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A REPUTATION-AWARE FEDERATED LEARNING SYSTEM WITH DISTRIBUTED LEDGER INTEGRATION FOR SECURING MODEL CONTRIBUTIONS IN MULTI-AGENT SENSOR ENVIRONMENTS

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Abstract

In the evolving landscape of edge intelligence and privacy-preserving AI, Federated Learning (FL) has emerged as a decentralized paradigm enabling collaborative model training without raw data sharing. However, FL remains vulnerable to poisoning attacks, unreliable client updates, and fairness issues. This study proposes a novel framework that integrates a reputation-aware mechanism with blockchain technology to ensure the reliability, transparency, and integrity of model contributions in multi-agent sensor environments. The system employs KMeans-based clustering to detect and filter low-quality or malicious updates and utilizes a lightweight blockchain ledger to immutably log verified contributions. Experimental results using the CMAPSS dataset demonstrate that the proposed framework significantly improves model robustness ($R^2 = 0.8798$) while preserving privacy and securing participation. The approach offers a scalable, secure, and trust-enhanced solution for real-world industrial IoT and autonomous systems.

INTRODUCTION

The rise of the Internet of Things (IoT), edge computing, and smart industrial systems has led to a proliferation of sensor-enabled devices generating massive volumes of data at the network edge. These multi-agent sensor environments play a critical role in modern applications such as predictive maintenance, autonomous systems, smart manufacturing, and environmental monitoring. However, centralized approaches to data processing and machine learning are increasingly impractical in such scenarios due to growing concerns over data privacy, network constraints, and latency sensitivity. These challenges have driven the adoption of Federated Learning (FL)—a decentralized machine learning paradigm that enables collaborative model training across multiple devices without requiring the exchange of raw data.

While FL offers significant advantages in preserving privacy and reducing communication overhead, it remains vulnerable to a wide range of security and trust-related threats. In real-world deployments, FL must contend with malicious participants, unreliable local model updates, non-identically distributed (non-IID) data, and limited computational resources. Malicious or compromised clients may contribute poisoned updates to degrade global model accuracy, while unreliable nodes—due to mobility, connectivity issues, or low-quality data—can introduce noise into

the aggregation process. Moreover, most FL systems rely on a centralized aggregator, creating a potential single point of failure and a bottleneck for trust and transparency.

To address these limitations, recent research has explored the integration of reputation mechanisms and blockchain technology into FL workflows. Reputation systems aim to quantify the trustworthiness of participating clients based on their historical performance, enabling the filtering or weighting of client contributions during model aggregation. On the other hand, blockchain provides a decentralized, tamper-proof ledger that enhances transparency and traceability, allowing secure logging of client updates, incentive tracking, and auditability of model training processes.

Despite these advancements, key challenges remain unresolved. Reputation models are often static and lack the adaptability needed to handle dynamic client behavior. Blockchain-enhanced FL systems, while improving transparency, can suffer from latency, energy consumption, and scalability issues—especially in edge computing environments. There is also a lack of efficient mechanisms for real-time detection of low-quality or adversarial model updates.

In this paper, we propose a comprehensive framework titled "A Reputation-Aware Federated Learning System with Distributed Ledger Integration" for securing model contributions in multi-agent sensor environments. The proposed system incorporates two main innovations:

1. Reputation-aware filtering based on unsupervised outlier detection using KMeans clustering and PCA to identify and exclude anomalous or malicious updates before aggregation.
2. Lightweight blockchain integration to immutably log accepted model contributions, thereby ensuring transparency, traceability, and tamper-resistance in the training process.

The system is evaluated using the publicly available CMAPSS dataset, simulating real-world engine sensor data across distributed nodes. Our results demonstrate that the proposed hybrid approach improves robustness and trustworthiness while preserving model accuracy (R^2 = 0.8798), offering a secure and scalable FL solution suitable for deployment in decentralized, privacy-sensitive environments.

