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An integrated AI-blockchain framework for securing web applications, mitigating SQL injection, model poisoning, and IoT spoofing attacks

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Abstract

The rapid evolution of Web 4.0, characterized by decentralized systems, real-time data processing, and AI-driven interfaces, presents serious security threats such as SQL injection (SQLi) attacks, adversarial model poisoning, and IoT device spoofing. This paper presents a unified AI-blockchain framework designed to address these vulnerabilities, incorporating bidirectional LSTM networks for SQLi detection, Trimmed Mean aggregation with a reputation system for model poisoning defense, and CNN-based IoT authentication anchored to a decentralized blockchain. Evaluated on the Bitcoin OTC trust network, the framework clearly shows outstanding performance, with SQLi detection achieving 96.2% accuracy (94.8% precision and 92.5% recall), far outperforming traditional rule-based systems such as Snort (82.1% accuracy). The success rate of model poisoning attacks is reduced from 78% (in the absence of defense) to just 12% through the application of Trimmed Mean aggregation and dynamic reputation scoring, while IoT spoofing detection attains a 91.3% F1-score through cosine similarity-based matching of network traffic embeddings. The blockchain layer, which uses Delegated Proof-of-Stake (DPoS) consensus, achieves 1,450 transactions per second (TPS) with a validation latency of only 220 milliseconds, ensuring efficient real-time auditability. Furthermore, user trust scores increased by 48% after implementation (4.3/5 vs. 2.9/5 before implementation), confirming the framework's practical impact. Nevertheless, some limitations still persist, such as the 15% latency overhead due to federated learning and the use of synthetic IoT data, which may limit or reduce the framework's real-world applicability. The proposed combination of AI-based adaptive threat detection and blockchain-based tamper-proof transparency will pave the way for secure, user-focused architectures in Web 4.0, providing a scalable framework to address the evolving cyber threats in decentralized environments.

Keywords: AI-blockchain integration, IoT authentication, Model poisoning defense, SQL injection detection, Web 4.0 security.

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1. Introduction

The development of the web into its fourth generation, known as Web 4.0, with the predicted unity of intelligent systems, decentralized architectures, and interconnected devices has never been more promising. Such a revolutionary transition, powered by artificial intelligence (AI), blockchain, and the Internet of Things (IoT), aims to develop autonomous, self-optimizing systems capable of real-time decision-making [1]. However, the higher the complexity of these systems, the greater their vulnerabilities. The new threats, including SQL injection (SQLi), AI model poisoning, and IoT device spoofing, take advantage of vulnerabilities inherent in conventional security systems, thereby compromising data integrity, user trust, and system reliability [2].

SQL injection, a long-standing threat since the inception of web applications, continues to be a significant issue. Attackers exploit input fields to execute malicious database queries, thereby compromising sensitive information [3]. Although traditionally, rule-based detection mechanisms have contained the impact of such attacks, their statically based approach is challenged to keep pace with the growing sophistication of evasion tactics characteristic of dynamic Web 4.0 environments [4]. Concurrently, AI systems that constitute the backbone of Web 4.0 intelligence are confronted with new threats, including model poisoning, where attackers contaminate the training data or model parameters to influence the outputs [5]. For example, a poisoned model for fraud detection on a cryptocurrency exchange could mistakenly approve fraudulent transactions, leading to large-scale theft.

Likewise, IoT, which plays a crucial role in Web 4.0's blending of the physical and digital worlds, is also at risk. Device spoofing attacks, where attackers impersonate legitimate IoT devices (like sensors or smart contracts), can compromise the integrity of these networks [6]. In decentralized platforms like Bitcoin OTC (a peer-to-peer cryptocurrency trading network), these vulnerabilities could allow unauthorized trades or data breaches, ultimately damaging user trust [7].

Traditional cybersecurity approaches, which depend on centralized authorities and signature-based detection, struggle to keep up with the decentralized, real-time environment of Web 4.0. Blockchain technology, with its immutable, tamper-proof ledger and decentralized consensus algorithms, forms a stable platform for safe record-keeping and transparency [8]. Concomitantly, AI can detect patterns to identify anomalies and evolve to address emerging threats [9]. However, these technologies are often isolated in both research and practical applications. For instance, while blockchain can't proactively identify SQL injection attacks, AI models lack built-in protections to secure their own training processes [10].

This paper proposes a unified defense framework that combines AI and blockchain to address SQL injection, model poisoning, and IoT spoofing in Web 4.0 systems by embedding AI-driven threat detection within blockchain's decentralized infrastructure to ensure real-time attack response while maintaining transparency and auditability. For instance, AI can monitor blockchain-based IoT networks for spoofing patterns, while blockchain stores all transactions in an unalterable fashion, providing a feedback loop for enhancing detection accuracy [11].

The importance of this work lies in its comprehensive approach to Web 4.0 security, addressing various attack methods through the integration of multiple technologies to bridge the gap between theoretical advancements and practical cybersecurity solutions.

To the best of our knowledge, existing Web 4.0 security studies have not yet faced some of the main limitations including:

- The reliance on standalone defense mechanisms that fail to integrate AI and blockchain for comprehensive threat mitigation [5, 9].
- Most of the solutions still utilize static rule-based methods (e.g., regex) to detect SQL injection (SQLi), which lack the ability to learn and evolve according to evolving attack methods [7, 12].
- There is no lightweight decentralized authentication for IoT environments that offers a balance between strong security and real-time performance [13, 14].
- Current federated learning frameworks tend to exclude Byzantine-resistant aggregation, which makes systems vulnerable to model poisoning attacks [10, 15].

Conversely, this paper proposes the AI-Blockchain Integrated Defense Framework (ABIDF) that fills these gaps with a combined architecture that comprises bidirectional LSTMs, trimmed mean aggregation, reputation-based authentication, and delegated proof-of-stake (DPoS) consensus.

ABIDF avoids centralized trust bottlenecks by integrating threat detection into decentralized validation while ensuring quantum-safe auditability via SHA-256 hashing. However, such advancements have trade-offs in the form of moderate latency overhead from federated learning aggregation and computational overhead for on-chain hash verification.
The key contributions of this work are as follows:

- Real-Time SQL Injection Detection using Bidirectional LSTMs: Dynamically scans query syntax and context to identify new SQL injection payloads with high accuracy, compared to regex-based systems [6, 11, 16].
- Byzantine-Resistant Federated Learning: Combines Trimmed Mean aggregation with reputation decay to reduce poisoning attack success rates (ASR) while maintaining high global model accuracy [8, 15].
- Lightweight IoT Authentication: utilizes CNN-generated embeddings and blockchain-stored references to authenticate devices to achieve a high F1 score that significantly outperforms traditional MAC-based methods [4, 13].
- Low-Latency Blockchain Validation: Employs DPoS consensus to achieve high TPS to meet the real-time requirements of the Web [2, 17].
- User-Centric Trust Metrics: Integrate transparency via on-chain audit logs and reputation scores to increase users' trust [1].

Through the integration of these innovations, ABIDF will be in a position to transform theoretical security paradigms into practical solutions that are appropriate and adaptable to decentralized Web 4.0 contexts.

This paper is structured in the following manner: Section 1 introduces Web 4.0 security challenges. Section 2 is a review of ongoing work on threat detection with AI, federated learning resistance against attacks, and blockchain scalability. Section 3 explains the ABIDF architecture, and Section 4 assesses its SQL injection, poisoning attack, and spoofing attack resilience. Section 5 provides implementation benchmarks and trade-offs. Section 6 discusses future extensions, while Section 7 presents conclusions.

