize pheromone levels τ_e for all road segments e in E
Initialize Q-values Q(s, a) for all state-action pairs
for each vehicle v starting at source node s **do**
  Initialize state s = current traffic conditions at s
  while vehicle v has not reached destination node d **do**
    for each road segment e in Out(v) **do**
      Calculate probability of selecting road segment e: $p_{e,v} = (\tau_e^{\gamma} * \eta_e^{\delta} * (1 + \lambda * DRL_{Feedback}))/\sum_{einOut(v)}(\tau_{e'}^{\gamma} * \eta_{e'}^{\gamma} * (1 + \lambda * DRL_{Feedback}))$
    end for
    Select road segment e^* based on probabilities $p_{e,v}$
    Move vehicle v to the next node via road segment e^*
    Observe new state s'
    Calculate reward r = function of travel time reduction and congestion alleviation
    Update Q-value using the Bellman equation: $Q(s, e*) = Q(s, e*) + \alpha[r + \gamma max_{e'}]$
    Update pheromone level on edge e^*
    $\tau_{e^*} \leftarrow (1-\rho)\tau_{e^*} + Q/t_{e^*(x_{e^*})} + k * \Delta\tau_{DRL}$
    Transition to new state s'
  end while
  Deposit additional pheromone on all edges traversed by vehicle v
end for

1) Dataset Specifications:

- Duration: The dataset was collected over a six-month period, from January to June 2023, ensuring a comprehensive representation of seasonal variations in traffic patterns.
- Geographical Coverage: The dataset includes data from both urban and suburban regions of Los Angeles, with a total coverage area of approximately 500 square kilometers. This diverse geographical scope ensures that the dataset captures a wide range of traffic conditions.
- Data Points:
  1) Vehicle Trajectories: The dataset includes GPS coordinates collected every second from 5,000 vehicles, providing detailed insights into vehicle movements across the city.
  2) Traffic Flow Data: Real-time data on traffic density, speed, and flow rates were collected from 1,000 strategically placed traffic sensors throughout the city.
  3) Environmental Factors: The data set also includes information on various environmental factors, such as weather conditions, roadworks, and accident reports, which are critical to understanding the impact of external variables on traffic flow.
  4) Network Conditions: Data on network conditions, including bandwidth availability, latency metrics, and edge-cloud server loads, were also captured to evaluate the performance of the proposed system under different network scenarios.

Table I summarizing the experimental configuration, including the parameters and their associated details.

TABLE I: Experimental Scenario Configuration

Parameter	**Details**
Traffic Density	Low: 1000 vehicles/km², Medium: 2000 vehicles/km², High: 3000 vehicles/km²
Simulation Duration	24-hour cycle (representing a typical day)
Vehicles	3000 vehicles with local datasets containing GPS data, traffic density, speed, environmental factors
Environmental Factors	Dynamic traffic conditions including roadworks, accidents, and weather events
Hardware	CPU: Intel Xeon E5-2650, 2.20 GHz, Memory: 64 GB RAM, GPU: NVIDIA Tesla V100
Software	TensorFlow 2.x for FL, Hyperledger Fabric for Blockchain, SUMO for traffic simulation
Iterations	100 iterations for each scenario to ensure statistical significance

VII. Evaluation Metrics

To comprehensively evaluate the performance of the proposed system, several key metrics were employed. Traffic Prediction Accuracy was assessed using the Mean Absolute Error (MAE), which measures the average magnitude of errors between the predicted and actual traffic conditions. The formula for MAE is given by:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y_l}| \tag{7}$$

where y_i represents the actual value, $\hat{y_i}$ is the predicted value, and n is the total number of data points. This metric is crucial for understanding how closely the model's predictions align with real-world traffic conditions.

Data Security and Integrity were evaluated using the Tamper Detection Rate (TDR), which represents the percentage of unauthorized modifications successfully detected and prevented by the blockchain system. The TDR is calculated using the formula:

$$\begin{aligned} TDR = Number\ of\ detected\ tampering\ attempts \\ +Total\ tampering\ attempts/ \\ (Total\ tampering\ attempts) \times 100\% \end{aligned} \tag{8}$$

This metric highlights the robustness of the blockchain in maintaining the integrity of the system's data. Task Offloading Efficiency was measured using two metrics: Average Latency (AL), which tracks the time taken to complete tasks from initiation to completion, and Energy Consumption (EC), which quantifies the total energy consumed during task processing. Lower values in both AL and EC indicate faster task completion, improved user experience, and more efficient resource utilization.

