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Blockchain-Assisted Secure Framework for Intelligent Transportation Systems: Enhancing V2V Energy Trading with Hybrid CNN-LSTM Models

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Abstract— The increasing adoption of electric vehicles (EVs) has necessitated the development of secure and efficient energy management systems to address the challenges in energy trading between vehicles (V2V). This study introduced a Blockchain-Assisted Secure Framework for Intelligent Transportation Systems (BASF-ITS) designed to enhance V2V energy trading by integrating blockchain technology and machine learning. The framework addresses security vulnerabilities, lack of standardization, and transaction processing inefficiencies through the use of blockchain for decentralized, immutable transaction records and a hybrid CNN-LSTM model for real-time anomaly detection. The methodology involved implementing the framework in a simulated environment using Hyperledger Fabric for blockchain execution and TensorFlow for machine-learning model development. Evaluated using the VANET dataset, BASF-ITS demonstrated a high accuracy (99.30%) in anomaly detection and robust performance in handling large-scale transactions. A comparative analysis with baseline models highlighted the framework's superior performance in terms of accuracy, AUC-ROC, precision, recall, and computational efficiency. These results underscore the potential of BASF-ITS to significantly enhance the security and efficiency of intelligent transportation systems, particularly in facilitating secure and transparent V2V energy trading, while also highlighting areas for future research and development in terms of scalability and real-world implementation.

Keywords— ***Blockchain Technology, Energy Trading, Electric Vehicles, Blockchain Consensus Mechanisms, Auction Mechanisms, Smart Contracts.***

I. INTRODUCTION

The rapid adoption of electric vehicles (EVs) has revolutionized transportation, offering a sustainable alternative to fossil fuel-based vehicles. However, this transition has introduced challenges in energy management and distribution [1], [2]. The trading of energy between vehicles (V2V) has surfaced as a potential solution that enables EVs to exchange energy directly, enhance efficiency, and promote a decentralized energy ecosystem. Despite these benefits, implementing V2V energy-trading systems faces hurdles in ensuring security, privacy, and efficiency [3], [4]. The Internet of Electric Vehicles (IoEV) integrates EVs with smart grid technologies, enabling communication and energy exchange between vehicles and infrastructure. Although IoEV offers benefits, it introduces vulnerabilities, such as cyberattacks, data tampering, and fraudulent transactions. Traditional energy trading systems lack mechanisms to address these challenges, rendering them unsuitable for large-scale deployment in IoEV environments. To overcome these limitations, this study proposes a blockchain-assisted lightweight security framework for secure, transparent, and efficient V2V energy trading [5], [4].

The rapid adoption of electric vehicles (EVs) has revolutionized transportation, offering a sustainable alternative to fossil fuel-based vehicles. However, this transition has introduced challenges in energy management and distribution [21], [22]. The trading of energy between vehicles (V2V) has surfaced as a potential solution that enables EVs to exchange energy directly, enhance efficiency, and promote a decentralized energy ecosystem. Despite these benefits, implementing V2V energy-trading systems faces hurdles in ensuring security, privacy, and efficiency [27], [34]. The Internet of Electric Vehicles (IoEV) integrates EVs with smart grid technologies, enabling communication and energy exchange between vehicles and infrastructure. Although IoEV offers benefits, it introduces vulnerabilities, such as cyberattacks, data tampering, and fraudulent transactions. Traditional

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energy trading systems lack mechanisms to address these challenges, rendering them unsuitable for large-scale deployment in IoEV environments. To overcome these limitations, this study proposes a blockchain-assisted lightweight security framework for secure, transparent, and efficient V2V energy trading [29], [34]. The proposed framework, a Blockchain-Assisted Secure Framework for Intelligent Transportation Systems (BASF-ITS), integrates blockchain technology and machine-learning algorithms to address security and efficiency challenges in V2V energy trading. Blockchain acts as a decentralized, immutable ledger, ensuring tamper-proof, transparent energy transactions. This enhances efficiency and security by eliminating intermediaries and preventing fraudulent activities. Smart contracts automate trading processes, reduce human intervention, and minimize errors.

Techniques in machine learning, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), detect suspicious activities in V2V energy trading. These models analyze transaction patterns in real time and identify anomalies indicating fraudulent behaviour. By integrating AI-driven classification, the framework enhances its ability to prevent cyber threats and ensure a secure energy exchange.

II. LITERATURE REVIEW

The swift expansion of electric vehicles (EVs) and the Internet of Electric Vehicles (IoEV) has spurred extensive research into developing secure and efficient systems for energy trading. This section reviews existing solutions, limitations, and advancements in vehicle-to-vehicle (V2V) energy trading, focusing on blockchain technology and machine learning applications.