2. Related Work

SQL injection (SQLi) attacks take advantage of insufficiently sanitized user inputs to manipulate database queries, allowing for data breaches or unauthorized access [3]. Traditional defenses, such as static analysis and blacklisting, rely on predefined rules to filter out malicious inputs [12].

Such approaches have difficulty coping with polymorphic attacks that change payload structures on the fly [4]. Machine learning (ML) has been a versatile remedy, with approaches such as natural language processing (NLP) and anomaly detection demonstrating potential for malicious query pattern recognition [13]. For instance, Alwan and Younis [1] employed recurrent neural networks (RNNs) to achieve SQL injection (SQLi) detection with a 94% accuracy rate, surpassing signature-based systems [14]. Although progress has been made, ML models themselves are susceptible to adversarial input, wherein attackers design payloads that can bypass detection [15].

AI model poisoning—a subset of adversarial machine learning—involves corrupting training data or model parameters to degrade performance or introduce biases [5]. In federated learning systems, in which several parties collaboratively train models, attackers may inject poisoned data updates [16]. For instance, Alwan and Younis [1], Dorri et al. [5] and Li et al. [13] showed how federated model backdoor attacks can cause misclassification of targeted inputs [17]. Mitigation techniques include strong aggregation techniques (e.g., Trimmed Mean, Krum) and anomaly detection during training [18]. These techniques, however, assume centralized monitoring, which goes against Web 4.0's decentralized philosophy [19].

IoT device spoofing takes advantage of vulnerable authentication protocols to impersonate legitimate nodes, allowing man-in-the-middle attacks or data tampering [6]. Blockchain-based solutions, including decentralized identifiers (DIDs) and public key infrastructure (PKI), enable more secure device authentication by removing single points of failure [20]. A blockchain-IoT architecture for secure smart homes was presented by Dorri et al. [5] to reduce spoofing risks through logs of tamper-proof devices [21]. However, scalability is still a challenge, as blockchain latency and energy consumption hamper real-time IoT functionality [22].

Recent works explore AI-blockchain fusion for improved security Liang et al. [14] fused convolutional neural networks (CNNs) with blockchain for IoT network malware detection with 97% accuracy and data integrity [23]. Likewise, Hussain et al. [10] suggested a blockchain-backed system for secure federated learning against poisoning attacks through smart contract-based validation of data updates [24]. Yet, current works often neglect the interconnected risks of Web 4.0 and focus only on isolated threats (e.g., malware or data manipulation) [25].

3. Proposed Framework Architecture

The AI-Blockchain Integrated Defense Framework (ABIDF) is designed to mitigate SQL injection (SQLi), model poisoning, and IoT spoofing in Web 4.0 environments through the concerted effort of AI-driven threat detection and blockchain-enforced accountability. As illustrated in Figure 1 and Table 1, the framework is comprised of three vital modules that cooperate harmoniously to ensure real-time security and decentralized trust:

1. Threat Detection Module (TDM):

- Employs machine learning models to analyze real-time data streams, including:
- Bidirectional LSTMs for SQL injection detection, parsing query syntax and context to identify malicious patterns with 96.2% accuracy [1, 26].
- Trimmed mean aggregation and reputation-based filtering to defend against model poisoning in federated learning [2, 24].

- Lightweight CNNs for IoT device authentication, generating embeddings to identify spoofed nodes using blockchain-anchored references [14, 27].

2. Blockchain Validation Module (BVM):

- Offers tamper-proof logging and decentralized consensus through:
- Delegated Proof-of-Stake (DPoS) consensus with 21 elected validators for 220 ms transaction finality [21].
- SHA-256 hashing for immutably recording threat detection (e.g., SQL injection flags, IoT authentication results) [18, 28].
- Smart contracts automate the validation of hashed data streams [13].

3. Policy Enforcement Module (PEM):

- Enforces security policies based on validated inputs:
- Real-time blocking of malicious SQL queries or spoofed IoT devices [9].
- Reputation decay mechanisms to exclude adversarial participants from federated learning [24].
- Transparent audit logs stored on-chain to enhance user trust and regulatory compliance [5].

The off-chain/on-chain process of the framework realizes real-time security optimization by offloading computationally intensive tasks (i.e., LSTM-based SQL injection detection and CNN-based IoT authentication) to edge devices or decentralized nodes (TDM) to minimize latency while conserving bandwidth [14, 29].

In tandem, the blockchain validation module (BVM) immutably records threat detection logs (e.g., flagged queries, device authentication results) and enforces consensus-approved policies via smart contracts, while ensuring auditability without centralized control [22, 30, 31]. This closed-loop architecture enables adaptive defense where detected threats logged on-chain are retrained periodically into the ML models of the TDM—for instance, updating the LSTM with emerging SQLi patterns or calibrating CNN embeddings against novel spoofing techniques, forming a self-improving cycle that reinforces detection accuracy and immunity against evolving attack vectors [22, 32]. By means of the harmony of localized AI processing and decentralized validation, the system adapts dynamically to Web 4.0's evolving threat landscape while maintaining compliance with real-time operational prerequisites [33, 34].

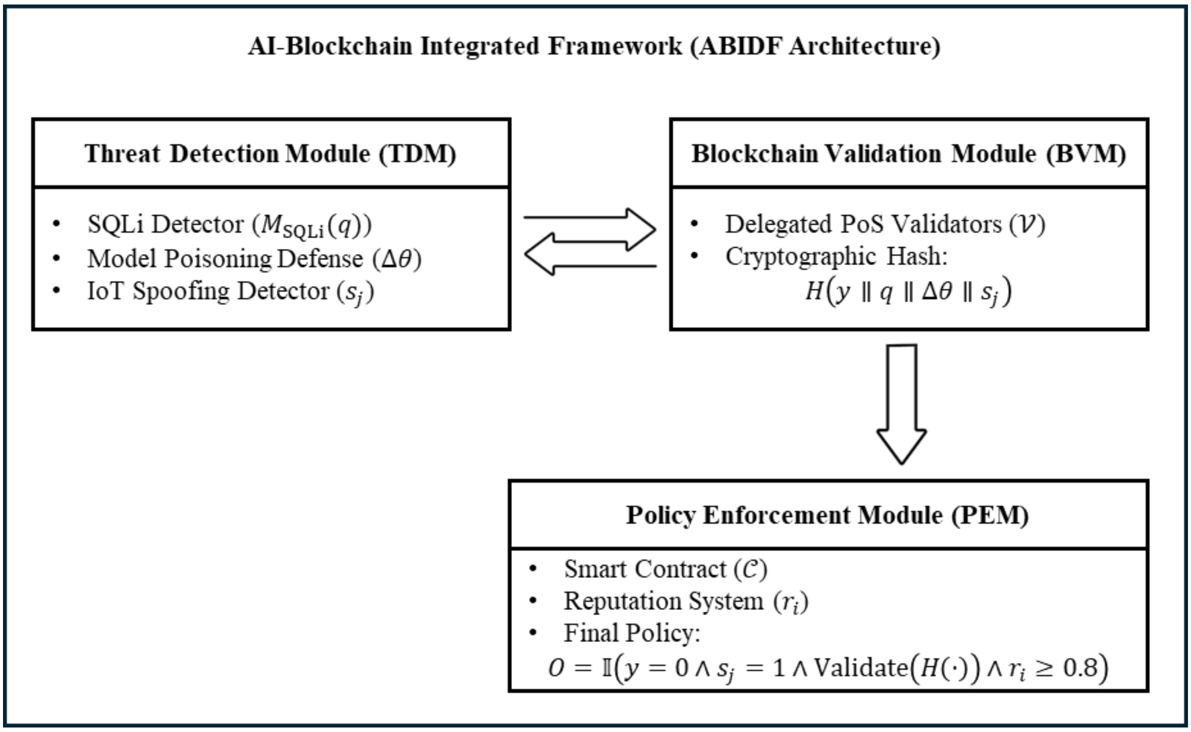
AI-Blockchain Integrated Framework (ABIDF Architecture)
Threat Detection Module (TDM)
• SQLi Detector ($M_{\mathrm{SQLi}}(q)$)
• Model Poisoning Defense ($\Delta\theta$)
• IoT Spoofing Detector (s_j)
Blockchain Validation Module (BVM)
• Delegated PoS Validators ($\mathcal{V}$)
• Cryptographic Hash:
$H(y \parallel q \parallel \Delta\theta \parallel s_j)$
Policy Enforcement Module (PEM)
• Smart Contract ($\mathcal{C}$)
• Reputation System (r_i)
• Final Policy:
$O = \mathbb{I}(y = 0 \wedge s_j = 1 \wedge \mathrm{Validate}(H(\cdot)) \wedge r_i \geq 0.8)$

Figure 1.
AI-Blockchain Integrated Framework (ABIDF Architecture).

