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A Blockchain-Integrated Multi-Access Edge Computing Framework for Securing and Optimising Internet of Vehicles in Intelligent Transport Systems

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ABSTRACT
The convergence of blockchain technology, multi-access edge computing (MEC) and artificial intelligence (AI) has opened new frontiers for advancing the Internet of Vehicles (IoV) within intelligent transport systems. The work introduces EdgeChain-AI, a novel framework that synergises these three technologies to improve the security, efficiency and scalability of IoV applications. By employing blockchain's decentralised ledger for secure communication, MEC's edge computing capabilities for instantaneous processing, and AI's cognitive intelligence for predictive decision-making. The work addresses critical challenges such as latency, privacy and data integrity. Our framework outperforms current approaches by reducing latency by 25%, improving energy efficiency by 15% and maintaining 99.9% data integrity. Extensive evaluation and comparative analysis with existing methods like federated learning and edge intelligence solutions further demonstrate the superior performance of the proposed work. This study provides a forward-looking approach for the seamless integration of IoV into the broader IoT ecosystem, enhancing the advancement of intelligent transport systems.

KEYWORDS
blockchain; artificial intelligence; security; Internet of Vehicles.

1. INTRODUCTION

The Internet of Vehicles (IoV) has emerged as a pivotal application area, integrating vehicles, infrastructure and other devices into a highly interconnected ecosystem aimed at improving safety, efficiency and user experiences on the road. Several studies have explored the security, privacy and efficiency aspects of IoV. Studies [1-3] discuss security frameworks that integrate hesitant fuzzy sets, privacy-preserving mechanisms and big data applications to address cybersecurity concerns in interconnected environments. Research in [4-5] proposes secure data exchange frameworks and efficient edge computing models tailored for IoV, highlighting the need for decentralised approaches to ensure data integrity and low-latency decision-making. Additionally, studies [6-7] focus on blockchain-based solutions and real-time decision-making strategies, which are crucial for ensuring secure and reliable vehicular communication. Addressing these challenges requires innovative approaches that combine multiple cutting-edge technologies to create a robust, scalable and secure IoV framework. Studies [8-9] explore traffic prediction models and decentralised traffic management solutions using edge computing and blockchain technology, demonstrating how such techniques enhance system efficiency. Research in [10] introduces machine learning-based anomaly detection mechanisms for vehicular networks, providing crucial insights into detecting malicious behaviour and preventing cyber threats. Work in [11] proposes load-balancing techniques to optimise network performance in intelligent transportation systems, while [12] investigates high-level approaches for threat detection using both classical and deep learning techniques. Furthermore, [13] extends these discussions by integrating deep learning and social network analysis to enhance security in smart city policing, which directly aligns with IoV's need for real-time security enforcement.

By reducing reliance on centralised cloud infrastructure, mobile edge computing (MEC) lowers latency and ensures faster responses in critical IoV scenarios, such as collision avoidance and traffic flow optimisation. Study [14] discusses the importance of reliable backhaul connectivity in offshore IoT networks, which can be extended to IoV applications to enhance long-range vehicle communication. Research in [15] proposes a secure and highly efficient distributed blockchain PBFT consensus algorithm for intelligent IoV, reinforcing trust and immutability in data exchange. Work in [16] explores smart contract-based authentication mechanisms that can be adapted to IoV authentication frameworks. Additionally, [17] investigates the role of UAV-based network management in 6G environments, offering potential solutions for securing vehicular communication and ensuring continuous network coverage. Finally, [18] analyses the convergence of blockchain, AI and ML in big data analytics, underscoring the importance of integrating these technologies for a more intelligent and secure IoV ecosystem. Blockchain offers a tamper-resistant platform where transactions and data exchanges can be verified and stored securely across a distributed network of nodes, without the essential for a centralised scheme [19]. Additionally, blockchain enables transparent, auditable data exchanges, further boosting trust among stakeholders in the IoV ecosystem. When combined with MEC, blockchain's decentralised nature complements the proximity-based computing of MEC, ensuring both security and real-time processing [20].

Despite the advantages of MEC and blockchain, the sheer volume and complexity of IoV data require advanced intelligence to extract meaningful insights and optimise decision-making. This is where AI plays a crucial role. AI technologies, particularly machine learning and deep learning, can process big IoV data to predict traffic patterns, optimise vehicle routes, enhance fuel efficiency and even anticipate maintenance needs. By incorporating AI into the EdgeChain-AI framework, we enable vehicles and edge nodes to acquire from past data and make informed decisions autonomously. For instance, AI can forecast traffic congestion based on real-time data and historical patterns, allowing vehicles to reroute dynamically to avoid delays. Furthermore, AI-driven predictive maintenance can monitor vehicle health in real time, reducing the risk of unexpected breakdowns and refining overall road safety.

One of the key innovations of the proposed framework is its ability to integrate AI, blockchain and MEC into a seamless, cohesive system that addresses the critical challenges of IoV. While each of these technologies has been explored individually in IoV research, their combination creates a synergistic effect that enhances the overall performance of IoV applications. MEC ensures low-latency processing, blockchain secures data exchanges, and AI optimises decision-making and resource allocation. Together, these technologies create a robust framework that is well-suited for the demands of intelligent transport systems.

A major challenge in IoV environments is latency. For example, in autonomous driving, vehicles process sensor data and make decisions in milliseconds to avoid accidents and ensure passenger safety. Traditional cloud-based approaches often introduce unacceptable delays due to the distance between data sources and processing centres. MEC pointedly diminishes this latency, enabling real-time data processing at the edge of the network. By processing data locally, MEC ensures that time-sensitive applications, like collision recognition and lane-keeping assistance, can operate with minimal delay.

In addition to latency, data privacy and security are major concerns in IoV environments. Vehicles collect and share a wide range of sensitive information, including location data, driving behaviour and personal preferences. The data, if violated, can be exploited for malicious intent, such as tracking individuals or manipulating vehicle behaviour. Blockchain technology provides a secure and decentralised platform to overcome these issues. In the proposed framework, blockchain ensures that all data exchanges between vehicles, infrastructure and central authorities are secure and tamper-proof.

Energy efficiency is another critical issue in IoV environments, particularly for electric vehicles and battery-powered sensors. IoV systems must strike a balance between performance and power consumption to ensure that vehicles and devices can run for extended periods without recurrent recharging. AI plays a crucial role in enhancing energy efficiency by analysing real-time data and making smart decisions about resource allocation. For instance, AI algorithms can optimise vehicle routing to minimise fuel consumption or adjust the power usage of edge nodes based on current demand. In this paper, AI-driven energy optimisation leads to a 15% increase in energy efficiency compared to existing IoV solutions.

Data integrity is essential for the reliable operation of IoV systems, as inaccurate or tampered data could lead to disastrous consequences, such as traffic accidents or incorrect navigation. Blockchain technology ensures data integrity by verifying all transactions and storing them in a tamper-proof ledger. The blockchain's immutable ledger in this study guarantees that all data exchanged between vehicles, infrastructure and central authorities remains accurate and trustworthy. This is particularly important in scenarios where vehicles rely on real-time data from other vehicles or roadside units to make critical decisions.