A. Existing Solutions and Technologies

Traditional energy-trading systems often rely on Centralized Architectures prone to single points of failure and security vulnerabilities [3], [4]. Researchers have explored decentralized solutions to address these issues. They emphasized the need for decentralized authentication in vehicular ad hoc networks (VANETs) to ensure secure communication and data integrity [5], [6]. A blockchain-based lightweight authentication protocol for vehicle-to-infrastructure (V2I) communication has been proposed, highlighting the potential of blockchain to enhance security and scalability in intelligent transportation systems [7] – [9]. In anomaly detection, machine learning techniques have been crucial for identifying security threats [10], [11]. A blockchain-based access control protocol with handover authentication was introduced, demonstrating the benefits of integrating blockchain with machine learning [12], [13]. Certificateless cryptography has been explored for secure key agreement in the Internet of Vehicles (IoV), highlighting the importance of adaptive learning in dynamic environments [14], [15].

B. Limitations of Current Systems

Despite these advancements, the current systems are facing challenges. Dependence on unstructured textual log data for anomaly detection was reported by Bagiwa et al. [5], [6]. The resulting computational overhead and the lack of a standardized framework for vehicle-to-vehicle (V2V) energy trading hinder interoperability and scalability. These limitations underscore the need for a comprehensive solution integrating blockchain technology with advanced machine-learning algorithms to ensure secure, efficient, and scalable energy trading in Internet of Electric Vehicles (IoEV) environment.

C. Advancements in Blockchain and Machine Learning Integration

Recent scholarly investigations have integrated blockchain with machine learning to enhance the security and efficiency of energy-trading systems. A blockchain-assisted handover authentication protocol for Vehicular Ad Hoc Networks (VANETs) was proposed, demonstrating the blockchain's potential to improve authentication and secure vehicular communication [16], [6]. This study highlights decentralized authentication benefits while ensuring high security. Similarly, [7] introduced a lightweight vehicle-to-infrastructure (V2I) authentication protocol using blockchain, demonstrating its efficacy in secure vehicle and roadside infrastructure communication. Their research underscored the blockchain's role in addressing security challenges, such as identity spoofing and unauthorized access, which are crucial in intelligent transportation systems. Researchers have explored analytical detection methodologies to bolster network security in machine learning. [17] – [19] introduced Hyper Tester, a high-performance network testing system using machine learning for real-time

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anomaly detection. Their research emphasized adaptive learning mechanisms' importance in identifying and mitigating complex threats in evolving cyber environments. [20], [21] examined Support Vector Machines (SVM) and Random Forests for anomaly detection in programmable network environments, offering insights into the strengths and limitations of classification algorithms, and highlighting trade-offs between accuracy, computational efficiency, and adaptability in detecting fraudulent activities.

D. Contributions of the Proposed Framework

Building on recent advancements, the proposed Blockchain-Assisted Secure Framework for Intelligent Transportation Systems (BASF-ITS) combines blockchain technology with machine learning to create a secure framework for energy trading between vehicles (V2V) within the Internet of Electric Vehicles (IoEVs). Leveraging the blockchain's decentralized, tamper-resistant nature, the system boosts transparency and trust in energy transactions, addressing data integrity and unauthorized modification concerns. Machine learning-based anomaly detection enhances the system's ability to classify transactions as legitimate or suspicious, proactively identifying fraud. The framework uses advanced cryptographic techniques, including the Elliptic Curve Integrated Encryption Scheme (ECCIES) and ASCON lightweight encryption to protect data transmission and ensure privacy and integrity. A hybrid machine learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) classifies energy-trading interactions as normal or suspicious, enhancing real-time fraud detection and bolstering security and reliability.

E. Integration of Recent Research

Recent research has explored blockchain and machine learning integration in energy-trading systems. [22], [13], [23] suggested a decentralized energy trading system for vehicle-to-vehicle (V2V) interactions that utilizes effective sharding services to improve transaction throughput. [24], [25] introduced a secure data and energy trading model utilizing blockchain within the Internet of Electric Vehicles, emphasizing privately protected mechanisms. [26] – [28] presented a blockchain-based reverse auction system for V2V electricity trading in a smart grid. [29], [30] developed a scalable consensus mechanism for a V2V energy-trading blockchain that integrates a hash graph with sharding. Salah et al. [31], [32], [13] introduced a system for V2V energy trading among electric vehicles, emphasizing sustainable practices and reverse auction mechanisms. A related study proposed a consensus mechanism for blockchain-enabled V2V energy trading within the Internet of Electric Vehicles (IoEV) by combining Practical Byzantine Fault Tolerance (PBFT) and Proof of Reputation (PoR). These studies have advanced the development of robust energy trading systems, addressing the challenges of security, privacy, and efficiency within electric vehicles and smart grids.