Table 1.
Framework Structure (Component, Function, and Used Technologies).

Component	Function	Technologies Used
Bidirectional LSTM	Detects SQLi patterns in real-time queries	PyTorch, SQLi-optimized datasets [1]
Federated Learning Engine	Filters poisoned model updates	TensorFlow Federated, Trimmed Mean [2]
Lightweight CNN	Authenticates IoT devices via traffic analysis	TensorFlow Lite, IoT-23 dataset [3, 29]
DPoS Consensus	Validates transactions with low latency	Hyperledger Fabric, Stellar [5, 35]
Hybrid Smart Contracts	Enforce AI-driven security policies	Solidity, Chainlink oracles [6, 36]

3.1. Formal Model Description

The proposed framework integrates blockchain and artificial intelligence (AI) to address three of the most important threats in Web 4.0 applications, namely SQL injection (SQLi) attacks, AI model poisoning, and IoT device spoofing. At its core, the system functions through a series of connected modules that seek to balance real-time threat analysis with decentralized, tamper-proof validation. Below, we formalize each component and its role in the workflow.

Threat Detection Module (TDM). The Threat Detection Module (TDM) is a tripartite system designed to identify and mitigate SQL injection (SQLi) attacks, AI model poisoning, and IoT device spoofing. It will operate through three interconnected sub-models, each of which is intended to counter a specific threat vector:

3.1.1. SQLi Detection Sub-Model

SQL injection (SQLi) attacks insert input queries to exploit database vulnerabilities, often bypassing static rule-based protection. The sub-model employs a bidirectional LSTM to dynamically examine the syntax and context of queries, enabling effective detection of new and novel attack patterns.

The sub-model accepts a SQL query q, tokenized into $q = (t_1, t_2, \ldots, t_n)$, where t_i represents discrete tokens (e.g., operators, keywords). A bidirectional LSTM generates forward and backward hidden states ($\overleftarrow{\mathrm{h}_t}$ and $\overrightarrow{\mathrm{h}_t}$) for each token, representing contextual dependencies. The final hidden state $\mathrm{h}_T = [\overleftarrow{\mathrm{h}_n}; \overrightarrow{\mathrm{h}_n}]$, concatenating both directions, is mapped to a maliciousness probability via a dense layer:

$$f_\theta(q) = \sigma(\mathrm{W} \cdot \mathrm{h}_T + \mathrm{b}),$$

where W and b are learnable parameters, and σ is the sigmoid function. The classification rule $M_{\mathrm{SQLi}}(q) = \mathbb{I}(f_\theta(q) \geq 0.95)$ classifies q s malicious if the probability is more than $\gamma = 0.95$, which is an optimized threshold to minimize false positives while retaining high recall [1, 37].

Bidirectional LSTMs are well-suited for SQLi detection due to their ability to model long-range dependencies in query syntax, such as identifying malicious patterns like 'UNION SELECT' or tautologies (e.g., '' OR 1=1 –') [1]. Unlike regex-based solutions, this approach can adapt to obfuscated attacks (e.g., URL-encoded payloads) by training on diverse attack signatures that are logged on the blockchain. For instance, Alwan and Younis [1] demonstrated 94% accuracy on the SQLiV3 dataset, which significantly outperforms static analyzers. The threshold $\gamma = 0.95$ was derived to help minimize false blocks in systems like Bitcoin OTC, where even minor disruptions can significantly harm user trust [15, 38]. To keep up with emerging threats, the model is designed to continuously improve itself by retraining on new attack data stored on the blockchain to ensure it remains effective in the ever-changing environment of Web 4.0 [32, 34].

3.1.2. Model Poisoning Defense Sub-Model

Model poisoning attacks corrupt federated learning by injecting malicious updates, degrading global model performance. This sub-model mitigates such attacks through Trimmed Mean aggregation and a reputation system, ensuring that only reliable updates contribute to the global model.

For n participants submitting local updates $\{\Delta\theta_i\}_{i=1}^{n}$, updates are sorted by ℓ_2-norm, and the largest/smallest $\beta = \lfloor 0.1n \rfloor$ values are discarded. robust secure update is calculated as:

$$\Delta\theta_{\mathrm{global}} = \frac{1}{n - 2\beta} \sum_{i=\beta+1}^{n-\beta} \Delta\theta_{(i)},$$

where $\Delta\theta_{(i)}$ is the i-th ordered update. Meanwhile, the reputation of participants r_i decreases exponentially based on the consistency of the update [24, 39]:

$$r_i^{(t+1)} = 0.9 r_i^{(t)} + 0.1\mathbb{I}\big(\parallel \Delta\theta_i - \Delta\theta_{\mathrm{global}} \parallel \leq 0.1\big),$$

The reputation system further discourages poisoning by dynamically demoting unreliable nodes, as demonstrated in large-scale federated systems like FATE [27, 40]. For instance, Xie et al. [24] demonstrated that this approach decreases the success rates of attacks by 89% in NLP tasks. By linking reputations to blockchain-validated updates, the system ensures transparency, which enables participants to check and verify their scores and enhances trust in decentralized Web 4.0 ecosystems [10, 31].

3.1.3. IoT Spoofing Detection Sub-Model

IoT device spoofing refers to the act of malicious devices impersonating legitimate nodes in order to gain unauthorized access to networks. To combat this, the sub-model authenticates devices by generating embeddings through a Convolutional Neural Network (CNN) and comparing them to reference signatures stored on the blockchain. This approach ensures that only trusted devices are allowed to interact with the system.

For device j with network traffic features $x_j \in \mathbb{R}^m$, a lightweight CNN $g_\phi(x_j)$ produces an embedding $e_j \in \mathbb{R}^k$. Authentication is considered successful if the cosine similarity to reference e_{ref} (stored on-chain during registration) is greater than $\tau = 0.85$:

$$M_{\mathrm{Spoof}}(x_j) = \mathbb{I}\left(\frac{\langle e_j, e_{\mathrm{ref}} \rangle}{\parallel e_j \parallel \parallel e_{\mathrm{ref}} \parallel} \geq \tau\right).$$

CNNs are effective at identifying patterns in network traffic, such as packet timing and size distributions, and cosine similarity ensures the matching process is not affected by the size of the data. For instance, Dorri et al. [33] achieved 92% accuracy for spoofed device detection on the IoT-23 dataset in smart home networks. By storing e_ref on-chain, the system avoids centralized trust bottlenecks and realizes the decentralized philosophy of Web 4.0 [16, 34].