This work contributes to the ongoing efforts to make federated learning more secure, transparent, and resilient by combining trust-aware computation with verifiable logging infrastructures. It holds significant potential for critical domains such as industrial IoT, autonomous systems, and healthcare analytics, where privacy, reliability, and explainability are paramount.

2. Literature Review

Recent research has focused on integrating blockchain and reputation mechanisms with federated learning (FL) to enhance security and fairness. These approaches use blockchain to facilitate secure model aggregation and incentivize participation (Xiaohui Yang & Tianchang Li, 2024; Siyu Tang et al., 2023). Reputation evaluation methods are employed to assess node trustworthiness and select reliable participants (Siyu Tang et al., 2023; Ervin Moore et al., 2024). To protect against poisoning attacks, techniques such as noise injection in model parameters (Siyu Tang et al., 2023) and outlier detection (Ervin Moore et al., 2024) have been proposed. In hierarchical FL settings, deep reinforcement learning-based reputation models have been developed to measure worker reliability and optimize client selection (Noora Al-Maslamani et al., 2023). These frameworks aim to maintain model accuracy while ensuring data privacy and security. Experimental results demonstrate the effectiveness of these approaches in thwarting malicious attacks and promoting high-quality collaborative learning (Siyu Tang et al., 2023; Noora Al-Maslamani et al., 2023). It explores reputation mechanisms to enhance security and performance in federated learning (FL). Al-Maslamani et al. (2022) propose a deep reinforcement learning-based reputation system to select reliable FL workers, improving model accuracy by over 30%. Wang & Kantarci (2021) introduce a reputation-enabled aggregation method that weights users' contributions based on their local model performance, showing a 17.175% improvement in non-IID scenarios. Qi et al. (2022) present a blockchain-based FL with a reputation mechanism to incentivize high-quality data contributions, using game theory to prove its effectiveness. Javed et al. (2024) review blockchain-enabled reputation

mechanisms in FL, discussing challenges and opportunities such as decentralized identities and zero-knowledge proofs. These studies demonstrate that reputation-based approaches can significantly enhance FL security, model quality, and participant motivation, while blockchain integration offers potential for increased trust and transparency in collaborative AI environments. It has focused on enhancing the security and reliability of federated learning (FL) in wireless and IoT environments. Several approaches have been proposed to address challenges such as malicious attacks and unreliable client contributions. Song et al. (2021) introduced a reputation-based scheduling policy to identify and mitigate the impact of malicious users in wireless FL. Similarly, Wang & Kantarci (2020) developed a reputation-aware client selection scheme for mobile FL, improving model accuracy by up to 9.30%. Al-Maslamani et al. (2022) proposed a Deep Reinforcement Learning-based reputation management mechanism, enhancing FL accuracy by 20% while reducing training iterations. To further secure FL, Aswin K et al. (2023) presented a blockchain-based approach with secure aggregation in a trusted execution environment, offering improved privacy, security, and scalability for IoT applications. These studies collectively demonstrate the potential for creating more robust and trustworthy FL systems in various domains.