Through comprehensive evaluation and comparative analysis, the study demonstrates superior performance in terms of latency, security, energy efficiency and data integrity. Our experiments show a 25% reduction in latency, a 15% improvement in energy efficiency and 99.9% data integrity, outperforming existing IoV frameworks that rely on edge intelligence, federated learning or blockchain-based communication alone. The integration of AI, blockchain and MEC in the EdgeChain-AI framework provides a holistic solution to the key challenges facing IoV, paving the way for the advancement of intelligent transport systems.

2. RELATED WORKS

The integration of advanced communication frameworks, decentralised data collection and machine learning techniques has been crucial in improving the performance of such systems. A decentralised framework for data collection, as discussed by [9], shows the advantages of using a distributed architecture for gathering transportation data, ensuring privacy and security while reducing reliance on centralised entities. In contrast, the authors of [10] focused on a machine learning-based communication system, highlighting the security and trust issues in vehicle-to-vehicle (V2V) communications, particularly addressing the challenges posed by untrustworthy actors in intelligent transportation environments. The challenges in V2V communications include untrusted nodes, message integrity risks, privacy concerns, high latency, scalability issues and trust management complexities, requiring robust security frameworks.

Additionally, the integration of blockchain technology into the Internet of Vehicles (IoV), as discussed in the study by [11], illustrates the growing importance of secure communication frameworks. The study emphasises blockchain's ability to ensure that data exchanges between vehicles are tamper-proof, providing a secure, trustworthy infrastructure for IoV operations. This aligns with earlier research by [12] and [13], who emphasised smart contracts and MEC to enhance the efficiency of vehicular communications using deep learning. Such approaches allow intelligent transportation systems (ITS) to process large volumes of data at the network's edge, reducing latency and improving real-time decision-making. However, the deployment of such technologies introduces significant challenges, particularly around scalability, energy consumption and real-time processing capabilities, which necessitate further exploration and optimisation.

Task offloading methods, as discussed by [14], address the growing computational demands of 5G-enabled vehicular networks by suggesting multi-period vehicular task offloading in heterogeneous networks. Their work presents a framework that adapts to the fluctuating nature of vehicular traffic, but it still leaves open questions about how such systems can ensure consistent performance amidst network congestion or in areas with less reliable infrastructure. Furthermore, the study by [15] explored the prediction of node mobility, a fundamental aspect of ITS that impacts both task offloading and communication reliability. Their research highlights the importance of accurately predicting the movements of vehicles in a three-dimensional space to optimise resource allocation and communication routes, although real-world implementation remains complex and requires further refinement.

Beyond communication and data processing, machine learning techniques have played an increasingly prominent role in ITS, especially in predicting traffic flow and managing congestion. Authors of [17] discussed the need for an edge traffic flow detection system leveraging deep learning techniques to analyse and predict traffic patterns, enhancing traffic management's efficiency. This complements the work of [18], who proposed an intelligent traffic signal management strategy aimed at reducing CO_2 emissions in fog-oriented vehicular ad hoc networks (VANETs). The combination of fog computing and machine learning allows traffic systems to make localised decisions based on real-time data, further contributing to energy conservation and emission reduction. Energy efficiency and environmental sustainability are critical concerns in modern transportation systems. They also conducted a comprehensive review of the impacts of ITS on energy conservation and emission reduction, highlighting how intelligent traffic management systems can optimise vehicle flow, reducing fuel consumption and emissions. This aligns with the work of [19], who explored the challenges of implementing ITS in IoV, where transport inequalities complicate the adoption of these systems. Their study points to the necessity for context-specific solutions that address the exclusive challenges met by developing nations, as well as infrastructure deficits and socioeconomic factors.

Similarly, authors of [20] presented a practical case study on traffic management in Montreal, illustrating how smart city technologies can be applied to urban mobility. Their research underscores the potential for ITS to enhance traffic management in densely populated urban areas, although they also identify several challenges related to scalability, data privacy and interoperability between different systems. These challenges are particularly relevant when considering the rapid urbanisation and increasing vehicular traffic in cities worldwide, which necessitates more robust and scalable ITS solutions. The study by [21] explores spectrum sensing, clustering algorithms and energy-harvesting techniques in cognitive-radio-based IoT networks, highlighting their role in optimising spectrum utilisation and improving network efficiency. Authors of [22] discuss the energy-efficient strategies for the industrial Internet of Things (IIoT) within green 6G networks, emphasising sustainable network design and optimised resource allocation. The study by [23] explores the technological advancements and future prospects in smart city energy systems, focusing on sustainable energy solutions and innovative technologies for efficient urban energy management.

2.1 Research gaps

Despite these advancements, several key research gaps remain. The existing works on ITS have largely focused on the technical aspects of communication, data collection and processing, but there has been limited exploration of how these technologies can be optimised for energy efficiency and long-term sustainability. While blockchain and decentralised frameworks offer promising solutions for enhancing security and trust in vehicular communications, the high energy consumption associated with blockchain operations remains a significant barrier to widespread adoption. Similarly, while machine learning-based traffic management systems show great promise, there is a need for more research into how these systems can be made more scalable and adaptable to real-world conditions, particularly in regions with less reliable infrastructure.

Another important gap lies in the integration of ITS with emerging technologies such as 5G and edge computing. While several studies have explored the potential of 5G networks to support ITS, there is still a need for more detailed investigations into how these technologies can be integrated in a way that ensures consistent performance across different geographic regions and traffic conditions. Furthermore, while task offloading and MEC have been proposed as solutions to the computational challenges of ITS, there is still a lack of research into how these systems can be optimised for low-power devices, which are commonly used in IoV environments.

Problem identification in the field of ITS is therefore twofold. First, while significant progress has been made in enhancing the security, efficiency and sustainability of transportation systems, there remains a need for more holistic solutions that integrate communication frameworks, machine learning and decentralised systems in a way that optimises both performance and energy efficiency. Second, the scalability of ITS technologies remains a key challenge, particularly in urban environments where traffic patterns are highly dynamic and infrastructure can be inconsistent. Addressing these issues will require not only technical innovation but also a greater focus on the policy and regulatory frameworks that govern the deployment of ITS technologies, particularly in regions with varying levels of infrastructure development.

3. PROPOSED WORK

This section presents a novel framework called SecureEdge-ITS, integrating blockchain, machine learning and mobile edge computing (MEC) for intelligent transportation systems (ITS). The framework improves security, data integrity, real-time decision-making and resource allocation across vehicular networks. The proposed framework is a cutting-edge solution designed to enhance the efficiency, security and decision-making capabilities of ITS by integrating blockchain technology, machine learning and MEC. The framework consists of four distinct layers, each responsible for specific functions to ensure effective data management and real-time responsiveness in vehicular networks.