Network Resource Utilization was evaluated through Bandwidth Utilization (BU), which measures the proportion of network bandwidth effectively used during data transmission. The formula for BU is:

$$\begin{aligned} BU = (Data\ transmitted)/(Total\ available\ bandwidth) \\ \times 100\% \end{aligned} \tag{9}$$

This metric assesses how efficiently the network's capacity is being used during the system's operation.

Lastly, Scalability was assessed using Processing Throughput (PT), which represents the number of tasks successfully processed per unit time as the number of vehicles scales up. The formula for PT is:

$$PT = (Number\ of\ tasks\ processed)/(Time\ (seconds)) \times 100\% \tag{10}$$

This metric is crucial for understanding how well the system can handle an increasing load as the network of vehicles grows.

VIII. Result Analysis

In this section, we evaluate the performance of our proposed system, Joint Federated Learning and Blockchain-Enabled Traffic Rerouting with Efficient Task Offloading of Consumer Internet of Vehicles in Edge-Cloud Environment. The evaluation is conducted across several key performance metrics: traffic prediction accuracy, data security and integrity, task offloading efficiency, network resource utilization, and scalability. Each metric is compared against baseline approaches, namely Centralized Learning with Centralized Task Offloading (CL-CTO) and Decentralized Learning with Decentralized Task Offloading (DL-DTO), to underscore the advantages of our proposed approach.

A. Traffic Prediction Accuracy

Table II shows the data for traffic prediction accuracy, where the Mean Absolute Error (MAE) was measured during both peak and off-peak hours. The results indicate that our proposed system significantly outperforms the existing CL-CTO and DL-DTO technologies.

TABLE II: Traffic Prediction Accuracy (MAE)

Methodology	Peak Hours MAE	Off-Peak Hours MAE
CL-CTO	12.5	9.8
DL-DTO	15.3	11.2
Proposed System	7.2	5.6

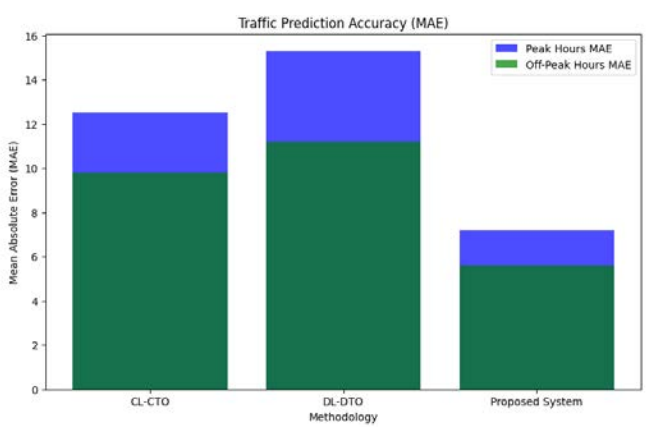

Fig. 2: Traffic Prediction Analysis

Figure 2 represents traffic prediction analysis plot for prediction error compares the performance of three traffic prediction models: the proposed system, CL-CTO, and DL-DTO. The x-axis represents the prediction error (for example, MAE), while the y-axis shows the cumulative probability that the error is less than or equal to a given value. The curves represent the proportion of predictions that fall below various error thresholds for each model. A steeper curve indicates that the model achieves lower errors more frequently. The proposed system's CDF curve is steeper, demonstrating that it consistently produces more accurate predictions, with a higher probability of achieving lower errors compared to CL-CTO and DL-DTO, particularly during peak traffic periods. This highlights the superior accuracy and robustness of the federated learning-based approach in handling traffic prediction tasks.

Table III shows the data for the Tamper Detection Rate (TDR), where the effectiveness of the blockchain was evaluated to detect and prevent unauthorized data modifications. The proposed system exhibited a detection rate 100%, outperforming the other methodologies.