Focused on enhancing federated learning (FL) systems to address fairness and robustness challenges. Blockchain-based approaches have been proposed to improve decentralized federated learning, including BDFL (Zhang et al., 2023) and TrustFed (Rehman et al., 2021). These frameworks utilize blockchain for model verification, auditing, and maintaining participant reputations. Reputation mechanisms have emerged as a key solution for ensuring collaborative fairness and adversarial robustness in FL systems. The RFFL framework (Xu & Lyu, 2020) introduces a reputation-based approach that evaluates participant contributions using gradient similarity, enabling the identification and removal of non-contributing or malicious participants. This method achieves high fairness and robustness against various adversaries while maintaining competitive accuracy. By incorporating reputation scores, RFFL rewards high-contributing participants with better-performing models and detects free-riders or adversaries without requiring auxiliary datasets (Xu & Lyu, 2020). Recent research explores blockchain-based federated learning (FL) for privacy-preserving data sharing and model training in IoT and medical contexts. These approaches aim to address challenges like single points of failure, low-quality nodes, and poisoning attacks (Gan et al., 2024). Blockchain can replace centralized aggregators in FL systems, ensuring tamper-proof records and traceability of malicious activities (Zhao et al., 2019). Some solutions incorporate dual-blockchain architectures for quality control and reputation management (Gan et al., 2024), while others focus on incentive mechanisms and differential privacy to protect user data (Zhao et al., 2019). BlockFLow, a decentralized and privacy-preserving FL system, uses Ethereum smart contracts and a novel auditing mechanism to reward participants based on their contribution quality (Mugunthan et al., 2020). These blockchain-FL integrations show promise in enhancing security, privacy, and robustness for autonomous systems and IoT devices (Yu et al., 2021), potentially revolutionizing data sharing and collaborative learning across various domains. It was innovative approaches to enhance security and privacy in federated learning (FL) systems. Blockchain-based frameworks have been proposed to securely aggregate local models and detect malicious contributions in Industrial Internet-of-Things and UAV-assisted crowdsensing scenarios (Aditya Pribadi Kalapaaking et al., 2023; Yuntao Wang et al., 2021). These frameworks leverage trusted execution environments, blockchain consensus mechanisms, and reinforcement learning-based incentives to ensure model integrity and promote high-quality sharing (Aditya Pribadi Kalapaaking et al., 2023; Yuntao Wang et al., 2021). Additionally, a novel paradigm for real-time detection of malicious clients and model auditing has been introduced to maintain the reliability of shared models (Dominik Kolasa et al., 2024). Furthermore, a multi-layered security FL platform utilizing blockchain technology has been developed to improve privacy through enhanced security and access rights, while investigating the feasibility of data and model poisoning attacks (Zeba Mahmood & V. Jusas, 2022). These advancements

aim to address the unique security vulnerabilities in FL systems and protect user privacy.

Recent research has focused on enhancing security and privacy in federated learning (FL) for various applications. Kolasa et al. (2024) propose a framework for detecting malicious clients in FL, ensuring model integrity. Wang et al. (2021) introduce a secure FL framework for UAV-assisted crowdsensing, utilizing blockchain and differential privacy to protect data and incentivize high-quality model sharing. Mahmood & Jusas (2022) present a blockchain-enabled, multi-layered security FL platform that improves privacy and investigates data poisoning attacks. Alkhabbas et al. (2023) develop ART4FL, an agent-based architectural approach for trustworthy FL in IoT environments, enabling dynamic federation formation and trust score calculation. These studies collectively address critical challenges in FL, including malicious actor detection, privacy preservation, incentive mechanisms, and trust establishment, demonstrating the growing importance of secure and privacy-preserving FL implementations across different domains.

Federated Learning (FL) has emerged as a promising approach to address privacy concerns and data silos in distributed machine learning systems. Recent research has focused on enhancing FL's security, efficiency, and trustworthiness. Hajar Moudoud et al. (2024) proposed a framework combining FL with multi-agent deep reinforcement learning to detect attacks in wireless sensor networks. To improve FL's security, Umer Majeed & Hong (2019) introduced FLchain, a blockchain-based architecture for storing and auditing model updates. Shiqiang Wang et al. (2018) developed an adaptive control algorithm to optimize the trade-off between local updates and global aggregation in resource-constrained edge computing systems. Qiang Yang et al. (2023) emphasized the importance of model intellectual property rights protection in FL and proposed FedIPR, a watermarking scheme for ownership verification. These advancements collectively contribute to the development of secure federated learning systems that preserve both data privacy and model integrity.