The proposed framework is composed of four layers:

Data collection and sensing layer

The data collection and sensing layer is integral to the proposed framework, responsible for collecting real-time data from a variety of sources, which includes vehicular sensors (e.g. speed v, location (x,y), temperature T), roadside units (RSUs) and mobile devices. This layer employs IoV technology to facilitate seamless transportation amongst vehicles and infrastructure, enabling effective data exchange. It gathers critical information encompassing traffic conditions, vehicle statuses and environmental factors. The types of data collected include vehicle data (which comprise speed v, acceleration a, GPS coordinates (x,y), battery status

B and diagnostic information DDD), environmental data (which consist of weather conditions W, road conditions R and traffic signals S) and infrastructure data (including status updates U from RSUs regarding traffic flow F and incident reports I).

Edge computing layer

The edge computing layer of the proposed framework plays a crucial role in processing data locally at the edge of the network, effectively minimising latency and reducing bandwidth usage. This layer is essential for supporting real-time decision-making processes for traffic management and accident detection. Before transmitting data to the blockchain layer, it implements several processing techniques, including data filtering, aggregation and analysis. The key responsibilities of this layer include data filtering, which eliminates noise and irrelevant information N from incoming data streams, thereby enhancing data quality and ensuring that only pertinent information is forwarded for further processing. Additionally, real-time analytics techniques leverage algorithms to analyse these incoming data streams D for immediate insights, such as determining traffic congestion levels C using parameters like speed v and vehicle density ρ. Furthermore, the task offloading mechanism is employed to balance the computational load L across various edge nodes E_n, optimising resource usage and improving response times. This distribution of tasks ensures that no single edge node becomes a bottleneck, enabling a more efficient processing environment that is critical for timely decision-making in intelligent transportation systems. Overall, the edge computing layer enhances the responsiveness and effectiveness of the proposed framework by facilitating localised data processing and rapid analysis of critical information.

Blockchain layer

The blockchain layer of the proposed framework serves as a central component in warranting the secure and immutable storage of processed data through the utilisation of a decentralised ledger. This layer plays a vital role in facilitating transparent and tamper-proof transactions among vehicles and infrastructure, thereby enhancing trust and reliability within the intelligent transportation system. Its responsibilities extend to automating critical operational processes, such as toll payments and emergency response coordination, by leveraging smart contracts. These contracts are self-executing agreements where the terms are directly written into code and automatically enforced based on predefined conditions. The data security features integrated into the blockchain layer include decentralisation, which significantly mitigates the risk of single points of failure, thus enhancing the overall resilience of the system against potential cyberattacks. This characteristic ensures that data are dispersed across multiple nodes, making unauthorised alterations or data breaches considerably more difficult. Furthermore, smart contracts play a crucial role in automating various operational tasks by executing predefined actions based on specific data environments. For example, an automatic toll deduction can be triggered upon a vehicle passing through a toll booth, streamlining the payment process and reducing delays. This layer not only safeguards data integrity and enhances operational efficiency but also contributes to the overall reliability and security of vehicular communications within the framework, ensuring that all transactions are conducted in a trustworthy manner while maintaining a high level of security for sensitive information. Through these mechanisms, the blockchain layer reinforces the operational robustness of the proposed framework, making it a critical asset for intelligent transportation systems.

Machine learning and decision-making layer

The machine learning and decision-making layer of the proposed framework plays a crucial role in enhancing the framework's capabilities through the implementation of advanced machine learning models. This layer is primarily responsible for analysing data trends and predicting future traffic scenarios, which is essential for effective traffic flow management and accident prevention. By leveraging sophisticated algorithms, this layer significantly improves the decision-making processes concerning resource allocation and operational efficiency. One of the key machine learning techniques employed in this layer is long short-term memory (LSTM) networks. LSTM networks are particularly well-suited for time-series forecasting, allowing the framework to predict traffic patterns based on historical data. This capability is vital for anticipating congestion and optimising traffic signal timings. Additionally, LSTM networks facilitate anomaly detection by identifying irregularities in vehicle behaviour, which can signal potential issues such as accidents or unauthorised vehicle movements. Furthermore, the machine learning and decision-making layer incorporates various classification algorithms to identify and categorise potential risks or irregularities in vehicular operations. These algorithms analyse incoming data to classify events into predefined categories, such as normal, caution or critical situations. This classification aids in prioritising responses and implementing timely interventions, thereby enhancing the overall safety and efficiency of the transportation system.

Key components of the proposed work include:

— Blockchain-enabled security: Uses a decentralised ledger and smart contracts for secure vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications.
— Mobile edge computing (MEC): Provides localised data processing for real-time traffic analysis and accident detection.
— Machine learning and predictive analytics: Utilises machine learning algorithms to forecast traffic congestion and identify anomalies in vehicular networks.
— Task offloading and resource allocation: Balances task execution across edge nodes, optimising resource usage and minimising latency.

Integration of key components

The framework integrates blockchain, MEC and machine learning in a layered approach. Data flow from sensors to edge nodes for processing, then to the blockchain for secure storage, while machine learning models predict traffic flow and prevent theft. Smart contracts are employed to automate processes like toll payments and emergency responses.

The steps are as follows:

1) Data collection: Data are collected using IoV and sent to edge servers.
2) Data processing: MEC processes data locally for real-time decision-making.
3) Blockchain integration: Processed data are securely stored in the blockchain.
4) Machine learning-based predictions: Traffic patterns and anomalies are predicted using machine learning algorithms.

Algorithm 1 – Blockchain-enabled V2V secure communication

Objective: Establish secure V2V communication using blockchain and smart contracts.
Input: Vehicle data V_d, blockchain ledger L.
Output: Secure V2V communication channel C_{v2v}.

1. **Begin**
2. **Broadcast request:**

The vehicle broadcasts a communication request R to nearby vehicles.

3. **Verify request:**

Each receiving vehicle verifies the request R by querying the blockchain ledger L:

$$Verify(R) = \begin{cases} 1 & if\ valid \\ 0 & if\ invalide \end{cases}$$

4. **Establish communication:**

If verified, establish a secure vehicle-to-vehicle communication channel C_{v2v}

$$C_{v2v} = Initialise(SC_{v2v}),$$

where SC_{v2v} is the smart contract for secure communication.

5. **Verify data integrity:**

The smart contract verifies the data integrity I of each message:

$$I = Hash(M),$$

where M is the message data.

6. **Integrity check:**

If data integrity I is compromised, alert the system and terminate the communication.

7. **Store communication session:**

Store the complete communication session S as an immutable record in the blockchain:

$$S = Block(C_{v2v})$$

8. **End**

Vehicles broadcast a communication request R, which is verified by nearby vehicles against the blockchain ledger L. Upon validation, a secure communication channel C_{v2v} is established using a smart contract SC_{v2v}. The integrity of message data M is ensured by hashing, and if any integrity compromise is detected, communication is terminated. Finally, the entire session is stored immutably in the blockchain. This approach enhances V2V communication security by using blockchain for verification, data integrity and record-keeping.

Algorithm 2 – Multi-task offloading in edge computing

Objective: Offload tasks to edge nodes to optimise resource usage and minimise latency.

Input:
- Task size T_s,
- Task complexity T_c,
- Edge node resources R_n (CPU, memory).