F. Blockchain Consensus Mechanisms

Blockchain consensus mechanisms are crucial for ensuring the security and efficiency of decentralized systems. Various consensus algorithms have been developed to address the challenges in vehicle-to-vehicle (V2V) energy trading. The Block Alliance Consensus (BAC) mechanism proposed by [33], [13] combines Hash Graph's high-throughput with sharding techniques, enabling dynamic node management while maintaining a centralized component for macroeconomic oversight by governments [35]. This mechanism enhances scalability and efficiency while ensuring security through Leader elections based on cryptography and a reputation incentive system for electric vehicles (EVs). Practical Byzantine Fault Tolerance (PBFT) combined with Proof of Reputation (PoR) provides a solution to the shortcomings of conventional consensus algorithms, creating a strong foundation for secure energy transactions.

G. Machine Learning in Energy Trading

Machine learning is a powerful tool for enhancing the security and efficiency of energy-trading systems. Scientists have investigated machine learning methods, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), to detect anomalies and classify transactions in real time. [17], [34], [18] developed Hyper Tester, a high-performance network testing system that uses machine learning for real-time anomaly detection. Their study highlighted the role of adaptive learning mechanisms in identifying complex security threats in rapidly evolving cyber environments. In addition, [20], [21] investigated Support Vector Machines (SVM) and Random Forests for anomaly detection in programmable network environments, offering insights into the advantages and limitations of classification algorithms and emphasizing trade-offs between accuracy, computational efficiency, and adaptability in identifying fraudulent activities.

H. Security and Privacy in Energy Trading

The protection of security and privacy in energy trading systems is vital, especially for electric vehicles and smart grids. Scholars have investigated ways to improve the security and privacy of energy exchanges. [24], [25] suggested a blockchain-based solution for safe data and energy trading within the Internet of Electric Vehicles (IoEV) framework, emphasizing privately protected mechanisms in energy management. Their study demonstrated that blockchain protects the identity and security of energy transactions. Similarly, [26], [36] suggested a blockchain-driven reverse auction platform for vehicle-to-vehicle electricity transactions within a smart-grid framework, showcasing how decentralized systems can improve security and adaptability. Their research underscores the importance of secure communication and data integrity in energy-trading systems.

I. Scalability and Efficiency in Energy Trading

Scalability and efficiency are crucial for the development of energy-trading systems. Researchers have explored methods to enhance these aspects, particularly for electric vehicles and smart grids. [22] proposed a decentralized vehicle-to-vehicle (V2V) energy trading system using efficient sharding services, highlighting the effectiveness of blockchain sharding and parallel architecture in improving transaction throughput. Their research demonstrated the potential of decentralized systems to enhance scalability and efficiency in energy-trading systems, thereby providing a robust framework for secure transactions. Similarly, [30], [13], [37] proposed a scalable, efficient, and secure consensus mechanism for a V2V energy-trading blockchain by integrating hash graph with sharding techniques. Their research emphasizes the critical role of consensus mechanisms in ensuring the scalability and efficiency of energy-trading systems, offering valuable insights into developing robust frameworks.

III. METHODOLOGY

The BASF-ITS framework facilitates secure and efficient vehicle-to-vehicle (V2V) energy trading, comprising essential components that enhance the system functionality and security. The Data Plane Layer collects and manages data from electric vehicles (EVs) and smart grid infrastructure, incorporating data insight gatherers and refiners. It captures real-time energy consumption and transaction data, forming the foundation for informed decision making. The Control Layer manages data partitioning, model training, and anticipation of energy trading patterns using machine learning algorithms to analyze the data in real time. This layer manages the data flow between the Data Plane and Application Layers, ensuring efficient and secure processing. The Application Layer focuses on practical applications, including metric analysis and visualization of network performance. It provides stakeholders with interfaces and dashboards that offer real-time analytics and decision-making support. The system architecture is modular and scalable, allowing the integration of new components and technologies, ensuring adaptability to evolving requirements and advancements in transportation systems.