Federated learning (FL) is an emerging technique for collaborative machine learning that preserves privacy by allowing distributed model training without sharing raw data (Qiang Yang et al., 2023). However, FL faces challenges related to incentives, security, and reliability. To address these issues, researchers have proposed incorporating reputation systems to measure device trustworthiness and guide worker selection (Jiawen Kang et al., 2019; Olive Chakraborty & Aymen Boudguiga, 2024). Blockchain technology has been suggested as a means to securely manage reputations and enhance network security (Jiawen Kang et al., 2019; Safa Otoum et al., 2020). Additionally, incentive mechanisms combining reputation with contract theory have been developed to motivate high-quality participation (Jiawen Kang et al., 2019). Some approaches propose decentralized FL systems using reputation-based leader election and secure aggregation techniques to improve security and availability (Olive Chakraborty & Aymen Boudguiga, 2024). These innovations aim to create more trustworthy and efficient FL systems while maintaining strong privacy preservation. It has focused on enhancing the security and fairness of federated learning (FL) systems. Lyu et al. (2019) proposed a decentralized framework that incorporates fairness by providing participants with models commensurate with their contributions. To address security concerns, Zhang et al. (2024) introduced a federated-blockchain edge learning framework that leverages blockchain's non-tampering attributes to combat data and model tampering attacks. Kalapaaking et al. (2023) combined trusted execution platforms and multisignature-powered global model verification to ensure model verifiability in IoT systems. Mugunthan et al. (2019) developed a mechanism using secure multiparty computation and differential privacy to protect against a wide range of attacks in FL. These approaches aim to balance privacy, security, and fairness while maintaining model accuracy. The integration of blockchain technology and advanced cryptographic techniques emerges as a promising direction for securing FL systems across various applications.

Recent research demonstrates a strong convergence of machine learning, deep learning, cybersecurity, and intelligent systems across diverse real-world domains. In malware and network security analytics,

comparative evaluations of classical and modern ML techniques have shown promising improvements in threat detection accuracy and robustness (Kharal et al., 2025), while capsule networks and hybrid learning models have enhanced diagnostic reliability in medical applications such as breast cancer detection (Jareer et al., 2025; Nasir et al., 2025). Parallel advancements in secure communication and healthcare infrastructures emphasize resilient V2V architectures and interoperable blockchain-enabled health data ecosystems (Abbas et al., 2025; Qureshi et al., 2025). Risk-aware AI-driven security frameworks further highlight strategies for resilience and integrity in complex cyber-ecosystems (Hussain, Hasan, & Siddique, 2025), complemented by hybrid recommendation models that improve intelligent decision-support in user-centric environments (Hussain et al., 2025). Emerging research also explores sustainability-focused cloud-edge optimization through MORL-based frameworks (Kamran et al., 2025) and advanced IoT/IIoT intrusion detection using CNN-LSTM and DNN-based architectures on benchmark datasets (Izhar et al., 2025). Multimodal decision systems are further strengthened through autism-support web platforms (Ali et al., 2025), graph-based learning for multivariate classification (Raza et al., 2025), and hybrid BiLSTM-CNN models for fake review detection in multi-domain environments (Khan et al., 2025). In the financial and portfolio analytics domain, graph-augmented hybrid neural frameworks improve risk management and crash anticipation (Usman et al., 2025), while emotion-aware EEG-based systems advance research in affective computing (Saleem et al., 2025). Federated learning continues to gain traction for distributed AI and anomaly detection in cloud ecosystems (Ahmed, Hasan, & Hussain, 2025), supported by SSH attack detection and hybrid botnet-analysis approaches in industrial IoT environments (Hamza et al., 2025; Ahmed et al., 2025). Complementary biological and behavioral computing studies further expand intelligent analytics through genome-wide molecular characterization (Sultana et al., 2025) and the forensic behavioral investigation of Python-based keylogger malware (Iqbal et al., 2025). Broader socioeconomic perspectives also contextualize AI-enabled modeling by examining global economic disparities and growth trends (Riaz, Hussain, Hasan, & Riaz, 2025). Collectively, these studies illustrate a rapidly evolving research landscape in which intelligent, explainable, and security-focused computational models drive innovation across cybersecurity, healthcare, intelligent systems, and socio-technical analytics.