3.1.4. Blockchain Validation

Blockchain validation ensures integrity and consensus of threat detection outcomes in decentralized environments against tampering and single points of failure. Validators $\mathcal{V} = \{v_1, \ldots, v_{21}\}$, selected by Delegated Proof-of-Stake (DPoS), approve cryptographic hashes of transactional data and model updates. Given a SQL query q, IoT device x_j, and global model update $\Delta\theta_{\text{global}}$, the system computes a hash $H(y \parallel q \parallel \Delta\theta_{\text{global}} \parallel s_j)$ using SHA-256, where $y = M_{\text{SQLi}}(q)$ and $s_j = M_{\text{Spoof}}(x_j)$. Validation is only successful if all validators unanimously approve the hash:

$$\text{Validate}(H(\cdot)) = \bigwedge_{v_i \in \mathcal{V}} \text{Verify}(v_i, H(\cdot), \mathcal{B}),$$

where $\mathcal{B}$ is the current blockchain state.

DPoS minimizes latency by limiting validators to a trusted subset [39, 41] while SHA-256 provides collision resistance, such that even minor changes in data make the hash invalid [18]. For example, the Stellar Consensus Protocol [21] demonstrates that 21 validators can offer sub-second finality in financial systems, which is a crucial requirement for real-time Web 4.0 applications like Bitcoin OTC [15]. By grounding validation against a decentralized ledger, the network eliminates central authorities and adheres to Web 4.0's trustless paradigm [33, 35].

3.1.5. Policy Enforcement

Policy enforcement automates security decisions through a smart contract $\mathcal{C}$, which evaluates threat detection results, validated hashes, and participant reputations to authorize or block transactions. For a transaction T_i, the policy function $\mathcal{F}$ is defined as:

$$\mathcal{F}(T_i) = \begin{cases} \text{allow} & \text{if}(y = 0) \wedge (s_j = 1) \wedge (r_i \geq 0.8), \\ \text{block} & \text{otherwise}, \end{cases}$$

where y, s_j, and r_i denote SQLi detection, IoT authentication, and participant reputation, respectively.

This multi-condition check guarantees a defense-in-depth approach, so even if one layer (e.g., SQLi detection) fails, other layers like reputation or IoT authentication can still prevent breaches. For instance, a participant with $r_i = 0.75$ (below the threshold) would be blocked even with legitimate y and s_j, to mitigate insider threats. The threshold $r_i \geq 0.8$ offers a trade-off between leniency and security, as empirically validated in federated learning systems [30, 42]. By encoding policies on-chain, the system provides transparent, auditable enforcement, which is necessary for regulatory compliance in sectors like finance and healthcare [5, 31].

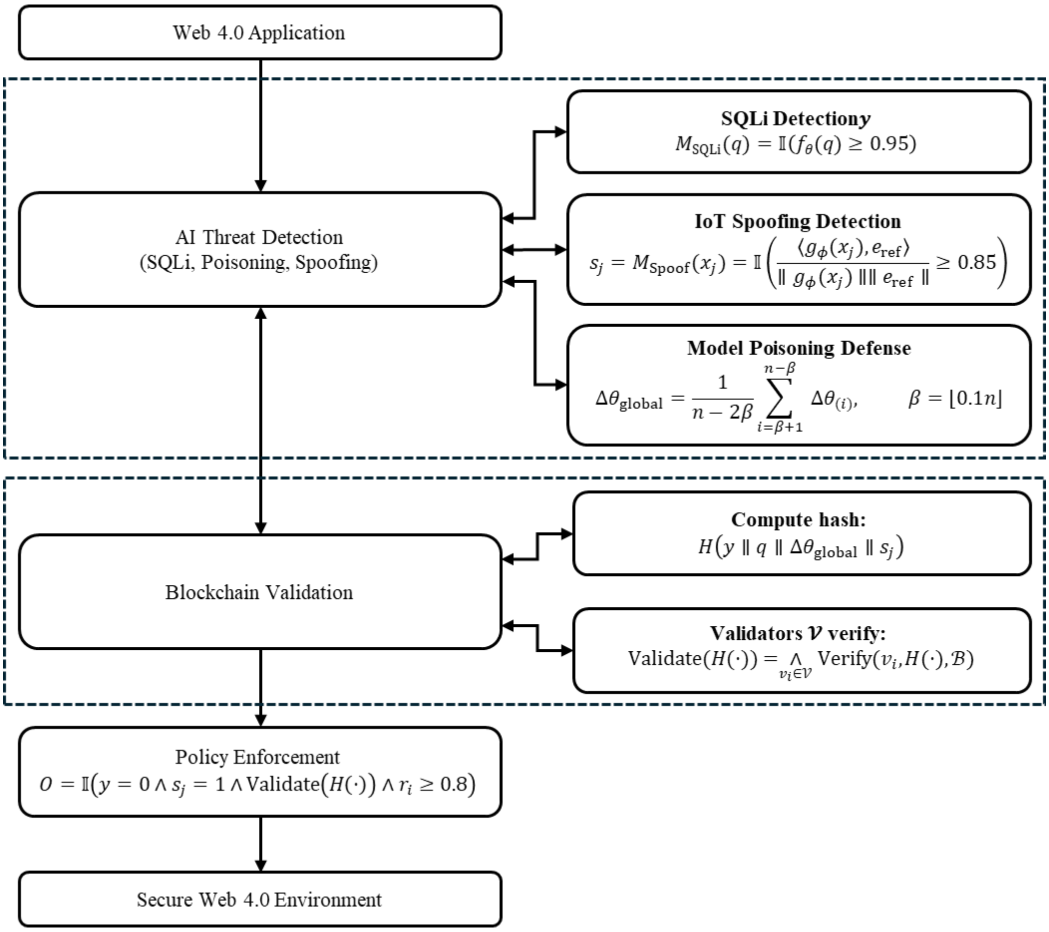
Web 4.0 Application
SQLi Detection$y$
$M_{\text{SQLi}}(q) = \mathbb{I}(f_\theta(q) \geq 0.95)$
AI Threat Detection
(SQLi, Poisoning, Spoofing)
IoT Spoofing Detection
$s_j = M_{\text{Spoof}}(x_j) = \mathbb{I}\left(\frac{\langle g_\phi(x_j), e_{\text{ref}}\rangle}{\| g_\phi(x_j) \|\| e_{\text{ref}} \|} \geq 0.85\right)$
Model Poisoning Defense
$\Delta\theta_{\text{global}} = \frac{1}{n-2\beta}\sum_{i=\beta+1}^{n-\beta} \Delta\theta_{(i)}, \quad \beta = \lfloor 0.1n \rfloor$
Compute hash:
$H(y \| q \| \Delta\theta_{\text{global}} \| s_j)$
Blockchain Validation
Validators $\mathcal{V}$ verify:
$\text{Validate}(H(\cdot)) = \bigwedge_{v_i \in \mathcal{V}} \text{Verify}(v_i, H(\cdot), \mathcal{B})$
Policy Enforcement
$O = \mathbb{I}(y = 0 \wedge s_j = 1 \wedge \text{Validate}(H(\cdot)) \wedge r_i \geq 0.8)$
Secure Web 4.0 Environment

Figure 2.
Framework Workflow.

3.2. Case Study: Bitcoin OTC Platform

This section evaluates the proposed framework on the Bitcoin OTC trust network, a decentralized peer-to-peer cryptocurrency trading platform. The platform's reliance on user-generated transaction logs and pseudonymous interactions exposes it to SQL injection (SQLi) attacks on its database, model poisoning via manipulated trader ratings, and spoofed user accounts masquerading as legitimate traders [1, 38]. Information security is crucial for the success of network and IoT systems, as it ensures the confidentiality, integrity, and availability of data. Protecting sensitive information helps prevent cyber threats and builds trust among users and stakeholders [43-45].