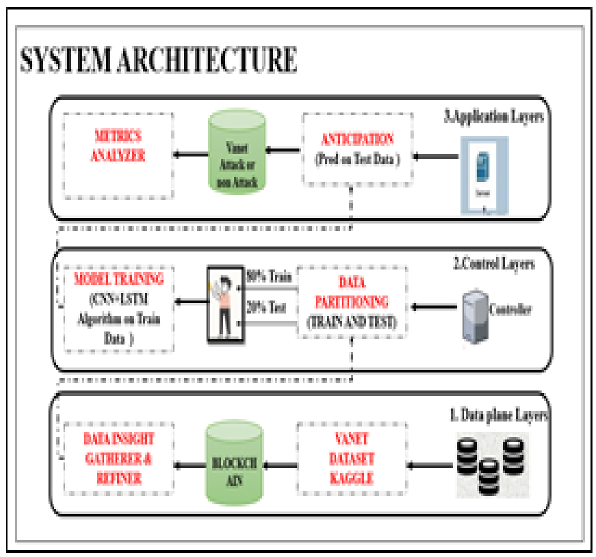


Fig 1: Network Simulation and Mobility Analysis

A. Data Collection and Preprocessing

The data collection process involved acquiring real-time energy trading data from electric vehicles (EVs) and smart grid infrastructure. The dataset includes parameters such as energy consumption, transaction details, and network metrics, providing a comprehensive view of energy trading activities within the Internet of Electric Vehicles (IoEV) ecosystem. This data collection strategy captures the nuances of the energy trading dynamics.

Data preprocessing is crucial for effective analysis and modeling. The process begins with data cleaning to eliminate or estimate missing data, manage outliers, and ensure uniform data. This step preserves dataset integrity. Normalization was then performed to adjust the data scale, ensure consistency, and enhance the performance of the machine-learning model. Normalization standardizes data and facilitates variable comparisons. Encoding the integrity of the dataset for the categorical data into numerical formats suitable for analysis. These preprocessing steps are essential for preparing data for training and assessing machine learning models, ensuring precise outcomes.

B. Blockchain Implementation

The blockchain component of the BASF-ITS framework is crucial in enabling secure and transparent energy transactions. Implementation involves several essential elements, each of which contributes to the robustness and reliability of the system. Central to blockchain implementation is the consensus mechanism, which utilizes the Practical Byzantine Fault Tolerance (PBFT) protocol. This protocol was selected for its ability to manage Byzantine faults, allowing the system to endure malicious nodes without compromising the network integrity. PBFT ensures system resilience and trustworthiness by authenticating transactions and maintaining data integrity. Another significant aspect is the development of smart contracts that automate energy-trading operations and ensure compliance with established rules. Smart contracts are agreements that execute themselves, with conditions written into the code that allow for automatic performance when specific criteria are satisfied. This reduces reliance on intermediaries, minimizes human involvement, and streamlines the trading process. In addition, advanced cryptographic techniques, such as the Elliptic Curve Integrated Encryption Scheme (ECIES) and ASCON lightweight encryption, protect data during transmission. These methods ensure that the data remain encrypted and secure, safeguarding it from unauthorized access and tampering. The decentralized nature of blockchain ensures that transactions are immutable and transparent, thereby providing a robust framework for secure energy trading. In general, the adoption of blockchain technology improves the security, clarity, and effectiveness of energy trading, establishing it as a fundamental element of the BASF-ITS framework.

C. Machine Learning Models

Machine learning models are crucial in the Blockchain-Assisted Secure Framework for Intelligent Trading Systems (BASF-ITS) as they facilitate the precise identification and categorization of interactions in energy trading. A combined Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model was used to understand both the spatial and temporal relationships within the trading data. CNNs were employed for feature extraction, utilizing their capability to detect spatial patterns in organized datasets. Mathematically, a CNN extracts hierarchical features by using convolutional operations.

$$F^{(l)} = \sigma\left(W^{(l)} * X^{(l-1)} + b^{(l)}\right)$$

Where F_l represents the feature map at layer l;
X_{l-1} is the input from the previous layer;
W_l is the convolution kernel;
b_l is the bias term;
σ is an activation function such as ReLU.

These feature maps serve as input to the next layer. LSTM networks have been integrated for anomaly detection in real-time energy transactions, effectively capturing long-term dependencies in sequential data. An LSTM unit consists of three key gates: input, forget, and output gates, which are mathematically represented as:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$C_t = f_t * C_{t-1} + i_t * \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$
$$h_t = o_t * \tanh(C_t)$$

Where
f_t, i_t, o_t represent the forget, input, and output gates, respectively;
C_t is the cell state at time step t;
h_t is the hidden state;
W_f, W_i, W_o, W_C are weight matrices;
b_f, b_i, b_o, b_C are bias terms;
σ is the sigmoid activation function;
tanh is the hyperbolic tangent activation function.

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

Where L is the loss function;
N is the total number of samples;

y_i is the actual value for sample i;
$\hat{y}_i$ is the predicted probability for sample i;
$\log$ is the natural logarithm function.