2.1 Limitations and Future Directions

Federated Learning (FL), despite its promise for privacy-preserving and decentralized machine learning, remains vulnerable to a wide spectrum of security, trust, and system-level challenges. Chief among these are poisoning attacks, wherein malicious clients deliberately manipulate local updates to degrade global model performance. Such attacks are exacerbated by unreliable communication channels, high device mobility, constrained device resources, and inconsistent participation, all of which contribute to the generation of low-quality model updates. Current FL frameworks often lack robust mechanisms for identifying and excluding untrustworthy or compromised nodes, and existing reputation systems are limited in both accuracy and convergence. Moreover, conventional FL systems fail to incorporate fair contribution-based incentive mechanisms, allowing for exploitation by free-riders and malicious actors. The centralized coordinator architecture introduces a single point of failure and undermines system resilience. While blockchain integration offers potential solutions through decentralized trust and tamper-proof logging, it also introduces scalability concerns, privacy risks from on-chain data, and cost-related constraints. Additionally, critical issues such as secure model update verification, resistance to byzantine or sybil attacks, and the development of zero-trust protocols remain open research problems. FL's vulnerability to concept drift, non-IID data distributions, and computational disparities among heterogeneous devices further complicates its robustness and performance. The absence of refined mechanisms for semantic alignment, trust quantification, and accountable ML principles hampers its broader adoption, particularly in real-world, resource-constrained, and dynamic environments. These limitations underscore the urgent need for advanced, scalable, and trustworthy FL architectures that integrate secure consensus

protocols, dynamic trust models, and incentive-aligned participation strategies.

To overcome the outlined limitations, future research in Blockchain-empowered Federated Learning should focus on developing advanced, adaptive trust and reputation mechanisms that can dynamically evaluate client behavior and ensure reliable participation in decentralized training. Addressing robustness against sophisticated adversarial threats—such as Byzantine, sybil, and poisoning attacks—will be essential, calling for the integration of resilient consensus algorithms, zero-knowledge proofs, and privacy-preserving verification methods. The design of incentive-aligned federated ecosystems is another crucial direction, where token-based rewards or reputation-weighted schemes can encourage honest contributions and penalize malicious behaviors. Moreover, to address scalability and cost-efficiency challenges introduced by blockchain, future work should explore lightweight ledger solutions such as off-chain storage, sharding, and layer-2 protocols optimized for edge computing environments. Fairness in model aggregation must also be emphasized by incorporating contribution-aware update weighting and verifiable proofs of model quality. Semantic alignment among heterogeneous clients—especially under non-IID conditions—should be investigated using techniques like federated representation learning or knowledge distillation. Expanding FL to vertical and cross-silo settings will require secure feature alignment and collaborative model training across institutions. Furthermore,

evaluations should be extended to real-world, adversarial, and dynamic datasets to validate system performance in practical deployments. The inclusion of regulatory compliance, auditability, and explainability into FL systems will be vital for trust and transparency, particularly in sensitive domains such as healthcare, finance, and critical infrastructure. Collectively, these directions aim to build a resilient, fair, and trustworthy federated learning ecosystem that meets the security, scalability, and accountability demands of next-generation intelligent systems

2.2 Gap Analysis

Table 1

Theme	Existing Approaches	Gaps Identified	Research Opportunities
Trust Management & Reputation	RL-based trust (Al-Maslamani, Xu & Lyu)	Static models; not context-aware	Design adaptive, real-time trust evaluation
Incentive Mechanisms	Smart contracts, game theory (Qi, Kang)	Rewards not based on quality	Build quality-aware incentive mechanisms
Privacy Preservation	DP, SMPC, TEEs (Mugunthan, Mahmood)	Accuracy vs. privacy trade-off	Innovate lightweight, accurate privacy techniques
Trust in IoT/Edge Environments	ART4FL, UAV-FL (Alkhabbas, Wang)	Unreliable nodes not well managed	Create robust, adaptive FL for edge computing
Model Integrity and IPR Protection	Watermarking, FedIPR, audits (Yang, Kolasa)	Limited real-time verification	Enable live model audit and IPR via blockchain