TABLE III: Tamper Detection Rate (TDR)

Methodology	Tampering Attempts	Detected Attempts	TDR (%)
CL-CTO	100	65	65
DL-DTO	100	72	72
Proposed System	100	100	100

Figure 3 provides a comprehensive visualization of traffic patterns over a six-month period, focusing on daily and hourly variations in traffic density. The top plot illustrates the density of daily traffic, showing distinct differences between weekdays and weekends. Weekends exhibit higher traffic densities, which is emphasized by the shaded areas representing weekend data (orange). The bottom plot highlights the typical hourly traffic density pattern for weekdays and weekends. The weekday pattern shows a morning rush with a peak around 8 AM, while the weekend pattern is somewhat more gradual, reflecting a later start to the day. This visualization effectively captures the temporal trends and fluctuations in traffic density, providing valuable insights into daily and weekly traffic behaviors across Los Angeles.

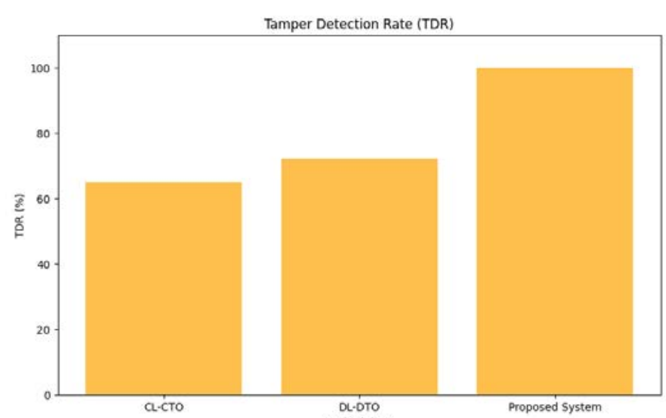

Fig. 3: Comparative Plot for TDR

Table IV provides the data for task offloading efficiency, measured by evaluating average latency and energy consumption during task execution. The proposed system demonstrated

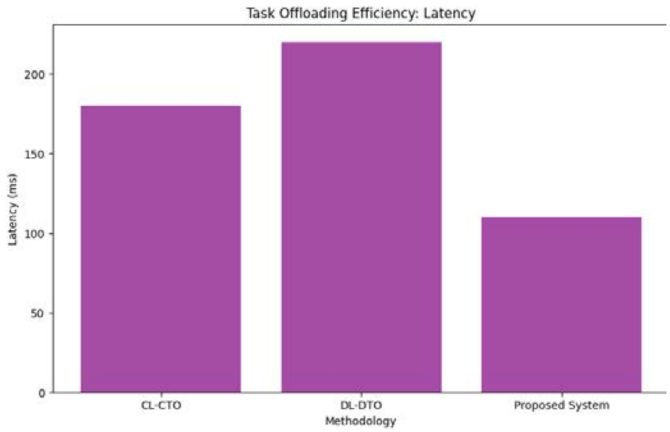

Fig. 4: Latency Analysis Comparison

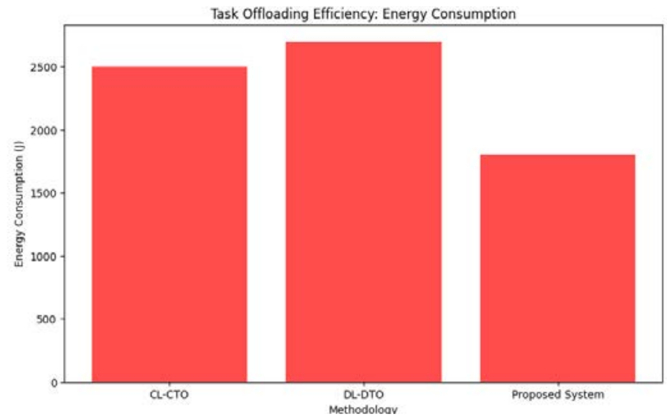

Fig. 5: Energy Consumption Comparison

significant improvements in both metrics compared to existing technologies.