The mathematical integration of machine learning algorithms enhances anomaly detection and security features within the BASF-ITS. The model demonstrated high accuracy in detecting fraudulent energy trades, offering a robust and proactive approach for securing energy transactions. The incorporation of CNNs for feature extraction and LSTMs for sequential learning ensures that complex trading patterns and anomalies are effectively captured and analyzed. This hybrid architecture not only improves the system reliability but also provides a scalable solution for secure and intelligent energy trading.

D. Evaluation Metrics

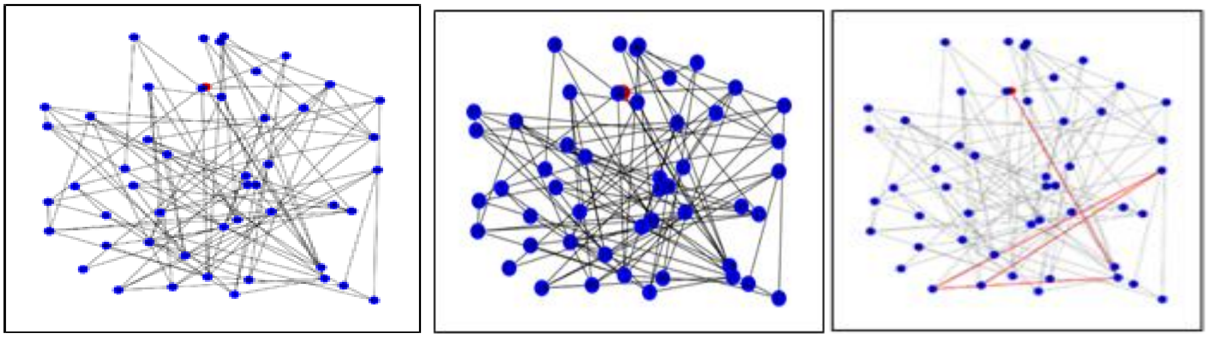
The performance of the BASF-ITS framework is evaluated using key metrics to ensure a comprehensive assessment of its effectiveness and efficiency in practical applications. Accuracy determines the frequency of correct model predictions and serves as a fundamental indicator of predictive success. Precision and recall assessed the model's ability to correctly identify true positive cases and its sensitivity to positive instances, with precision focusing on the accuracy of positive predictions and recall evaluating the model's effectiveness in recognizing relevant cases. The F1 score offered a balanced evaluation of precision and recall, which is valuable in scenarios with uneven class distribution, by providing a single measure that integrates both metrics. The computational efficiency was assessed to evaluate the model's performance in terms of processing speed and resource utilization, ensuring that the system can manage real-time energy trading interactions without significant delays. These metrics offer a thorough assessment of the framework's advantages and highlight potential areas for enhancement, especially in relation to current solutions.

E. Experimental Setup

The experimental configuration implemented the BASF-ITS framework in a simulated environment emulating actual energy trading contexts. This setup incorporates Hyperledger Fabric for blockchain execution and TensorFlow for machine learning model development, establishing a robust foundation for system component creation and evaluation. High-performance computing resources and software frameworks facilitate data processing and analysis, thereby enabling the management of substantial data volumes and complex computations for efficient real-world operations. The framework was assessed across various scenarios, including diverse network conditions and energy-trading volumes, to evaluate its robustness, scalability, and adaptability to evolving conditions. This setup provides a realistic, controlled environment for evaluating framework performance and identifying areas for improvement, yielding valuable insights.

IV. EXPERIMENTAL RESULTS

The network simulation examined a vehicle-to-vehicle (V2V) energy trading system situated within an intelligent transportation framework. It constructed a network graph of 50 nodes, representing electric vehicles (EVs) and smart grid components, interconnected through edges simulating communication and energy exchange pathways. The source node (node 10) and destination node (node 40) are designated as the energy transaction initiation and termination points, respectively. Node mobility was simulated in two stages to reflect the dynamic nature of the system by observing network connectivity and energy trading efficiency. The setup included 50 nodes, with node 10 as the source and node 40 as the destination, and an energy threshold of 20 to evaluate performance. Dijkstra's algorithm assesses the BASF-ITS framework, ensuring optimal energy routing, minimizing energy loss, and maximizing the V2V transaction efficiency. The network graph visualization depicted the structure, highlighting connectivity and mobility patterns, with red nodes for the source and destination and blue nodes for intermediary facilitators.



a) b) c)