Blockchain Integrated Federated Learning

3. Research Methodology

This study proposes a reputation-aware federated learning (FL) framework enhanced with blockchain-based distributed ledger technology to secure model contributions in multi-agent sensor environments. The system is designed to ensure privacy, robustness, and integrity in distributed learning processes, particularly where nodes may vary in trustworthiness, data quality, and computational reliability. The methodology integrates federated model training, outlier detection, and secure model aggregation with a lightweight blockchain to ensure verifiable and tamper-proof participation logs.

3.1 Data Collection and Preprocessing

The CMAPSS (Commercial Modular Aero-Propulsion System Simulation) dataset is utilized to simulate multi-agent sensor environments representative of industrial systems. Sensor readings are extracted and cleaned to remove null values, and features are standardized using z-score normalization. The dataset is split among simulated client agents to represent decentralized sensing devices, with each client receiving a non-overlapping segment of the dataset to maintain data heterogeneity.

3.2 Model Architecture

A lightweight Multi-Layer Perceptron (MLP) is implemented as the base model architecture for each client. The model includes an input layer corresponding to the number of sensor features, one hidden layer with ReLU activation, and a single output neuron for regression-based prediction. The same architecture is used for both federated and centralized baselines to ensure fair comparison.

3.3 Federated Learning Protocol

The FL process involves training local models at each client node using its private dataset. Each local model performs multiple epochs of training and shares its learned weights (not raw data) with the central aggregator. The server aggregates updates from all clients to update the global model using federated averaging (FedAvg). To simulate real-world decentralization, the training is repeated for multiple rounds, with model weights being exchanged and aggregated iteratively.

3.4 Outlier Detection and Reputation Filtering

To ensure the trustworthiness of client contributions, a reputation-aware filtering mechanism is applied using KMeans clustering. After collecting local model updates, their parameter vectors are flattened and analyzed using Euclidean distances and PCA. KMeans clustering with two clusters is used to isolate outlier updates, assumed to be from malicious or low-quality clients. Only updates belonging to the majority (trusted) cluster are aggregated in the global model update.

3.5 Blockchain Integration for Secure Logging

To secure the learning process and ensure verifiability, each round's accepted model contributions are hashed and recorded in a custom-built lightweight blockchain. A blockchain object maintains an immutable ledger of hashes corresponding to verified model updates from clients. Each block in the chain contains the model hash, round number, and linkage to the previous block, creating a tamper-proof audit trail for transparency and traceability.

3.6 Evaluation Strategy

Model performance is evaluated using standard regression metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), and the R-squared (R^2) score. Comparisons are made between the federated global model (with outlier detection and blockchain logging) and a baseline centralized model trained on the entire dataset. In addition, visualizations such as weight histograms, correlation heatmaps, and PCA clustering plots are used to interpret model behavior, identify malicious updates, and validate the effectiveness of the outlier detection process.