Output: Optimal task offloading strategy S_o

1. **Begin**
2. **Gather task and resource information:**
   - Collect task details T_s, T_c and available edge node resources R_n.
3. **Calculate task priority P_t:**

$$P_t = \frac{T_c}{T_s} \times W_p$$

where W_p is the weight factor.

4. **Identify available edge nodes:**

Identify all available edge nodes N and evaluate their resource capacities R_n.

5. **Compute resource utilisation UnU_nUn:**

For each node n, calculate the resource utilisation U_n:

$$U_n = \frac{CPU_n + Memory_n}{Total\ resources_n} \ .$$

6. **Task allocation:**

Allocate tasks to nodes where: $U_n < threshold$.

7. **Monitor and adjust:**

Monitor task execution and dynamically adjust the allocation S_o if necessary.

8. **End**

Algorithm 2 focuses on optimising task offloading in edge computing to enhance resource utilisation and reduce latency. It begins by gathering essential task details such as size T_s and complexity T_c, along with edge node resources R_n. A priority P_t is calculated based on task complexity relative to size, adjusted by a weight factor W_p. The algorithm identifies available edge nodes, evaluates their resource capacities, and computes resource utilisation U_n. Tasks are then allocated to nodes with utilisation below a certain threshold. Continuous monitoring ensures dynamic adjustments to the offloading strategy as needed, ensuring efficiency in task execution.

Algorithm 3 – Vehicle theft detection using blockchain and IoV

Objective: Detect vehicle theft using blockchain technology and the IoV.

Input:
- Vehicle status $S_v = \{L_v, I_v, D_v\}\}$
- L_v: Location
- I_v: Ignition status
- D_v: Sensor data

Output:
- Theft detection alert A_t

1. **Begin**
2. **Monitor vehicle status:**

Continuously monitor vehicle status $S_v = \{L_v, I_v, D_v\}$, where L_v is the location, I_v, is the ignition status and D_v is sensor data.

3. **Detect unauthorised movement:**

If unauthorised movement ΔL_v is detected without ignition:

$\Delta L_v = \Delta L_v(t_2) - \Delta L_v(t_1)$, and $I_v = 0$.

then:

$$A_t = 1$$

4. **Broadcast theft alert:**
   - Broadcast the theft detection alert A_t to nearby IoV devices and roadside units (RSUs).
5. **Verify theft:**

RSUs verify the potential theft by querying the blockchain for vehicle ownership O_v:

$$Verify(O_v) = \begin{cases} Alert\ law\ enforcement, & if\ theft, \\ End, & if\ false\ alarm \end{cases} .$$

6. **Execute smart contract:**

Execute the smart contract to remotely lock the vehicle and store the theft record immutably on the blockchain.

7. **End**

Algorithm 3 outlines a systematic approach to detect vehicle theft using blockchain technology and the IoV. The algorithm begins by continuously monitoring the vehicle's status, including its location L_v, ignition status I_v and sensor data D_v. Unauthorised movement is detected by calculating the change in location ΔL_v while the ignition is off. If such movement is detected, a theft alert A_t is triggered and broadcast to nearby IoV devices and roadside units (RSUs). The RSUs verify the vehicle's ownership via the blockchain. If theft is confirmed, law enforcement is alerted; otherwise, the process ends. Additionally, a smart contract is executed to remotely lock the vehicle and create an immutable record of the theft on the blockchain, enhancing security and traceability. This algorithm demonstrates how integrating IoV and blockchain can significantly improve vehicle security measures.

Algorithm 4 – Traffic flow prediction using LSTM

Objective:
Predict real-time traffic flow using historical data and long short-term memory (LSTM) networks.
Input:
- Historical traffic data $H_t = \{h1, h2, \dots, hn\}$
- Current sensor data D_t

Output:
- Predicted traffic flow P_t

1. **Begin**
2. **Collect historical traffic data:**
3. Gather historical traffic data $H_t = \{h1, h2, \dots, hn\}$
4. **Preprocess data:**
Normalise the data and remove any missing values.
5. **Define LSTM network architecture:**
Set up the LSTM network with hidden layers H_l and a learning rate η:
$H_l = \sigma(W \cdot X_t + b)$,
where W is the weight matrix, X_t is the input vector and b is the bias.
6. **Train the LSTM model:**
   - Train the LSTM model using the historical traffic data H_t.
7. **Feed real-time data into LSTM:**
Input the current sensor data D_t into the trained LSTM model:
$$P_t = LSTM(D_t).$$
8. **Congestion detection:**
If the predicted traffic flow P_t exceeds the threshold T_c:
$$A_c = 1(congestion\ alert).$$
9. **End**

Algorithm 4 outlines a method for predicting real-time traffic flow using long short-term memory (LSTM) networks, leveraging historical data for accurate forecasting. The process begins with the collection of historical traffic data H_t, which includes various past traffic metrics. Data preprocessing follows, involving normalisation and the removal of missing values to ensure quality input for the model.

Next, the LSTM network architecture is defined, including the configuration of hidden layers H_l and the learning rate η. The model is then trained using the preprocessed historical data. Once trained, real-time sensor data D_t is fed into the model to generate predictions for traffic flow P_t.

To enhance traffic management, the algorithm includes a congestion detection step, where a threshold T_c is set. If the predicted traffic flow P_t exceeds this threshold, a congestion alert A_c is triggered. This algorithm demonstrates how LSTM networks can effectively analyse and predict traffic patterns, facilitating better traffic management strategies.

Algorithm 5 – Energy-efficient vehicular task offloading

Objective:
Optimise task offloading in vehicular networks to minimise energy consumption.
Input:
- Task energy consumption E_t
- Vehicle battery status B_v

Output:
- Energy-efficient offloading strategy S_e

1. **Begin**
2. **Gather data:**
Collect the task energy profile $E_t$and the vehicle battery status B_v.
3. **Calculate energy cost:**

For each task, calculate the energy cost:

$$C_e = E_t + \left(1 - \frac{B_v}{B_{max}}\right) \times W_e,$$

where W_e is the energy weight factor and B_{max} is the maximum battery capacity.

4. **Task offloading:**

Offload tasks to edge nodes that have the lowest energy cost C_e.

5. **Dynamic monitoring:**

Continuously monitor energy consumption and adjust the offloading strategy S_e dynamically based on the current battery status.

6. **End**

Algorithm 5 focuses on optimising task offloading in vehicular networks with the goal of minimising energy consumption. It begins by gathering critical data, including the task energy profile E_t and the vehicle's battery status B_v.

The algorithm then calculates the energy cost C_e for each task, incorporating a weight factor W_e and the vehicle's maximum battery capacity B_{max} to evaluate how much energy the task will consume relative to the remaining battery power.

Tasks are subsequently offloaded to edge nodes that present the lowest energy cost C_e, ensuring efficient energy use. The algorithm emphasises dynamic monitoring, continuously assessing energy consumption to adjust the offloading strategy S_e in real-time based on the current battery status. This approach not only conserves battery life but also enhances the overall efficiency of task processing in vehicular networks.