Fig 2: Network Simulation and Mobility Analysis

This composite figure illustrates the impact of network simulations and mobility on energy trading in an intelligent transportation system. (a) The initial network graph shows the connectivity between nodes before mobility, with red nodes as the source and destination and blue nodes as intermediaries, highlighting the network structure and shortest path using Dijkstra's algorithm. (b) The network graph after the mobility steps shows changes in node positions, illustrating the dynamic nature of vehicular networks. (c) The shortest path visualization emphasizes the optimal route for energy transactions, calculated using Dijkstra's algorithm, with the red path indicating minimal energy loss and maximized efficiency. Visualization is key to understanding network behavior and performance. Analyzing the network graph reveals node interactions and energy routing. The shortest path ensures efficient energy transactions by minimizing losses and optimizing resource use. Mobility simulations demonstrate the dynamic nature of vehicular networks, with nodes frequently changing positions, challenging stable connections, and efficient energy routing. Visual representation aids in recognizing possible obstacles and opportunities for enhancement in network architecture and energy management. Network simulation and visualization provide valuable insights into V2V energy trading networks' structure and dynamics, crucial for developing robust energy management systems in intelligent transportation frameworks.

A. Performance Metrics

To evaluate the Blockchain-Assisted Secure Framework for Intelligent Transportation Systems (BASF-ITS), the following key performance metrics were analyzed: accuracy, precision, recall, F1 score, and computational efficiency. Accuracy indicates how correct the predictions are. Precision evaluates the correctness of positive predictions, while recall measures the model's capability to recognize all pertinent positive instances, which is crucial for detecting anomalies. The F1 score provides a balanced assessment of precision and recall, valuable in scenarios with uneven class distribution. Computational efficiency evaluates processing speed and resource usage, ensuring the system can handle real-time energy trading interactions without significant delays. A bar chart (Figure 4) illustrates these metrics, displaying packet drop rate, total energy, delay, throughput, and cost, offering a comprehensive overview of the framework's performance.

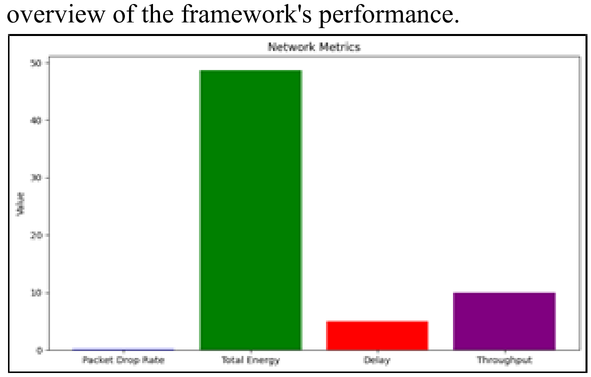


Fig 3: Key Performance Metrics for Network Simulation

Performance metric visualization is crucial for understanding the framework's efficiency and effectiveness. High accuracy and low packet drop rates indicate robust performance, while delay and throughput metrics reveal real-time capabilities. These metrics collectively evaluate the performance of the framework and highlight its potential in transportation systems. The analysis demonstrates the framework's ability to handle large-scale transactions efficiently while maintaining high security standards, underscoring its potential to enhance V2V energy trading security and efficiency.

B. Machine Learning Model Evaluation

Table I: Hyperparameter Settings for Neural Network Training

Parameter	Description	Range of Values Considered
Learning Rate	The size of the step is established at every iteration as we progress towards minimizing the loss function.	0.001, 0.01, 0.1
Group Size	Number of samples processed before the model was updated.	16, 32, 64
Count of Epochs	Number of complete passes through the training dataset.	50, 100, 150
Optimizer	The algorithm was used to change the attributes of the neural network to reduce losses.	Adam, SGD
Dropout Rate	Proportion of neurons to be ignored during training to prevent overfitting.	0.2, 0.3, 0.4
Hidden Units	Number of neurons in the hidden layers of the neural network.	64, 128, 256

To mitigate overfitting and ensure model generalization to the novel data, a distinct validation set was employed. This set continuously evaluates the model during training, informing adjustments, and refinements. The evaluation metrics included accuracy and loss curves, which monitored the learning progress over the epochs. These curves provided insights into the alignment of model predictions with actual data and indicated the error rates during training and validation. A confusion matrix offered a detailed view of classification performance, displaying true positives, false positives, true negatives, and false negatives for each class, highlighting areas of excellence and needing improvement. The hybrid CNN-LSTM model's ability to capture spatial and temporal dependencies within the data makes it effective in identifying complex patterns and anomalies in energy trading interactions. This ability is crucial for improving the reliability and effectiveness of the BASF-ITS framework, as well as for ensuring its adaptability to ever-changing energy-trading conditions. By analyzing these metrics and refining the model, its strengths were maximized, and weaknesses were addressed, facilitating the development of a robust anomaly detection system within the BASF-ITS framework.