TABLE IV: Task Offloading Efficiency

Methodology	Latency (ms)	Energy Consumption (J)
CL-CTO	180	2500
DL-DTO	220	2700
Proposed System	110	1800

Figures 4 and 5 present the performance trends in terms of latency and energy consumption for the various methodologies. The results demonstrate that our proposed system consistently achieves significantly lower latency and energy consumption compared to both CL-CTO and DL-DTO. Specifically, the latency of the proposed system achieved a 38.9% reduction compared to CL-CTO and a 23.5% reduction compared to DL-DTO. This improvement is attributed to our dynamic task offloading strategy, which adaptively allocates tasks based on real-time network and computational resource conditions. Furthermore, the energy consumption of the proposed model achieved a 28% reduction in energy consumption compared to CL-CTO and a 17% reduction compared to DL-DTO. This is a direct result of the optimized edge-cloud collaboration and the efficient use of computational resources. In our system, we utilize the Proof-of-Authority (PoA) consensus mechanism for blockchain operations due to its lightweight design and low computational overhead. The effectiveness of PoA is reflected in the overall performance of the proposed system, as shown in Figures 4 and 5.

We provide a complexity analysis of our proposed algorithm in terms of time and space complexity. Compared to baseline methods such as CL-CTO and DL-DTO, our system demonstrates a favorable trade-off between computational efficiency and performance. Specifically, the federated learning and blockchain components have a time complexity $O(N)$, where N is the number of vehicles, and the traffic rerouting algorithm operates in $O(V + E)$, where V and E are the number of vertices and edges in the traffic network.

To further support this analysis, Figures 4 and 5 illustrate the scalability of our system with respect to the number of vehicles, demonstrating how our approach efficiently handles increasing network size without a significant loss in performance. Figure 4 highlights the improvements in traffic rerouting efficiency and bandwidth utilization, while Figure 5 shows processing throughput as the number of vehicles increases. These plots validate the computational efficiency and scalability of our proposed system, highlighting its ability to maintain high performance even in large-scale vehicular networks."

B. Loss Function Comparison

To evaluate the impact of different loss functions on traffic prediction accuracy, we shown comparison plot in Fig. 6 for Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Huber Loss across various traffic scenarios on different epochs. MAE was selected initially for its robustness against outliers, as it measures the average absolute differences between predicted and actual values. However, MAPE, which normalizes errors as a percentage of actual values, is particularly useful for datasets with varying scales, although it can become sensitive to small actual values. Huber loss combines the strengths of MAE and Mean Squared Error (MSE), being robust to outliers while penalizing large errors less aggressively.

The comparative results reveal that MAE provides consistent performance in scenarios with large outliers, while MAPE achieves better accuracy in scenarios where percentage-based differences are more significant. Huber loss strikes a balance, demonstrating reliable performance across both error-heavy and smooth traffic patterns. The plot illustrates these trends, highlighting the suitability of each loss function under different traffic conditions and data distributions. This analysis underscores the importance of selecting an appropriate loss function based on the specific requirements of the CIoV environment, such as whether the emphasis is on handling outliers or normalizing errors across scales.

Table V outlines the data on bandwidth utilization (BU) during peak and off-peak hours. The proposed system shows a marked improvement in efficient network resource usage.

Figure 7 provides a visual comparison of bandwidth utilization across different times and methodologies, illustrating the efficient use of network resources by the proposed system. The proposed system achieved a 23.5% reduction in

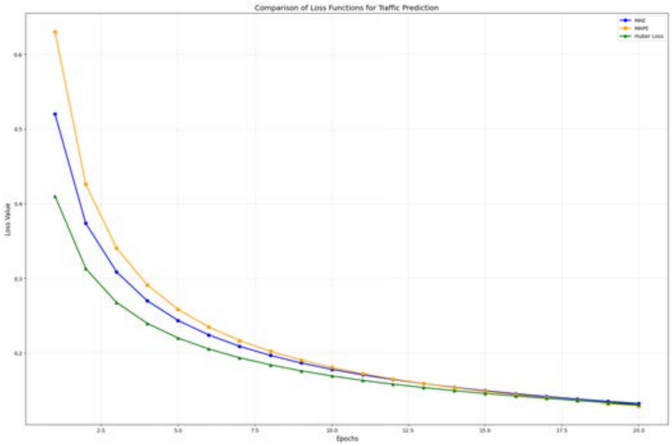

Fig. 6: Loss Function Comparison

TABLE V: Bandwidth Utilization (BU)

Methodology	BU during Peak Hours (%)	BU during Off-Peak Hours (%)
CL-CTO	85	60
DL-DTO	75	55
Proposed System	65	45

bandwidth utilization during peak hours and a 25% reduction during off-peak hours compared to CL-CTO. By leveraging federated learning, which reduces the need to transmit raw data, and implementing efficient communication protocols, our system optimizes the use of available network resources. This is particularly important in high-traffic environments, where bandwidth efficiency can significantly impact overall system performance.