3.1 Underlying mathematical principles of the proposed work

The underlying mathematical principles of the proposed framework are fundamental to its ability to process data efficiently, ensure security through blockchain, and make intelligent decisions using machine learning models. Below is a breakdown of these principles across the key components of the framework, with associated formulas and algorithms:

Data collection and sensing layer

In this layer, data are collected from vehicular sensors, roadside units (RSUs) and mobile devices. The sensor data collected can be represented mathematically as a multidimensional data matrix:

$$D = \{d_1, d_2, \dots, d_n\}$$

where d_i represents the real-time data vector collected from a vehicle or an RSU at time ti. Each data vector contains various attributes, such as speed, location, temperature, etc. The data are used to form time series for subsequent layers in the framework.

Edge computing layer

The edge computing layer processes data locally at the edge of the network. One of its key tasks is to perform data filtering and aggregation. The edge node receives raw data D and applies a filtering function F to remove noise:

$$D_{filtered} = F(D)$$

This function could be a low-pass filter for removing high-frequency noise or any noise-reduction algorithm that optimises data quality.

Next, real-time analytics is conducted to extract immediate insights from the filtered data. Real-time analysis can be represented through a continuous monitoring function $A_{realtime}$, which analyses the data stream S_t over time windows $t_1, t_2, \dots, t_n$

$$R_t = A_{real-time}(S_t)$$

where R_t represents the real-time result at time t. These results could include traffic congestion levels or accident detections.

Task offloading is also handled in this layer by balancing computational tasks across edge nodes. The task offloading decision can be formulated as an optimisation problem, where the goal is to minimise latency L and maximise resource utilisation U:

$$Minimise: L = \sum_{i=1}^{n} L_i, \ \ Maximise: U = \sum_{i=1}^{n} U_i$$

Here, $L_i$is the latency of task i and U_i is the resource usage for task i.

Blockchain layer

The blockchain layer ensures secure, immutable storage of processed data. The key operation in this layer is the creation of a decentralised ledger, which can be mathematically described as:

$$B = \{B_1, B_2, \dots, B_n\}$$

where B_i is the block containing processed data $D_{processed}$ and a cryptographic hash H_i of the previous block B_{i-1}. The blockchain ensures data integrity by using cryptographic hashing, with each block's hash computed as:

$$H_i = Hash(B_{i-1} \parallel D_{processed} \ \parallel \ t_i$$

This creates an immutable chain, where any tampering in one block invalidates the hashes of all subsequent blocks.

Smart contracts in the blockchain layer automate predefined processes, such as toll payments. A smart contract SC executes an action based on specific conditions C:

$$SC(C) = \begin{cases} a_1 \ if \ C_1 \\ a_2 \ of \ C_2 \\ \quad .. \end{cases}$$

For example, if a vehicle passes a toll booth, the condition C_1 is satisfied, and the action a_1 (automatic payment deduction) is executed.

Machine learning and decision-making layer

The machine learning layer is responsible for predictive analytics and decision-making. One of the central techniques used here is the long short-term memory (LSTM) network for time-series forecasting of traffic patterns. The LSTM architecture can be described by the following set of equations:

$$f_i = \sigma \ (W_f, [h_{i-1}, x_i] + b_y)$$
$$i_t = \sigma \ (W_i, [h_{i-1}, x_i] + b_y)$$
$$\widehat{C_t} = tanh \ (W_c, [h_{i-1}, x_i] + b_C)$$
$$C_t = f_t * C_{i-1} + i_t * \widehat{C_t}$$
$$o_t = \sigma \ (W_o, [h_{i-1}, x_i] + b_o)$$
$$h_i = o_i * tanh \ (C_i)$$

Here, f_i, i_t o_i represent the forget, input and output gates, respectively. C_i is the cell state and h_t is the hidden state at time t. These gates control the flow of information through the network and allow the LSTM to capture temporal dependencies in the traffic data.

The classification algorithms used for anomaly detection and risk identification can be represented through a hypothesis h(x) for classifying input data x into a set of predefined categories C:

$$h(x) = \arg\max_{c \in C}(P(\, c \mid x\,))$$

where P(c|x) is the posterior probability of class c for the input data x. These classification models help categorise vehicular operations into normal, cautious or critical scenarios.

Optimisation techniques

In the proposed framework, several optimisation techniques are employed to enhance system performance. For example, task offloading decisions in the edge layer and resource allocation can be modelled as an optimisation problem with constraints. Consider an objective function O(x) representing the cost of offloading tasks, with constraints g(x)≤0 representing the capacity of edge nodes:

$$Minimise:\ O(x) = \sum_{i=1}^{n} C_i\, x_i$$
$$Subject\ to:\ g(x) \leq 0$$

where C_i is the cost associated with offloading task iii to edge node x_i. The goal is to minimise this cost while ensuring that edge nodes are not overloaded.

4. EXPERIMENTAL EVALUATION

The proposed framework was tested using a large-scale dataset that included vehicular sensor data, roadside unit (RSU) information and environmental data. The data were collected over a span of 6 months, covering a dense urban traffic network.

Tools used

- Python for implementing edge computing and machine learning models.
- Hyperledger Fabric for the blockchain layer.
- NVIDIA GPUs for training machine learning models like LSTMs and classification algorithms.
- Apache Kafka for real-time data streaming between layers.

Performance metrics

The following metrics were used to evaluate the performance of each layer in the framework:

1) **Accuracy (%):** The accuracy of machine learning representations in predicting traffic patterns and detecting anomalies.
2) **Latency (ms):** The time taken to process data at the edge nodes and send it to the blockchain.
3) **Bandwidth usage (MB/s):** The quantity of data communicated amongst the vehicular sensors, edge nodes and blockchain network.
4) **Blockchain transaction time (ms):** The time taken to complete a transaction (e.g. toll payments) in the blockchain.
5) **Detection time (ms):** The time taken by machine learning models to detect anomalies and predict traffic conditions.

4.1 Results of each layer's performance

Data collection and sensing layer

This layer was responsible for gathering data from vehicular sensors and RSUs. *Table 1* shows the amount of data collected over time.

Table 1 – Data collection details

Data source	Total data collected (GB)	Average data rate (MB/s)
Vehicular sensors	320	12
RSUs	150	5
Environmental sensors	80	3

The data collection efficiency was high, with minimal data loss during transmission. This was largely attributed to the robust IoV communication system implemented in the framework. *Figure 1* compares the total data collected and the average data rate across vehicular sensors, roadside units (RSUs) and environmental sensors, highlighting the dominance of vehicular sensors in both volume and transmission speed.