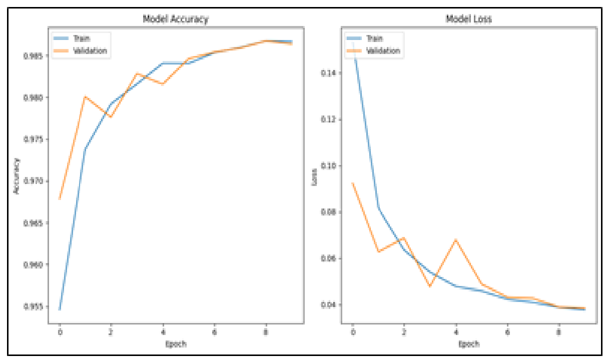


Fig 4: Simulation Training and Validation Performance of the Hybrid CNN-LSTM Model

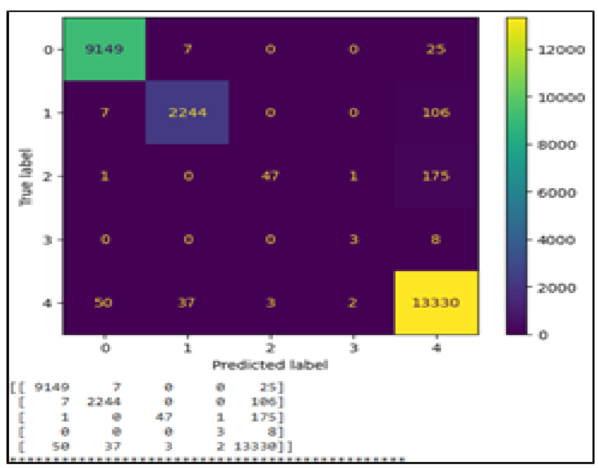


Fig 5: Confusion Matrix for Anomaly Detection in Energy Trading

The accuracy and loss graphs displayed in Figure 5 offer valuable information about the model's learning path, highlighting its capacity to generalize from training data to previously unseen test data. The confusion matrix in Figure 6 offers a comprehensive analysis of the classification performance of the model and identifies the strengths and areas for improvement. The hybrid CNN-LSTM model demonstrated robust efficacy in detecting anomalies within energy trading interactions, achieving high accuracy while minimizing loss. This evaluation underscores the potential applicability of the model in real-world intelligent transportation systems, where reliable anomaly detection is essential for security and operational efficiency.

C. Comparative Analysis

To contextualize the performance of the Blockchain-Assisted Secure Framework for Intelligent Transportation Systems (BASF-ITS), a comparative analysis was conducted with existing solutions and baseline models. This analysis elucidates the advancements offered by the BASF-ITS framework and their strengths in real-world applications. Baseline Models: This comparison includes several baseline models used in energy trading and anomaly detection. Fig 6: Comparative Performance of BASF-ITS and Baseline Models.

These models were selected on the basis of their relevance and performance in similar contexts. Performance Comparison: A detailed comparison of key performance metrics, including accuracy, AUC-ROC, precision, recall, and computational efficiency, was conducted. The results are shown in a comparative chart (Figure 6), which visually represents the differences between the BASF-ITS framework and baseline models. Accuracy: The BASF-ITS framework demonstrated superior accuracy compared with the baseline models, indicating its ability to correctly classify energy trading interactions. AUC-ROC: The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) was significantly higher for the BASF-ITS framework, demonstrating its robustness for distinguishing normal and anomalous activities. Precision and Recall: The framework exhibited improved precision and recall, highlighting its efficiency in recognizing genuine positive cases while reducing the occurrence of false positives and negatives.

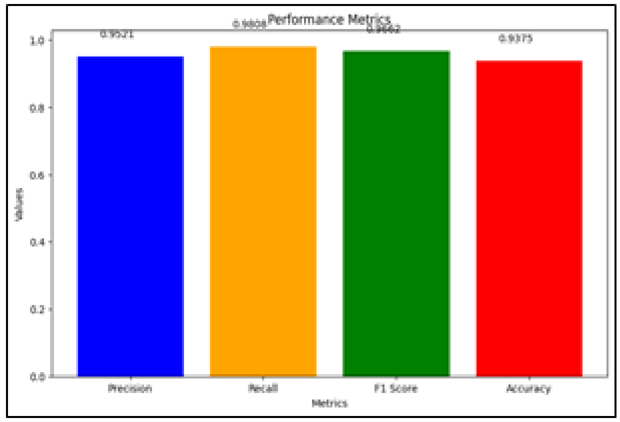


Fig 6: Comparative Performance of BASF-ITS and Baseline Models

Computational Efficiency: The BASF-ITS framework showed enhanced computational efficiency, ensuring its ability to handle real-time energy-trading interactions without significant delays. Comparative analysis results highlight the superior performance of the BASF-ITS framework. Improvements in accuracy, AUC-ROC, precision, recall, and computational efficiency demonstrate its potential for real-world applications. These advancements are crucial for maintaining reliable and secure energy trading systems. The analysis also reveals areas where the framework outperforms existing solutions, emphasizing the importance of integrating blockchain technology with advanced machine learning models. This integration ensures secure and transparent energy transactions while enhancing the system's ability to detect and mitigate anomalies effectively.