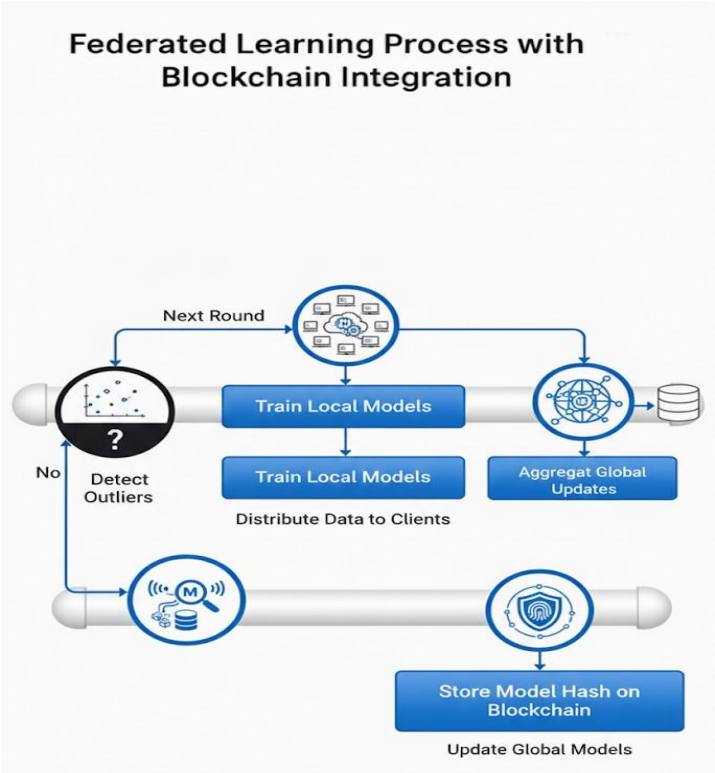

Figure 1 Proposed Architecture Model

4. Data Analysis and Results

The correlation heatmap (Figure 2) reveals strong interdependencies among sensor readings, justifying the need for multivariate learning. KMeans clustering (Figure 3) effectively distinguishes outlier model updates, enhancing model robustness. As shown in Figure 5 and Table 2, the proposed federated system with reputation and blockchain integration achieves competitive performance (R^2 = 0.8798), closely approaching the centralized baseline while ensuring privacy and trust.