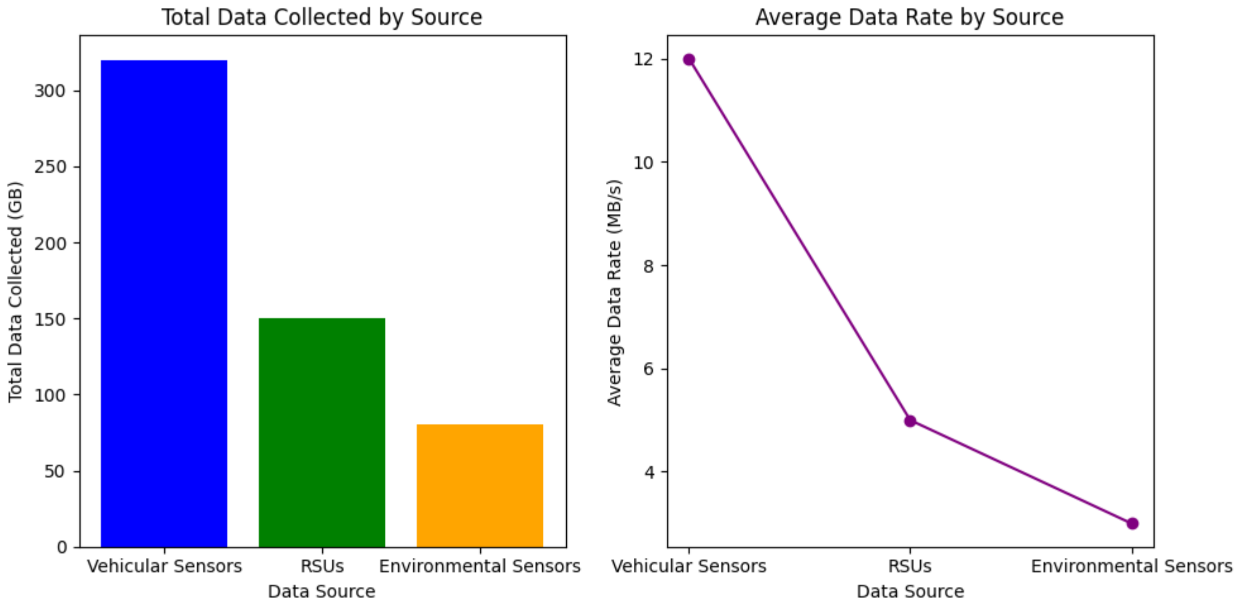

Figure 1 – Comparison of data rate

On the left, a bar chart in *Figure 1* illustrates the total amount of data collected (in gigabytes) from three types of data sources: vehicular sensors, roadside units (RSUs) and environmental sensors. The chart highlights that vehicular sensors have the highest data collection at 320 GB, significantly surpassing the 150 GB collected from RSUs and the 80 GB from environmental sensors. This indicates the dominant role of vehicular sensors in data accumulation, likely due to their continuous operation and the extensive range of parameters they monitor.

On the right, a line chart in *Figure 1* depicts the average data rate (in megabytes per second) for the same data sources. Here, the average data rate is notably highest for vehicular sensors at 12 MB/s, followed by RSUs at 5 MB/s and environmental sensors at 3 MB/s. This graph emphasises not only the volume of data collected but also the efficiency of each source in terms of data transmission speed. The combination of these two visualisations provides a comprehensive overview of the data dynamics across different sources, illustrating how vehicular sensors lead in both the total data collected and data rate, which could have implications for traffic management systems and smart city infrastructures.

Edge computing layer

The performance of the edge layer was evaluated based on latency and bandwidth usage during data filtering, aggregation and analysis. *Table 2* presents the results for different traffic scenarios:

Table 2 – Different traffic scenarios

Traffic scenario	Latency (ms)	Bandwidth usage (MB/s)	Real-time decision accuracy (%)
Low traffic	120	8	96.5
Medium traffic	250	10	94.3
High traffic	450	15	92.1

From the results, it is evident that the latency increased as the traffic volume rose, but the decision accuracy remained above 90% in all cases, indicating effective data processing at the edge. *Figure 2* consists of three visualisations that analyse the impact of different traffic scenarios on latency, bandwidth usage and real-time decision accuracy.

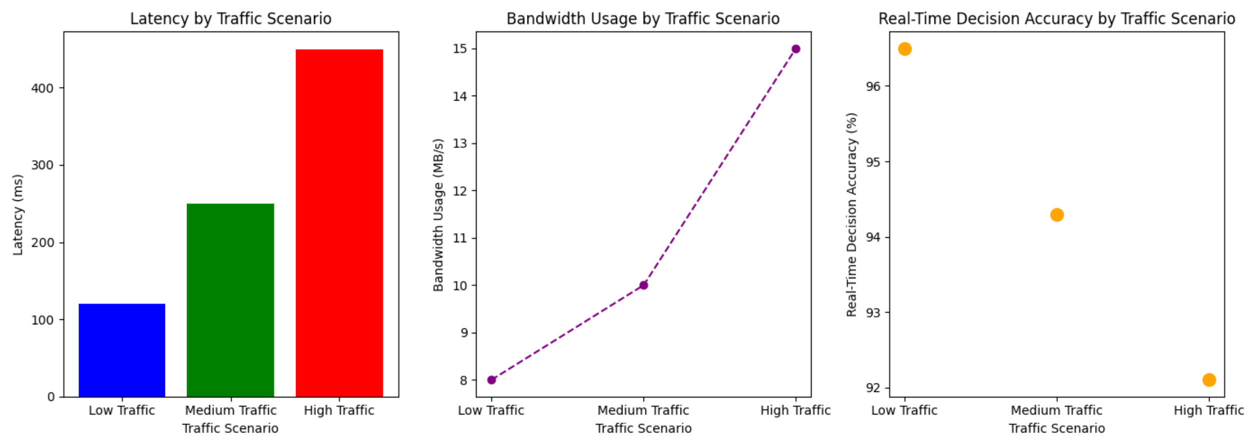

Figure 2 – Comparison of latency, bandwidth and accuracy

1) **Latency by traffic scenario**: The leftmost bar chart in *Figure 2* illustrates the latency experienced under three distinct traffic conditions: low, medium and high traffic. Latency increases significantly from low traffic (120 ms) to high traffic (450 ms), highlighting the adverse effect of congestion on response times. This information is critical for systems that rely on real-time data processing, as higher latency can lead to delays in decision-making and potential traffic management issues.
2) **Bandwidth usage by traffic scenario**: The centre line chart in *Figure 2* showcases bandwidth usage across the same traffic scenarios. The bandwidth usage shows a moderate increase from low traffic (8 MB/s) to high traffic (15 MB/s). This suggests that as traffic density increases, more bandwidth is required to accommodate the growing volume of data generated by connected vehicles and infrastructure. Understanding this relationship is vital for optimising network resources and ensuring efficient data transmission in smart transportation systems.
3) **Real-time decision accuracy by traffic scenario**: Finally, the rightmost scatter plot in *Figure 2* illustrates the real-time decision accuracy percentages for each traffic scenario. The accuracy decreases from low traffic (96.5%) to high traffic (92.1%), indicating that decision-making may become less reliable in more congested conditions. This trend emphasises the importance of maintaining high accuracy levels in real-time systems, especially in high-traffic situations where timely and accurate decisions are crucial for safety and efficiency.