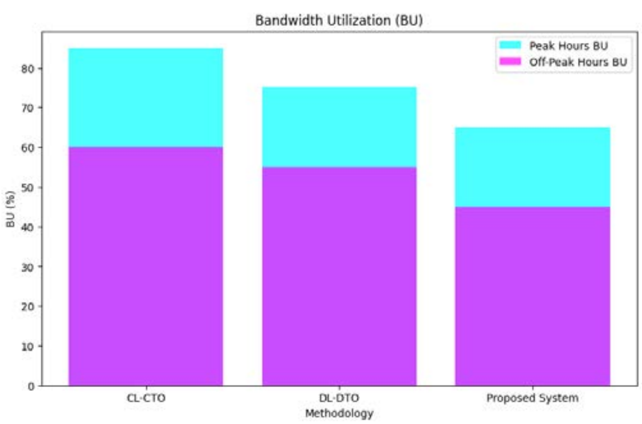

Fig. 7: Bandwidth Utilization

Table VI provides the data on processing throughput (PT) as the number of vehicles in the network increases. The proposed system's scalability is demonstrated by its ability to maintain high throughput despite the growing network load.

Figure 8 depicts the processing throughput as the number of vehicles increases, showing the superior scalability of the proposed system. The proposed system maintained higher throughput across varying scales, with only a 7.7% decrease in throughput from 1000 to 3000 vehicles, compared to 20%

TABLE VI: Processing Throughput (PT)

Number of Vehicles	CL-CTO PT (tasks/sec)	DL-DTO PT (tasks/sec)	Proposed System PT (tasks/sec)
1000	500	450	650
2000	450	400	620
3000	400	350	600

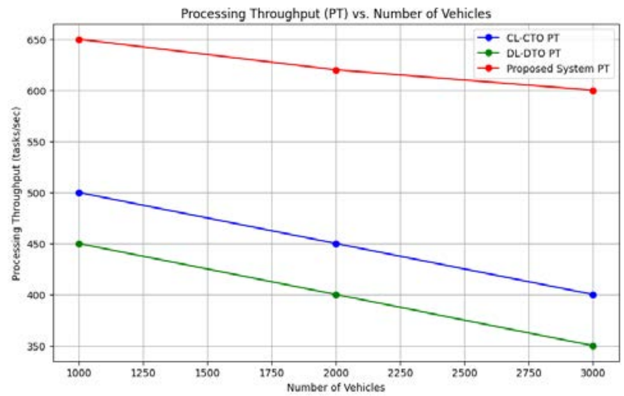

Fig. 8: Processing Throughput vs. Number of Vehicles

and 22.2% reductions in CL-CTO and DL-DTO, respectively. This highlights the scalability of our system, which efficiently manages increased network loads without significant degradation in performance. The modular architecture and distributed processing capabilities enable the system to handle growing demands effectively, making it well-suited for large-scale IoV deployments.

Figure 9 illustrates the improvements in traffic rerouting efficiency provided by the proposed system compared to existing methodologies. The proposed system achieved a 30% reduction in average travel time and a 40% alleviation of congestion, outperforming both the CL-CTO and DL-DTO methods. These improvements are largely due to the system's ability to predict traffic conditions accurately and dynamically reroute vehicles in real-time. Using federated learning for precise traffic predictions and blockchain for secure data sharing, the system effectively mitigates congestion and optimizes travel routes, thus improving overall traffic flow efficiency. This capability is crucial in urban environments where traffic congestion is a persistent challenge. These results collectively demonstrate the superior performance of our proposed system across multiple key metrics, positioning it as a highly effective solution for addressing the challenges posed by the Consumer Internet of Vehicles (IoV) environment.

