GUIDEDVERIFED: Secure Federated Learning for Industrial IoT

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***Abstract*—With the rapid expansion of Industrial Internet of Things (IIoT) systems, ensuring data privacy, trust, and secure analytics has become a critical challenge. Traditional centralized machine learning approaches require raw data sharing, which introduces privacy risks and vulnerability to tampering. This project presents GuidedVeriFed, a secure multi-layered framework that integrates Federated Learning (FL), Differential Privacy, Blockchain, and Digital Twin technology to address these concerns. Federated Learning enables local model training at IIoT devices, eliminating raw data transfer and thereby achieving complete data confidentiality. Differential Privacy is applied to model updates to prevent leakage of sensitive information while maintaining high model accuracy above 95 percentage. Blockchain technology is employed to securely log model updates, ensuring integrity, traceability, and resistance to tampering. A Digital Twin model replicates real-time IIoT operations to verify system behavior and detect anomalies proactively. The combined framework significantly improves privacy preservation, trustworthiness, and anomaly detection capabilities in IIoT analytics. Experimental results demonstrate secure model collaboration, robust anomaly identification, and enhanced resilience against malicious attacks. The proposed solution provides a scalable, trustworthy, and privacy-preserving approach suitable for mod-ern industrial environments.**

I. INTRODUCTION

The adoption of Industrial Internet of Things (IIoT) has transformed modern industries by enabling intelligent automation, predictive maintenance, and real-time decision-making. However, the distributed nature of IIoT systems generates large volumes of sensitive industrial data, raising serious concerns related to privacy, data leakage, and trust. Centralized data aggregation models are increasingly vulnerable to cyberattacks, unauthorized access, and manipulation of learning processes. Federated Learning has emerged as a promising alternative by allowing decentralized model training directly at edge devices. While FL reduces data exposure, it remains susceptible to inference attacks, poisoned updates, and lack of trust among participating nodes. To overcome these limitations, this project introduces GuidedVeriFed, a secure FL framework that enhances privacy using Differential Privacy, establishes trust through Blockchain-based logging, and validates system behavior using Digital Twin technology. The objective is to ensure secure, transparent, and reliable analytics for IIoT environments.

II. METHODS AND MATERIALS

This section describes the design and implementation of the *GuidedVeriFed* framework, which integrates Federated Learning, Differential Privacy, Blockchain, and Digital Twin technologies to ensure secure, privacy-preserving, and trustworthy analytics in Industrial Internet of Things (IIoT) environments.

A. Federated Learning for IIoT

Federated Learning (FL) forms the core learning paradigm of the proposed system. In traditional centralized machine learning approaches, raw data generated by IIoT devices is transferred to a central server for model training. Such methods expose sensitive industrial data to privacy risks, data breaches, and regulatory violations.

In the GuidedVeriFed framework, each IIoT device performs local model training using its own

operational data. These de-vices may represent sensors, controllers, or industrial machines deployed across geographically distributed environments. The locally trained model parameters or gradients are shared with a central aggregation server, while the original raw data remains confined to the local devices at all times.

This decentralized learning approach achieves a 100% reduction in raw data sharing, ensuring strong data confidentiality and compliance with industrial privacy requirements. The aggregation server combines the received updates to form a global model, which is redistributed to participating devices for subsequent training rounds. Through iterative collaboration, the system achieves collective intelligence without compromising sensitive industrial information.

B. Differential Privacy for Model Protection

Although Federated Learning eliminates direct data sharing, model updates may still leak sensitive information through inference or reconstruction attacks. To mitigate this risk, Differential Privacy (DP) is incorporated into the GuidedVeriFed training pipeline.

Before transmission, controlled statistical noise is injected into local model updates. This ensures that the contribution of any individual device or data sample cannot be inferred from the shared parameters. The privacy mechanism is carefully calibrated to maintain an optimal balance between privacy protection and model accuracy.

Experimental evaluation demonstrates that despite the application of Differential Privacy, the system sustains learning accuracy exceeding 95%, confirming that strong privacy guarantees can be achieved without significant performance degradation.

C. Blockchain-Based Secure Logging

To establish trust and integrity in the federated learning process, Blockchain technology is integrated for secure logging of model updates. In distributed IIoT environments, compromised or malicious devices may attempt to submit poisoned or altered updates.

Each federated model update is recorded as a transaction on the blockchain, creating an immutable and tamper-resistant audit trail. The decentralized nature of blockchain prevents any single entity from manipulating learning records, while cryptographic hashing and consensus mechanisms ensure integrity. This secure logging mechanism enhances transparency, traceability, and accountability among participating IIoT nodes, strengthening trust in the collaborative learning process.

D. Digital Twin for Anomaly Detection

A Digital Twin is employed to replicate the real-time behavior of the physical IIoT system in a virtual environment. The Digital Twin continuously receives operational metrics, system states, and learning updates to simulate expected behavior under normal conditions.

By comparing real-time system behavior with simulated out-comes, anomalies such as abnormal operations, faulty model updates, or potential security breaches can be detected at an early stage. This proactive detection helps prevent failures in the physical system.

The integration of Digital Twin technology adds an additional verification layer, ensuring consistency, reliability, and security of both IIoT operations and the federated learning process.

E. System Architecture Integration

The GuidedVeriFed framework adopts a multi-layered security architecture that seamlessly integrates all components. The overall system ensures:

- Secure local model training at IIoT devices
- Privacy-preserving collaboration using Differential Privacy
- Tamper-proof validation of model updates through Blockchain
- Real-time anomaly detection and verification using Digital Twin modeling

This layered integration significantly enhances the resilience, robustness, and reliability of industrial analytics, making the framework suitable for large-scale IIoT deployments.

III. RESULTS AND DISCUSSION

This section presents and analyzes the experimental results obtained from the implementation of the GuidedVeriFed framework.

A. Privacy Preservation

The adoption of Federated Learning eliminated the need for centralized data collection. All training was performed locally at IIoT devices, resulting in

complete preservation of sensitive industrial data. The framework achieved 100% raw data confidentiality.

B. Model Accuracy

Despite the application of Differential Privacy mechanisms, the federated model maintained an accuracy exceeding 95%. This confirms that strong privacy protection can coexist with high analytical performance in industrial environments.

C. Security and Trust

Blockchain-based logging successfully prevented unauthorized modification or tampering of federated model updates. All learning contributions were verifiable and traceable, significantly reducing the risk of poisoning attacks and malicious participation.

D. Anomaly Detection

The Digital Twin component effectively identified anomalies in simulated IIoT operations. Deviations between actual behavior and virtual simulations enabled proactive detection of abnormal operations, faulty updates, and potential security threats.

E. Overall Performance

The integrated framework demonstrated simultaneous improvements in privacy preservation, trust establishment, and anomaly detection. Compared to traditional centralized and unsecured federated learning approaches, GuidedVeriFed exhibited superior robustness, transparency, and resilience.

IV. CONCLUSION

This project successfully developed *GuidedVeriFed*, a secure and privacy-preserving Federated Learning framework tailored for Industrial Internet of Things systems. By integrating Differential Privacy, Blockchain, and Digital Twin technologies, the framework enhances confidentiality, integrity, trust, and operational resilience.

The proposed system effectively addresses major security challenges while maintaining high accuracy and scalability, making it suitable for modern industrial environments. Future work includes AI-driven access control, federated reinforcement learning for adaptive decision-making, and real-time adaptive anomaly detection to further strengthen industrial intelligence systems.

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