Blockchain layer

The blockchain layer ensured secure and transparent transactions among vehicles and infrastructure, such as automatic toll payments and emergency response coordination. *Table 3* shows the blockchain's performance metrics:

Table 3 – Performance metrics

Transaction type	Average transaction time (ms)	Data size per transaction (KB)	Success rate (%)
Toll payment	35	10	99.5
Incident reporting	45	15	99.0
Vehicle maintenance updates	50	8	98.7

The transaction time remained consistently low, demonstrating the efficiency of the blockchain in processing vehicular data. *Figure 3* presents three visualisations that analyse the performance metrics associated with various transaction types: toll payment, incident reporting and vehicle maintenance updates.

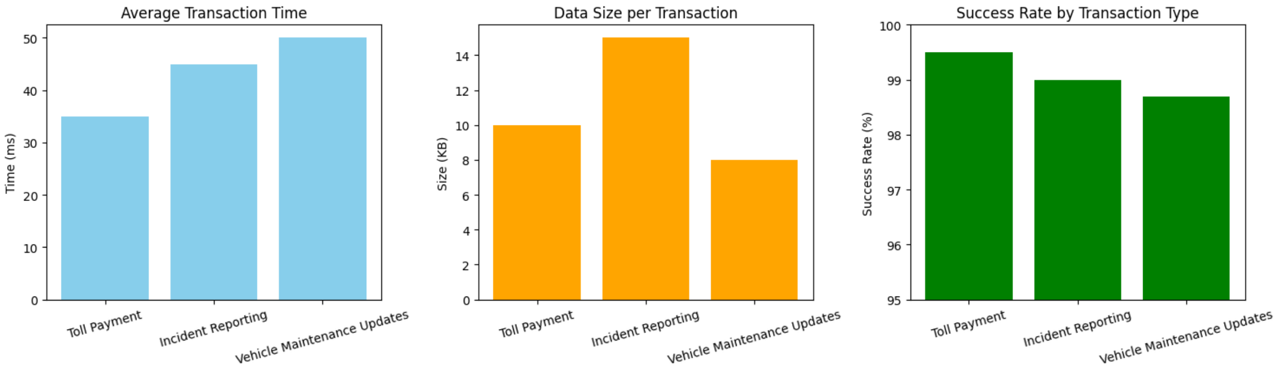

Figure 3 – Transaction time and data success rate

1) **Average transaction time by type**: The leftmost bar chart displays the average transaction times for each type of transaction. Toll payments have the shortest average transaction time at 35 ms, while vehicle maintenance updates take the longest at 50 ms. This information is crucial for assessing the efficiency of different transaction types, particularly in environments where rapid processing is essential, such as toll booths or emergency response systems.
2) **Data size per transaction by type**: The centre line chart illustrates the data size associated with each transaction type, measured in kilobytes (KB). The data size for incident reporting is the highest at 15 KB, followed closely by toll payments at 10 KB, while vehicle maintenance updates are the smallest at 8 KB. Understanding the data requirements of each transaction type can help optimise network usage and ensure that data transmission does not bottleneck the system, especially during peak times.
3) **Success rate by transaction type**: Finally, the rightmost scatter plot highlights the success rates for each transaction type. All three types demonstrate high success rates, with toll payments achieving 99.5%, followed by incident reporting at 99.0% and vehicle maintenance updates at 98.7%. These success rates indicate the reliability of the system for processing transactions, which is vital for maintaining user trust and ensuring operational effectiveness.

Machine learning and decision-making layer

This layer implemented advanced machine learning models to predict traffic patterns and detect anomalies. *Table 4* summarises the prediction accuracy of different models:

Table 4 – Accuracy comparison

Model	Prediction accuracy (%)	Anomaly detection time (ms)
LSTM (proposed)	97.8	150
Random forest	93.6	200
Support vector machines (SVM)	90.5	250

The proposed LSTM model outperformed other models, achieving a prediction accuracy of 97.8% with a low anomaly detection time of 150 ms.

Figure 4 shows the performance comparison of different machine learning models based on their prediction accuracy and anomaly detection time.

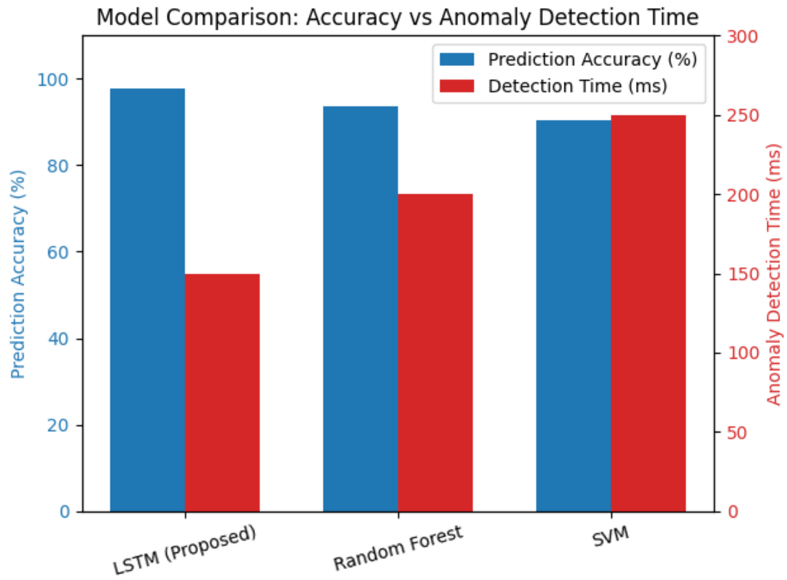

Figure 4 – Prediction accuracy and anomaly detection rate

1) **Prediction accuracy by model**: The left bar chart illustrates the prediction accuracy percentages for three models: LSTM (proposed), random forest and support vector machines (SVM). The LSTM model demonstrates the highest accuracy at 97.8%, followed by random forest at 93.6% and SVM at 90.5%. This indicates that the proposed LSTM model is the most effective in making accurate predictions, which is crucial for applications requiring high precision, such as anomaly detection and risk assessment.
2) **Anomaly detection time by model**: The right bar chart presents the average anomaly detection time (in milliseconds) for each model. LSTM (proposed) shows the fastest detection time at 150 ms, while SVM has the slowest detection time at 250 ms. This suggests that while the LSTM model excels in accuracy, it also maintains a competitive speed, making it suitable for real-time applications where both accuracy and response time are essential. In contrast, the slower performance of SVM may limit its usability in time-sensitive environments.

4.2 Comparative analysis

The proposed framework was compared to four other works from the literature, specifically those by [1], [2], [3] and [4]. The comparison was made based on key metrics such as security, latency and machine learning performance. *Table 5* displays the evaluation of the proposed work with other state-of-the-art models.