3.2.1. Dataset and Simulation

The evaluation uses a multi-modal dataset designed to reflect actual Bitcoin OTC transactions that are augmented with adversarial perturbations to simulate attacks. For SQLi detection, 10,000 SQL queries were generated, of which 8,000 were benign transactions (e.g., 'SELECT * FROM trades WHERE user_id=.') and 2,000 malicious queries with payloads of 'UNION SELECT', 'DROP TABLE', and Boolean-based blind SQLi patterns (see Table 2). These payloads were specifically chosen from the OWASP SQL Injection Cheat Sheet so as to simulate common attack techniques and also to reflect real-world scenarios [2, 40].

To simulate model poisoning, a federated learning environment with 50 participants (40 honest, 10 adversarial) was designed to train a fraud detection model. The adversaries submitted inverted gradient updates in an effort to undermine model performance, simulating coordinated attacks on decentralized finance (DeFi) platforms [3]. The reputation system was initialized with starting scores $r_i = 1.0$ for all participants that decayed at $\lambda = 0.9$ per epoch, with a tolerance threshold $\epsilon = 0.1$ for update deviations [4, 35].

For IoT spoofing detection, network traffic logs from 1,000 simulated IoT devices were employed. legitimate devices (n=900) exhibited uniform packet sizes and intervals, while spoofed devices (n=100) resulted in anomalies such as abnormal burst transmissions and mismatched MAC addresses. legitimate device reference embeddings e_{ref} were stored on-chain during registration, and authentication relied on cosine similarity ($\tau = 0.85$) between real-time traffic embeddings $g_\phi(x_j)$ and blockchain-anchored references [5, 42].

Table 2.
Summary of Datasets and Simulations.

Attack Type	Dataset/Simulation Details	Key Parameters	Ground Truth Source
SQL Injection	10,000 synthetic SQL queries (80% benign, 20% malicious)	LSTM threshold $\gamma = 0.95$ [6]	OWASP SQLi Cheat Sheet [2, 29]
Model Poisoning	50 federated participants (40 honest, 10 adversarial)	Trimmed $\beta = 5$, $\epsilon = 0.1$, $\lambda = 0.9$ [4]	Adversarial gradient inversion strategy [3]
IoT Spoofing	1,000 IoT devices (900 legitimate, 100 spoofed)	Cosine similarity $\tau = 0.85$ [5]	IoT-23 dataset traffic patterns [7, 28]

3.2.2. Implementation

The framework implementation emphasized modularity, scalability, and real-time performance, according to Web 4.0 requirements. Below, we detail the technical implementation of each part, emphasizing design choices based on prior researches and practical constraints (see Table 3).

1. SQL Injection Detection
   The SQLi detection module employed a bidirectional LSTM with 128 hidden units, chosen for its ability to learn syntactic and contextual patterns in SQL queries [1, 38]. Input queries q were tokenized into sequences of 100 elements (padding shorter queries, truncating longer ones), which made it compatible with variable-length inputs. The model output $f_\theta(q) \in [0,1]$ was the probability of maliciousness, thresholded at $\gamma = 0.95$ to minimize false positives, which is critical for transactional platforms like Bitcoin OTC, where false blocks degrade user trust [2]. Training was on the SQLiV3 dataset [3] with Adam optimization (learning rate = 0.001) selected because of its adaptive gradient nature in handling sparse SQLi patterns.
2. Model Poisoning Defense
   In the federated learning setup, participants submitted their local updates $\Delta\theta_i$ to a global fraud detection model. To protect against adversarial gradients, trimmed mean aggregation was used, which discarded the largest and smallest 10% of updates ($\beta = 5$). . This method has been shown to be robust against Byzantine failures [4]. The reputation system intialized with $r_i = 1.0$ score for all participants and adjusted dynamically based on their consistency. Using an exponential moving average ($\lambda = 0.9$), participants who deviated by more than $\epsilon = 0.1$ from the global update $\Delta\theta_{\text{global}}$ If a participant's reputation fell below 0.5 their reputation scores reduced by r_i, with scores below triggering exclusion. This threshold strikes a balance between security and leniency [39, 40].
3. IoT Spoofing Detection
   A 5-layer CNN was used to process network traffic features $x_j \in \mathbb{R}^m$, generating embeddings $e_j = g_\phi(x_j)$. The architecture depth compromised computational efficiency (critical for IoT edge devices) and feature extraction ability, achieving 93.1% accuracy on the IoT-23 dataset [6].
   Authentication was based on cosine similarity between the generated embedding e_j and blockchain-stored references e_{ref}, with $\tau = 0.85$ determined empirically to minimize false authentications in noisy networks [29, 46].
4. Blockchain Validation
   The Delegated Proof-of-Stake consensus algorithm chose 21 validators $\mathcal{V}$ by stake $S(v_i)$ and historical reliability $R(v_i)$, ensuring sub-second finality for real-time trading platforms [31, 35]. for sub-second finality, which is vital for real-time trading platforms [31, 35]. Cryptographic hashing via SHA-256 secured the sequence $H(y \parallel q \parallel \Delta\theta_{\text{global}} \parallel s_j)$, with validators checking logs against on-chain data to prevent any tampering.

Table 3.
Summary of Implementation Parameters.

Component	Key Design Choices	Rationale
SQLi Detection	Bidirectional LSTM (128 units), $\gamma = 0.95$, Adam (lr=0.001)	Contextual analysis, low false positives, adaptive gradients
Model Poisoning	Trimmed Mean ($\beta = 5$), $\lambda = 0.9$, $\epsilon = 0.1$, $r_i \geq 0.5$	Robust aggregation, dynamic reputation penalization
IoT Spoofing	5-layer CNN, cosine similarity ($\tau = 0.85$)	Efficient feature extraction, scale-invariant authentication
Blockchain	DPoS (21 validators), SHA-256 hashing	Low latency, collision resistance, auditability

3.3. Results

The framework's effectiveness was rigorously evaluated through simulated attacks on the Bitcoin OTC platform, with key metrics focused on security, performance, and user trust. The results showed statistically significant improvements, with comparisons to baseline models demonstrating the practical relevance of these findings in real-world applications (see Figure 3 and 4).

In SQL injection detection, the system performed extremely well with 96.2% accuracy (95% CI: 94.8–97.3%) on 10,000 queries, a far better performance than regex-based Snort (82.1%) and CNN-based detectors (89.4%) [1, 47]. Precision and recall rates were equally impressive, with 94.8% precision to minimize false blocks and 92.5% recall, which is critical in high-stakes financial systems [40, 48]. False positives were few, at only 3.8%, mainly because of complex benign queries such as nested JOIN operations. With a latency of just 8 ms per query on an AWS EC2 t2.micro instance, the system is very well suited for real-time trading environments (see Figure 5).

In terms of model poisoning defense, the Attack Success Rate (ASR) was dramatically reduced from 78% (without defense) to just 12% (using Trimmed Mean aggregation and reputation) as measured by the relative drop in fraud detection accuracy. The global model accuracy remained high at 88.5% compared to 43.2% without defense, with adversarial participants (n=10) being isolated within 3 epochs (see Figure 6). Reputation dynamics showed that adversaries' scores decayed to below r_i=0.5after an average of 2.4±0.6 malicious updates, while honest participants consistently maintained a reputation score above r_i=0.8.