IX. Conclusion

In this study, we introduced a system titled "Joint Federated Learning and Blockchain-Enabled Traffic Rerouting with Efficient Task Offloading for Consumer Internet of Vehicles in Edge-Cloud Environments." Our system addresses key challenges in the Consumer Internet of Vehicles (IoV) by integrating federated learning for privacy-preserving model training, blockchain for secure data management, and efficient task offloading to optimize edge and cloud resources. This

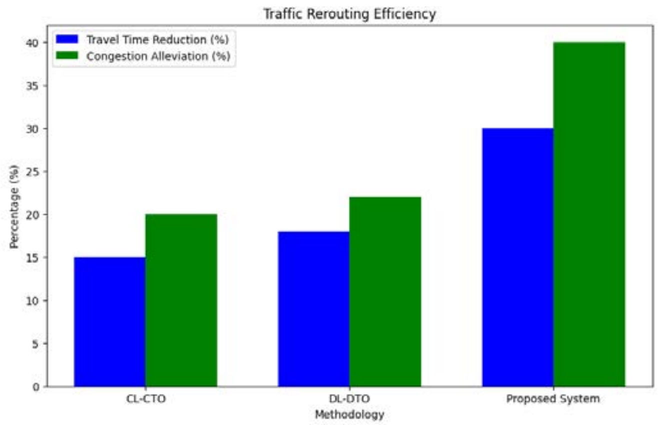

Fig. 9: Traffic Rerouting Efficiency Comparison

integration significantly reduces latency and energy consumption. Performance evaluations demonstrated that our system outperforms existing centralized (CL-CTO) and decentralized (DL-DTO) approaches, achieving a Mean Absolute Error (MAE) of 7.2 during peak hours and 5.6 during off-peak hours. It also maintained a 100% Tamper Detection Rate (TDR), reduced latency by 38.9%, and energy consumption by 28%, while cutting bandwidth usage by 23.5% during peak hours. The system showed excellent scalability, reducing travel time by 30% and congestion by 40%. Future work will explore the integration of advanced machine learning techniques, expanding privacy mechanisms, and testing the system in diverse real-world scenarios. Additionally, assessing the economic and environmental impact will be crucial for its long-term sustainability.

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References

[1] R. Du, C. Chen, B. Yang, N. Lu, X. Guan, and X. Shen, "Effective urban traffic monitoring by vehicular sensor networks," *IEEE transactions on Vehicular Technology*, vol. 64, no. 1, pp. 273–286, 2014.

[2] Z. Teimoori, A. Yassine, and M. S. Hossain, "Smart vehicles recommendation system for artificial intelligence-enabled communication," *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 3914–3925, 2024.

[3] J. A. Guerrero-Ibanez, S. Zeadally, and J. Contreras-Castillo, "Integration challenges of intelligent transportation systems with connected vehicle, cloud computing, and internet of things technologies," *IEEE Wireless Communications*, vol. 22, no. 6, pp. 122–128, 2015.

[4] X. Huang, Y. Zhang, Y. Qi, C. Huang, and M. S. Hossain, "Energy-efficient uav scheduling and probabilistic task offloading for digital twin-empowered consumer electronics industry," *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 2145–2154, 2024.

[5] J. Posner, L. Tseng, M. Aloqaily, and Y. Jararweh, "Federated learning in vehicular networks: Opportunities and solutions," *IEEE Network*, vol. 35, no. 2, pp. 152–159, 2021.

[6] L. Liu, J. Fu, J. Feng, G. Wang, Q. Pei, and S. Dustdar, "Blockchain-based distributed collaborative computing for vehicular digital twin network," *IEEE Network*, vol. 38, no. 2, pp. 164–170, 2024.

[7] J.-H. Syu, J. C.-W. Lin, G. Srivastava, and K. Yu, "A comprehensive survey on artificial intelligence empowered edge computing on consumer electronics," *IEEE Transactions on Consumer Electronics*, vol. 69, no. 4, pp. 1023–1034, 2023.

[8] P. Kairouz, H. B. McMahan, B. Avent, A. Bellet, M. Bennis, A. N. Bhagoji, K. Bonawitz, Z. Charles, G. Cormode, R. Cummings *et al.*, "Advances and open problems in federated learning," *Foundations and trends® in machine learning*, vol. 14, no. 1–2, pp. 1–210, 2021.