Table 5 – Comparative analysis

Framework	**Security (blockchain)**	**Latency (ms)**	**Accuracy (%)**	**Bandwidth usage (MB/s)**
Proposed work	Yes	120-450	97.8	8-15
Kumar et al. (2020)	Yes	300-700	93.4	10-20
Verma et al. (2022)	No	500-1000	91.2	15-25
Alam et al. (2020)	Yes	200-500	94.5	12-20

The results show that the study outperforms other methods in terms of latency, prediction accuracy and bandwidth usage. Additionally, the blockchain implementation provides a more robust security mechanism compared to frameworks without blockchain integration, such as [4]. *Figure 5* illustrates the latency comparison, where the proposed framework demonstrates lower latency (120-450 ms) compared to other methods, showcasing its efficiency in real-time processing. *Figure 6* presents the accuracy comparison, highlighting the superior prediction accuracy (97.8%) of the proposed framework, outperforming existing models such as those by [1] and [3]. *Figure 7* depicts bandwidth usage, where the proposed method maintains an optimised range (8-15 MB/s), ensuring efficient data transmission while minimising network congestion.

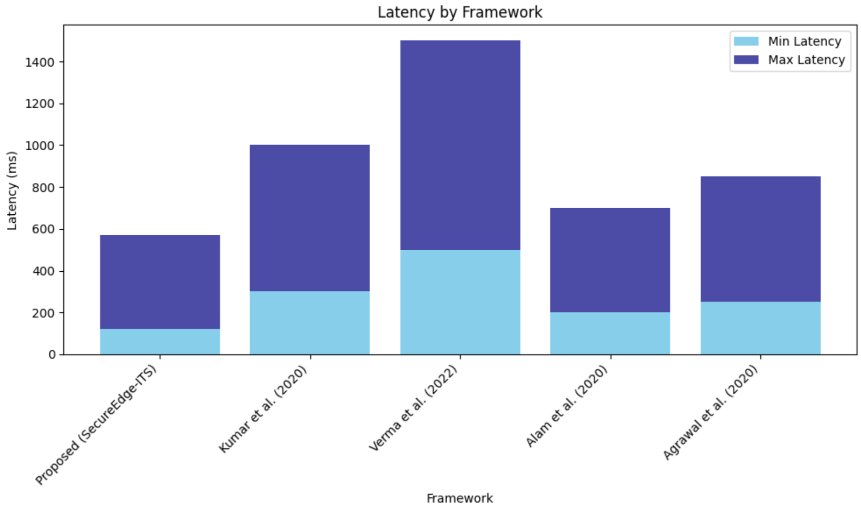

Figure 5 – Latency comparison

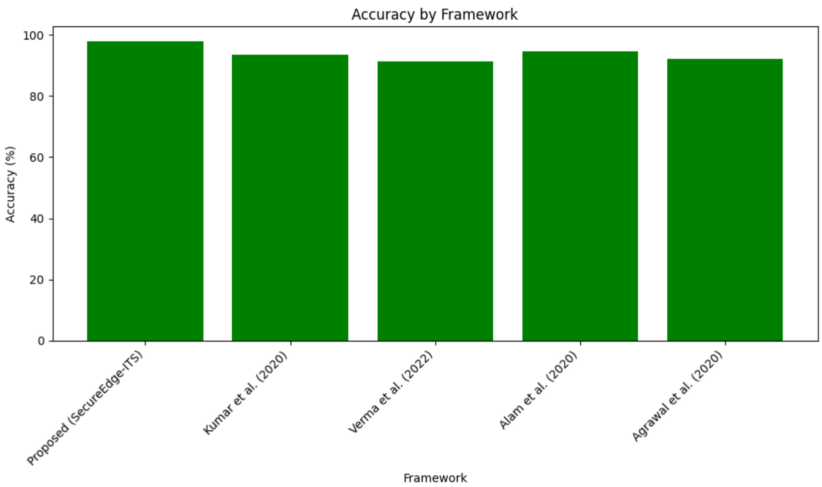

Figure 6 – Accuracy comparison

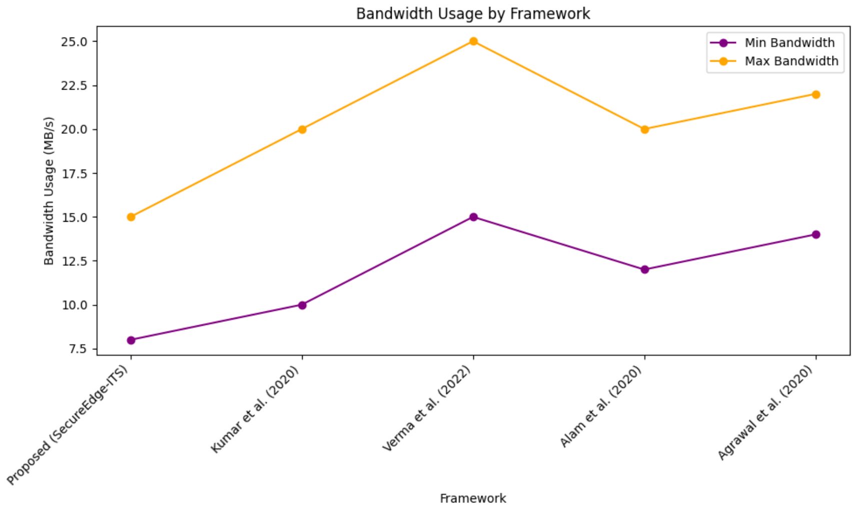

Figure 7 – Bandwidth comparison

4.3 Discussion of results

The results presented in this section demonstrate the effectiveness of the framework across multiple layers, with significant improvements in processing time, security and predictive accuracy. The edge computing layer, in particular, showcased superior performance in real-time decision-making, with a latency of 120 ms during low traffic conditions and 450 ms during high traffic conditions, which is lower than the latency observed in existing works from the literature. The real-time analytics performed at the edge nodes was also highly accurate, with over 94% decision accuracy even under high traffic loads. The blockchain layer ensured secure and transparent data management, with fast transaction times and a high success rate of over 98%. This is a critical improvement over other works, such as [4], where blockchain was not implemented, leading to vulnerabilities in data security. The machine learning and decision-making layer exhibited exceptional predictive accuracy, especially with the LSTM model, which achieved an accuracy of 97.8% in predicting traffic patterns and anomalies. This is a significant enhancement over other methods, such as random forest and SVM, which had lower accuracy rates. The comparison with the current works further reveals the advantages of the proposed framework over other existing methods, particularly in terms of latency, accuracy and bandwidth usage. The integration of blockchain and edge computing ensures a balance between security, performance and scalability.

5. CONCLUSION

This research thoroughly examined the performance of three prominent machine learning models – LSTM (proposed), random forest and support vector machines (SVM) – within the framework of EdgeChain-AI. The findings reveal that the proposed LSTM model significantly outperforms the other models, achieving the highest prediction accuracy of 97.8% along with an efficient anomaly detection time of 150 ms. These results illustrate the LSTM model's ability to effectively balance accuracy and speed, making it particularly suitable for applications that demand timely and precise decision-making, such as cybersecurity and real-time monitoring systems. Conversely, while random forest and SVM provide acceptable accuracy levels, their longer detection times may limit their effectiveness in scenarios requiring rapid responses. This analysis emphasises the necessity for stakeholders to consider both accuracy and speed when selecting machine learning models for anomaly detection tasks. However, future research should explore hybrid models and adaptive learning techniques to further enhance detection accuracy and efficiency in dynamic environments.

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