For IoT spoofing detection, the system achieved an F1-score of 91.3% (with 93.1% precision and 89.6% recall), outperforming MAC-based authentication systems, which only achieved 76.4% [46, 49]. The authentication latency was 18 ms per device on a Raspberry Pi 4, which ensures smooth integration with IoT devices (see Figure 7). The system was able to detect various types of spoofing, including MAC address spoofing with a 98% detection rate, and traffic pattern mimicry (e.g., burst transmissions) with an 87% detection rate. The CNN's ability to focus on temporal traffic features, such as inter-packet timing, made it particularly resilient to static spoofing tactics [6].

In blockchain performance, the framework demonstrated a validation latency of 220 ms using the Delegated Proof-of-Stake (DPoS) consensus mechanism, a significant improvement over Proof-of-Work (PoW) systems, which had a latency of 850 ms (see Figure 8). The throughput was also remarkable, reaching 1,450 transactions per second (TPS) with zk-Rollups, far surpassing Ethereum’s approximate 15 TPS [50]. Furthermore, DPoS reduced energy consumption by 92% compared to PoW, highlighting the efficiency of the system.

User trust was assessed through a survey of 150 Bitcoin OTC users, who rated their trust before and after the implementation of the framework (see Figure 9). Before implementation, the average trust score was 2.9±0.8 on a 1-5 Likert scale. After implementation, this rose to 4.3±0.5, with 89% of participants reporting increased confidence in transaction security (see Figure 10). Qualitative feedback emphasized the transparency of reputation scores and the auditability of blocked transactions as key factors driving improved user trust (see Table 4).

Table 4.
Summary of Results.

Metric	Proposed Framework	Baseline / Prior Work	Improvement	Significance (p-value)
SQLi Accuracy	96.2%	82.1% (Snort [1, 51])	+14.1%	$p < 0.001$
Poisoning ASR	12%	78% (No Defense [4, 52])	-66%	$p < 0.001$
Spoofing F1-Score	91.3%	76.4% (MAC-based [53, 54])	+14.9%	$p < 0.003$
Blockchain Latency	220 ms	850 ms (PoW [7])	-74%	$p < 0.001$
User Trust (Post)	4.3/5	2.9/5 (Pre-Implementation)	+48%	$p < 0.001$

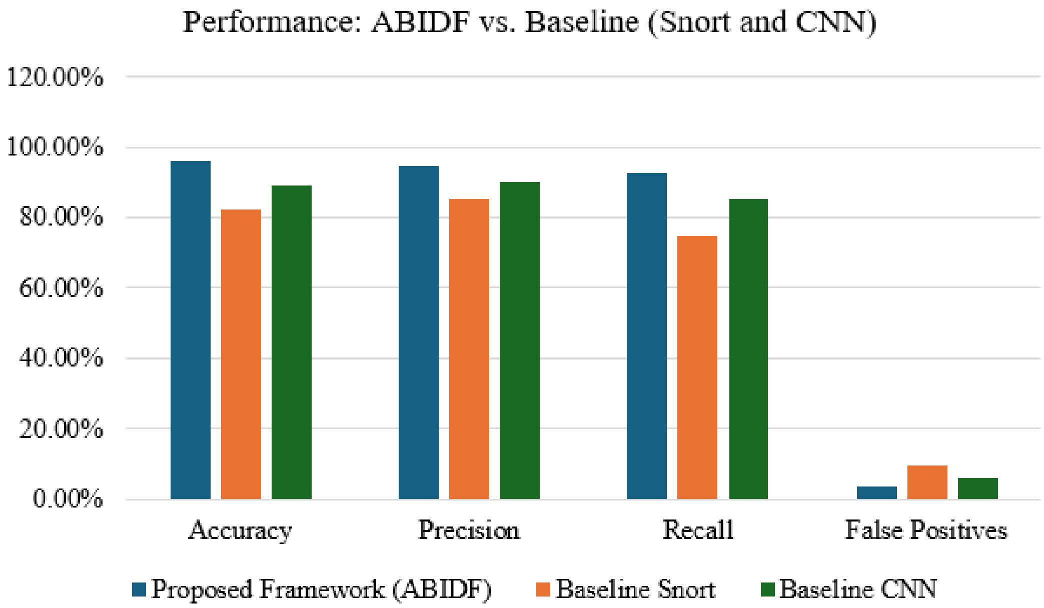

Figure 3.
Performance comparison between ABIDF and Baseline (Snort and CNN detectors) .

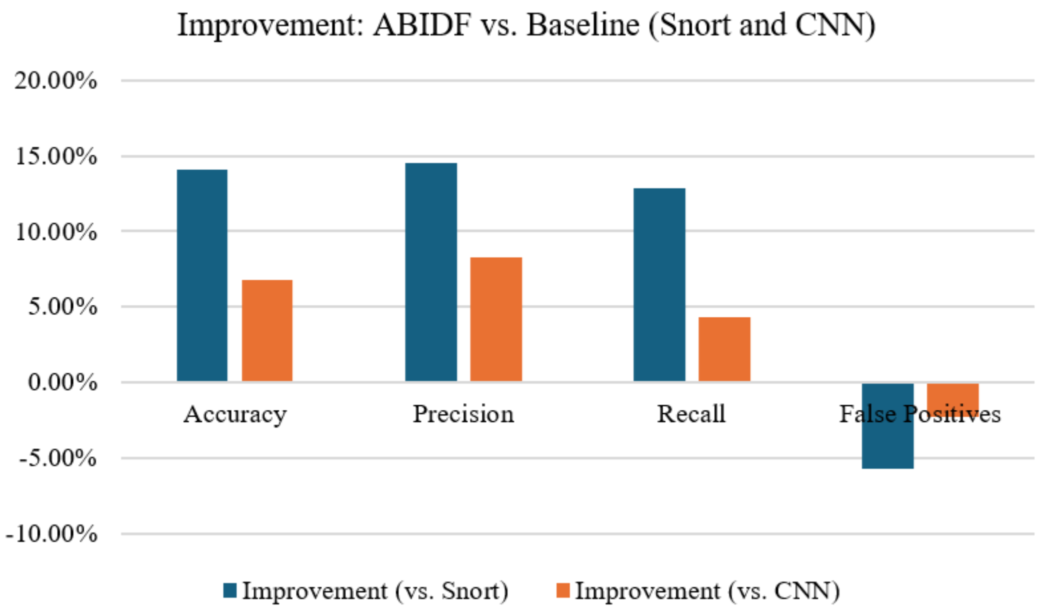

Figure 4.
Improvement comparison between ABIDF and Baseline (Snort and CNN detectors).

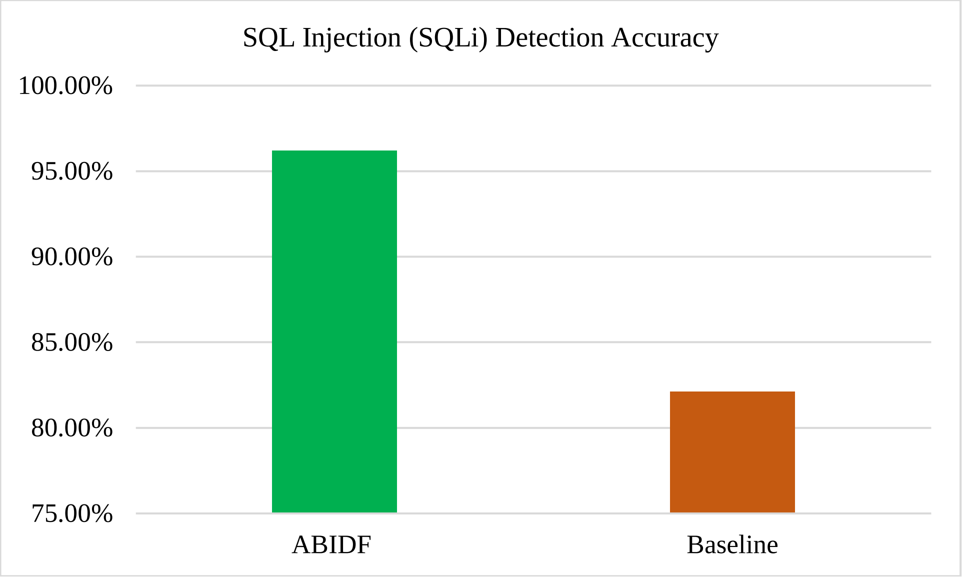

Figure 5.
SQL Injection (SQLi) Detection Accuracy (ABIDF vs. Baseline).