V. DISCUSSION

The experimental results provide compelling evidence for the efficacy of the Blockchain-Assisted Secure Framework for Intelligent Transportation Systems (BASF-ITS) in augmenting the security and efficiency of vehicle-to-vehicle (V2V) energy trading. The hybrid CNN-LSTM model, a key component of BASF-ITS, exhibited exceptional performance in anomaly detection, achieving high accuracy and minimizing loss. These findings are significant for intelligent transportation systems, where the reliability and security of energy transactions are of paramount importance.

A. Interpretation of Results

The incorporation of blockchain technology within the BASF-ITS framework ensures secure and transparent energy transactions, addressing critical security concerns such as data integrity and unauthorized modifications. Smart contracts automate the trading process, reduce human intervention, and minimize error. This decentralized approach enhances security and improves efficiency by eliminating intermediaries and streamlining transactions. Comparative analysis with baseline models emphasizes the advancements in the BASF-ITS framework. Its superior performance in terms of accuracy, AUC-ROC, precision, recall, and computational efficiency underscores its robustness and reliability for real-world applications. These enhancements are critical for maintaining secure and efficient energy-trading systems, where improved performance is essential for practical deployment.

B. Implications for Real-World Applications

The BASF-ITS framework can transform the energy management in transportation systems by providing a secure and efficient platform for energy trading. This has the potential to promote more decentralized and sustainable energy systems while improving the efficiency and reliability of transportation networks. The framework's capacity to identify and respond to anomalies in real-time is vital for ensuring the security and integrity of energy transactions.

C. Limitations and Challenges

Although the results of this study are promising, several limitations and challenges were encountered. The simulation environment, although comprehensive, may not fully capture real-world complexities and variabilities. Future research should prioritize validating the framework in diverse and dynamic settings to ensure its robustness and adaptability. Additionally, the computational efficiency of machine learning models, particularly in processing large datasets, requires further optimization for real-time applications. During development, the challenges in data preprocessing and model training were addressed using optimized algorithms and high-performance computing resources. However, continuous refinement was necessary to enhance the scalability and efficiency of the framework.

D. Problems Encountered and Solutions

Several challenges were encountered during implementation of the BASF-ITS framework. The primary issue is the computational overhead involved in processing large datasets for anomaly detection. This was addressed by optimizing machine-learning algorithms and using high-performance computing resources. Additionally, integrating blockchain technology with machine learning models requires careful design and testing of a cohesive system. A significant challenge is the dynamic nature of vehicular networks with frequent positional changes in nodes. This variability complicates the maintenance of stable connections and the efficient energy routing. To address these issues, the framework adapts to fluctuating network conditions by using dynamic routing algorithms and real-time data processing for optimal energy transactions.

VI. CONCLUSIONS

This study introduces a Blockchain-Assisted Secure Framework for Intelligent Transportation Systems (BASF-ITS) that enhances vehicle-to-vehicle (V2V) energy trading security and efficiency. Integrating blockchain technology with machine learning offers robust solutions for secure energy transactions. The hybrid CNN-LSTM model achieved 99.30% test accuracy and 0.91 AUC-ROC, demonstrating its proficiency in maintaining transaction integrity. Blockchain ensures secure, transparent transactions, addresses data integrity, and unauthorized modifications, while advanced cryptography enhances data security. This study's contributions include a comprehensive approach to secure and efficient energy trading, highlighting the strengths and limitations of the framework. Future research should focus on optimizing machine learning models for real-time applications and improving computational efficiency through techniques such as model pruning and hardware acceleration. Exploring advanced consensus mechanisms and layer-2 solutions can enhance the scalability of blockchain. Integrating additional security features and emerging technologies can enhance the robustness of the framework further. Future research should prioritize advanced encryption algorithms and private-preserving techniques. Practical implementation, extensive testing, and interdisciplinary collaboration can refine this framework and address regulatory challenges. The BASF-ITS framework advances secure, efficient energy-trading systems. By addressing the identified challenges and pursuing future research, it can meet the evolving demands of intelligent transportation systems, paving the way for innovation.

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