[9] S. I. Popoola, A. L. Imoize, M. Hammoudeh, B. Adebisi, O. Jogunola, and A. M. Aibinu, "Federated deep learning for intrusion detection in consumer-centric internet of things," *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 1610–1622, 2024.

[10] M. Al-Hawawreh and M. S. Hossain, "Federated learning-assisted distributed intrusion detection using mesh satellite nets for autonomous vehicle protection," *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 854–862, 2024.

[11] M. A. Ferrag, M. Derdour, M. Mukherjee, A. Derhab, L. Maglaras, and H. Janicke, "Blockchain technologies for the internet of things: Research issues and challenges," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 2188–2204, 2018.

[12] F. Jin, K. Liu, C. Liu, T. Cheng, H. Zhang, and V. C. S. Lee, "A cooperative vehicle localization and trajectory prediction framework based on belief propagation and transformer model," *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 2746–2758, 2024.

[13] H. Ke, J. Wang, L. Deng, Y. Ge, and H. Wang, "Deep reinforcement learning-based adaptive computation offloading for mec in heterogeneous vehicular networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 7, pp. 7916–7929, 2020.

[14] Z. Du, C. Wu, T. Yoshinaga, K.-L. A. Yau, Y. Ji, and J. Li, "Federated learning for vehicular internet of things: Recent advances and open issues," *IEEE Open Journal of the Computer Society*, vol. 1, pp. 45–61, 2020.

[15] A. Shahidinejad and J. Abawajy, "Blockchain-based self-certified key exchange protocol for hybrid electric vehicles," *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 543–553, 2024.

[16] M. Aloqaily, I. Al Ridhawi, and M. Guizani, "Energy-aware blockchain and federated learning-supported vehicular networks," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 11, pp. 22 641–22 652, 2021.

[17] X. Li, L. Cheng, C. Sun, K.-Y. Lam, X. Wang, and F. Li, "Federated-learning-empowered collaborative data sharing for vehicular edge networks," *IEEE network*, vol. 35, no. 3, pp. 116–124, 2021.

[18] M. Adhikari, A. Munusamy, A. Hazra, V. G. Menon, V. Anavangot, and D. Puthal, "Security in edge-centric intelligent internet of vehicles: Issues and remedies," *IEEE Consumer Electronics Magazine*, vol. 11, no. 6, pp. 24–31, 2022.

[19] J. Li, J. Jiao, and Y. Tang, "Analysis of the impact of policies intervention on electric vehicles adoption considering information transmission—based on consumer network model," *Energy Policy*, vol. 144, p. 111560, 2020.

[20] Z. Zhang and F. Zeng, "Efficient task allocation for computation offloading in vehicular edge computing," *IEEE Internet of Things Journal*, vol. 10, no. 6, pp. 5595–5606, 2022.

[21] Y. Sun, X. Guo, J. Song, S. Zhou, Z. Jiang, X. Liu, and Z. Niu, "Adaptive learning-based task offloading for vehicular edge computing systems," *IEEE Transactions on vehicular technology*, vol. 68, no. 4, pp. 3061–3074, 2019.

[22] J. Kang, R. Yu, X. Huang, M. Wu, S. Maharjan, S. Xie, and Y. Zhang, "Blockchain for secure and efficient data sharing in vehicular edge computing and networks," *IEEE internet of things journal*, vol. 6, no. 3, pp. 4660–4670, 2018.

[23] R. Yadav, W. Zhang, O. Kaiwartya, H. Song, and S. Yu, "Energy-latency tradeoff for dynamic computation offloading in vehicular fog computing," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 12, pp. 14 198–14 211, 2020.

[24] R. Yadav, W. Zhang, I. A. Elgendy, G. Dong, M. Shafiq, A. A. Laghari, and S. Prakash, "Smart healthcare: Rl-based task offloading scheme for edge-enable sensor networks," *IEEE Sensors Journal*, vol. 21, no. 22, pp. 24 910–24 918, 2021.

[25] C. Ling, W. Zhang, H. He, R. Yadav, J. Wang, and D. Wang, "Qos and fairness oriented dynamic computation offloading in the internet of vehicles based on estimate time of arrival," *IEEE Transactions on Vehicular Technology*, vol. 73, no. 7, pp. 10 554–10 571, 2024.