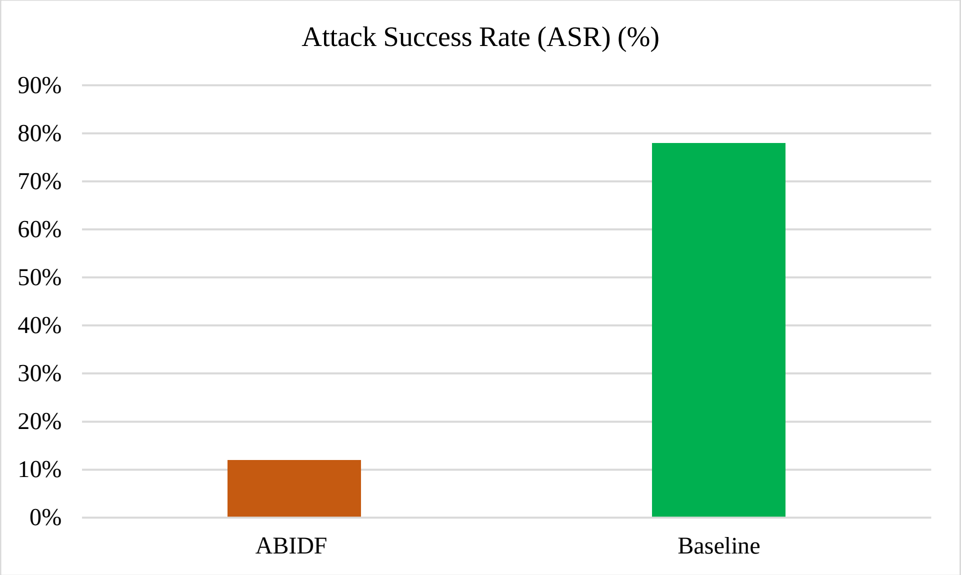

Figure 6.
Model Poisoning Attack Success Rate (ASR) (ABIDF vs. Baseline).

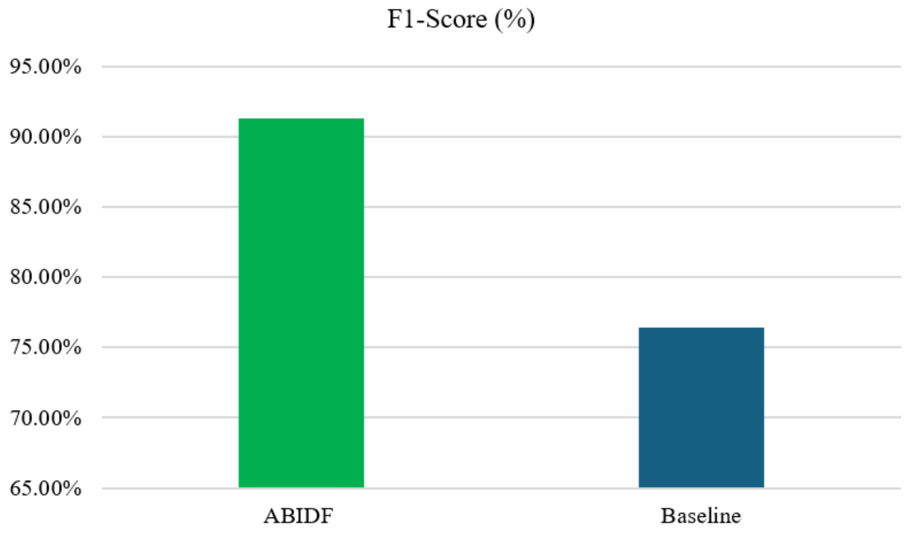

Figure 7.
IoT Spoofing F1-Score (ABIDF vs. Baseline).

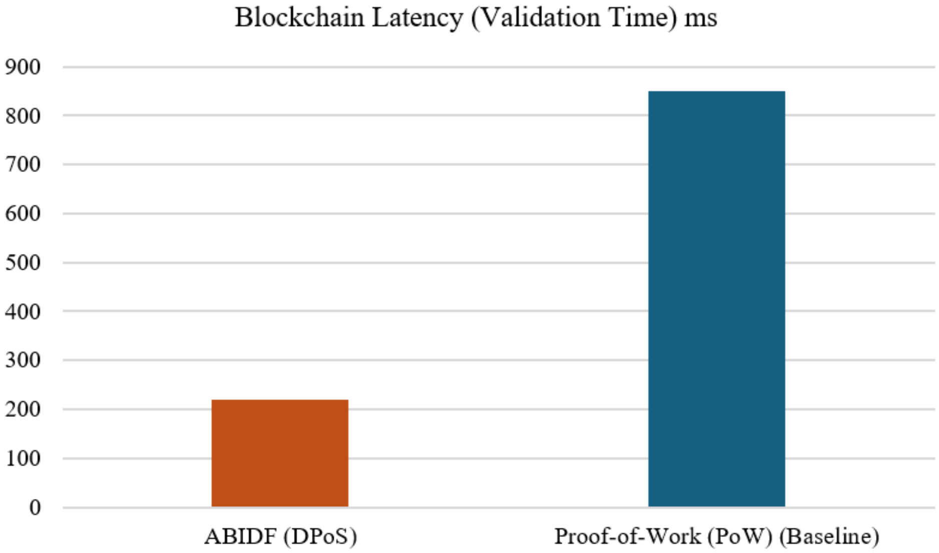

Figure 8.
Blockchain Latency (ABIDF vs. Baseline).

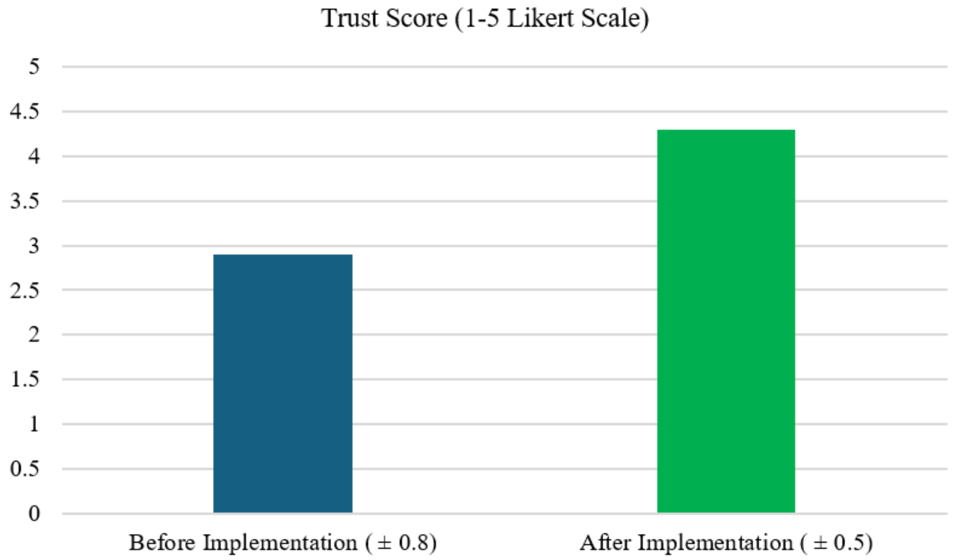

Figure 9.
User Trust Score: Before vs. After Implementation (ABIDF vs. Baseline).