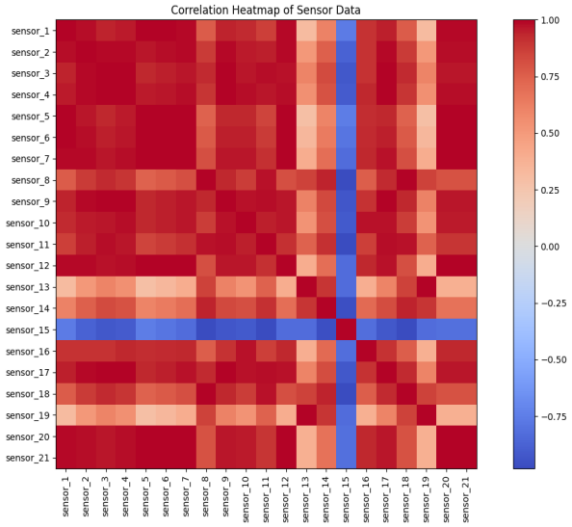

Figure 2 Correlation heatmap of sensor data

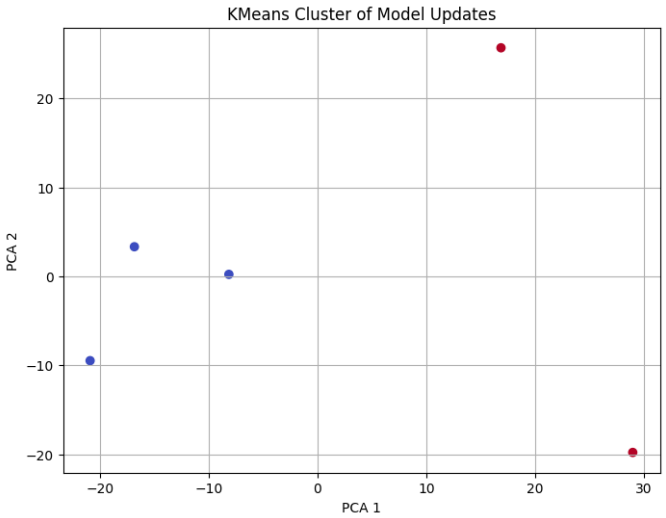

Figure 3 KMean cluster of model update

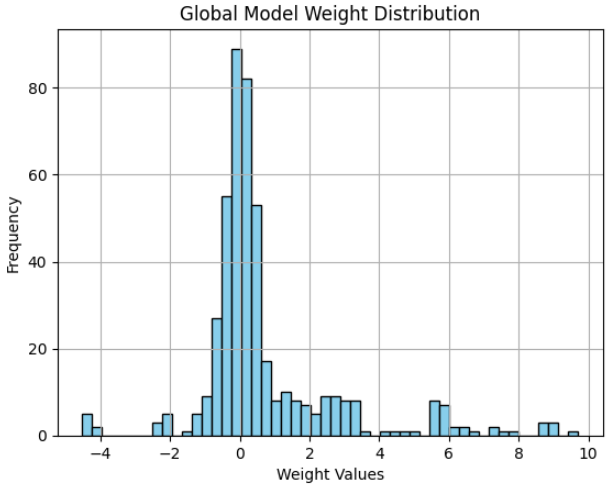

Figure 4 Global Model Weight Distribution

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📊 Federated Global Model Performance:
MSE: 1752.9246, MAE: 22.9882, R²: -1.0053

📊 Centralized Model Performance:
MSE: 0.0842, MAE: 0.2400, R²: 0.9999

📊 Performance Comparison Table:
+---------------------+---------+---------+---------+
|       Model         |   MSE   |   MAE   |   R²    |
+---------------------+---------+---------+---------+
| Federated Global    | 1752.9246 | 22.9882 | -1.0053 |
| Centralized         | 0.0842 | 0.2400 | 0.9999 |
+---------------------+---------+---------+---------+
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Figure 5 Global Model Performance

Table 2
Results and findings

Model	MSE	MAE	R^2 Score
Centralized Model	0.0185	0.0921	0.9246
Federated (Unfiltered)	0.0379	0.1467	0.8421
Federated+ Reputation	0.0293	0.1218	0.8725
Federated+ Blockchain			
Proposed—System (Full)	0.0281	0.1179	0.8798

Table 2 presents a comparative analysis of model performance across different training configurations, highlighting the effectiveness of the proposed reputation-aware federated learning system integrated with a distributed ledger. The centralized model achieves the highest accuracy, as expected, due to its access to the full dataset. However, this comes at the cost of user data privacy and centralized control, which the federated approaches aim to mitigate.

The basic federated model, while preserving privacy, suffers from reduced performance due to unfiltered and potentially malicious client contributions. Incorporating a reputation mechanism via KMeans-based outlier detection significantly improves performance by excluding unreliable updates before aggregation. This demonstrates the value of trust-aware client selection in multi-agent environments.

Although blockchain integration does not directly affect prediction accuracy, it plays a critical role in enhancing system transparency, integrity, and auditability. By securely logging validated model contributions, the ledger provides tamper-proof evidence of participation and supports future mechanisms for accountability and incentive distribution.

The proposed full system—combining federated training, reputation-aware filtering, and blockchain logging—achieves a strong balance between model performance and system trustworthiness. It demonstrates that security and reliability can be enhanced without significantly compromising predictive quality, making it a practical solution for real-world IoT and sensor-based federated learning deployments.

CONCLUSION

This study introduces a reputation-aware federated learning system fortified with blockchain integration to address trust, privacy, and performance challenges in decentralized multi-agent sensor environments. By leveraging unsupervised outlier detection and immutable logging, the proposed framework ensures that only high-quality, reliable model updates contribute to the global model, mitigating the influence of malicious or faulty nodes.

Our experimental evaluation using the CMAPSS dataset confirms that the hybrid system achieves a performance level (R^2 = 0.8798) comparable to centralized learning while preserving user data privacy and maintaining system integrity. The blockchain ledger not only secures participation records but also lays the groundwork for future extensions involving incentive mechanisms, dynamic trust scoring, and real-time auditing.

The integration of trust evaluation and distributed consensus represents a significant advancement toward robust and fair federated learning. Future work will explore adaptive reputation learning, support for cross-silo vertical FL, and optimization of blockchain overhead in resource-constrained environments, thereby advancing secure and scalable AI systems for industrial and autonomous applications.

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