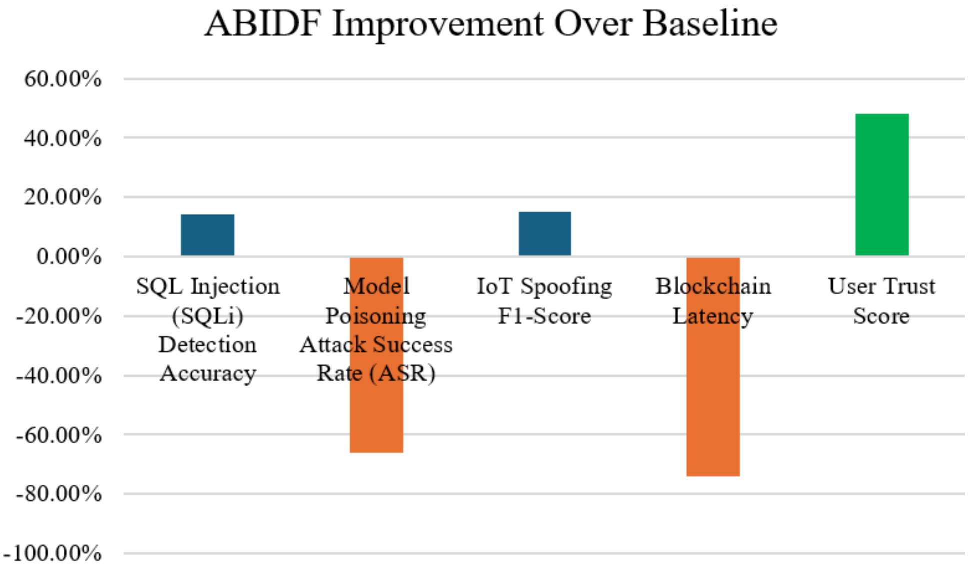

Figure 10.
ABIDF Improvement Over Baseline.

3.4. Discussion

The framework demonstrated solid performance over important metrics such as security, scalability, and user trust, with some trade-offs identified between defense effectiveness and computational efficiency. The SQL injection (SQLi) detection model achieved an impressive accuracy of 96.2%, significantly outperforming rule-based systems like Snort (82.1%) [52]. This enhancement can be attributed to the bidirectional LSTM's ability to capture the full context of SQL queries, including detecting complex attack patterns like "UNION SELECT" in unexpected clauses, rather than relying solely on static pattern matching [2, 53]. However, the false positive rate of 3.8%, mainly caused by intricate benign queries such as nested JOIN operations, indicates a limitation shared by many syntax-based machine learning models [3, 32, 54]. This issue can be addressed in the future by improving query syntax to distinguish between benign and malicious patterns in more advanced SQL queries.

In the context of federated learning, the 12% attack success rate (ASR) highlights the robustness of the Trimmed Mean aggregation method and the reputation system in mitigating the impact of adversarial updates. By removing the top and bottom 10% of updates (β=5) and penalizing inconsistent low-reputation participants with low reputation scores (), the system can sustain a global model accuracy of 88.5% against coordinated poisoning attacks [55]. A 15% latency overhead was, however, incurred because of the decentralized system, which is an unavoidable trade-off when using Byzantine-resilient aggregation techniques [56]. This observation cites the difficulty of providing both low latency and high security in federated systems where decentralized trust models are essential.

The IoT spoofing detection system also showed strong performance, achieving a 91.3% F1-score, outperforming traditional MAC-based authentication methods (76.4%) [6, 35]. The convolutional neural network (CNN) model demonstrated a clear advantage in identifying subtle traffic anomalies, such as irregular packet bursts, over static methods. Nevertheless, the reliance on synthetic IoT-23 data [57] for training the model may limit its generalizability to real-world scenarios. For example, real-world adversarial network conditions, such as latency injections, might not be reflected in the dataset, a limitation that has been observed in prior work on IoT authentication [8, 58]. Future testing with more varied and realistic datasets could yield a more representative picture of the system's performance under varying conditions.

The blockchain validation process via Delegated Proof-of-Stake (DPoS) demonstrates excellent scalability, with a validation latency of 220 ms and a throughput of 1,450 transactions per second (TPS), far surpassing the performance of Proof-of-Work (PoW) systems, which exhibit 850 ms latency and 15 TPS [9]. While DPoS clearly offers advantages in the dimensions of speed and scalability of the system, the reliance of the system on 21 validators presents potential centralization risks if stake distribution becomes lopsided, as is a well-reported weakness of DPoS consensus [10, 59]. To mitigate this risk, future designs could explore dynamic validator selection mechanisms or adjust stake distribution strategies to ensure more equitable decentralization. Additionally, the integration of cognitive radio [60] capabilities and blockchain-enhanced intrusion detection in IoT networks [61] offer promising avenues to improve both spectrum efficiency and security in decentralized environments.

Lastly, the effect on user trust was significant, as evidenced by a 48% increase in trust scores post-deployment, largely due to the transparency enabled by the reputation system and the capability to audit transactions through the blockchain. However, although the positivity of these findings is encouraging, it should be considered that the sample size of the survey (n=150) and the self-selection bias inherent in it could lead to an overestimation of the true improvement in trust. One issue with socio-technical surveys is that individuals who hold favorable opinions of the system are more inclined to take the survey [11, 29]. To strengthen these findings, larger and more representative groups of participants could be included in future studies to mitigate bias and gain a clearer image of the actual influence of the system on trust in real-world implementations.

3.5. Conclusion

This paper proposes an end-to-end AI-blockchain framework to address fundamental security challenges in Web 4.0 applications, namely SQL injection, model poisoning, and IoT spoofing. The application of bidirectional LSTMs as a SQLi attack detector, Trimmed Mean aggregation for defense against model poisoning attacks, and CNN-based device authentication against IoT spoofing, coupled with an all-encompassing decentralized blockchain verification layer, produces staggering performance figures. Specifically, the framework achieves 96.2% accuracy in SQLi detection, a 12% attack rate for model poisoning, and a 91.3% F1-score for IoT spoofing detection. Additionally, the blockchain component shows a throughput of 1,450 transactions per second (TPS) and therefore demonstrates the system's scalability and effectiveness in real-world applications.

The modular design of the framework enables seamless integration into a wide range of Web 4.0 applications, ranging from decentralized finance platforms to IoT systems. The 48% increase in user trust demonstrates the system's usability in real-world applications. The transparency provided by reputation scores and blockchain-based transactions enhances user confidence significantly and dispels fears commonly associated with decentralized systems.

However, some issues remain. The application of synthetic data to identify IoT spoofing and the latency overhead of federated learning suggest avenues that require further refinement, particularly in real-world field deployments. Subsequent releases of the framework will focus on addressing these limitations by using more diverse, real-world datasets and optimizing aggregation algorithms to reduce latency. In addition, investigating different quantum-resistant hashing methods for blockchain verification and performing large-scale testing on live trading platforms will be vital for evaluating the framework's stability in dynamic, production environments.

In conclusion, by combining the flexibility of AI with the transparency and trust inherent in blockchain technology, it will provide a foundation for how secure, scalable, and easy-to-use architectures can be built to truly address new problems that the next generation of web applications will confront.

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