Journal of Artificial Intelligence and Data Science Techniques

ISSN: 3029-2794

Volume 02 Issue 01 (February) 2025

Securing IoT Data Sharing with Federated Learning and Homomorphic Encryption for Enhanced Privacy

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Abstract:

The Internet of Things (IoT) spread has revolutionized data-driven innovation. However, it has also revealed significant privacy and security vulnerabilities. This makes traditional centralized data-sharing approaches increasingly inadequate for protecting sensitive data. This research explores the novel integration of federated learning (FL) and homogeneous encryption (HE) as a framework to improve privacy in data sharing in IoT networks. assisted federation learning. It provides decentralized machine learning and localized data. Homomorphic encryption also helps secure computations of encrypted data. Together, they offer a robust privacy protection system for IoT networks. This study examines the theoretical and practical aspects of the proposed framework, including scalability, performance, and real-world applications. Simulations performed in an IoT environment demonstrate the framework's ability to balance privacy and efficiency. The results indicate a significant improvement in safety while maintaining computational feasibility. This research improves methods for protecting privacy and lays the foundation for future IoT data-sharing innovations.

Index terms: IoT privacy, federated learning, homomorphic encryption, data sharing, decentralized machine learning

1. Introduction

The Internet of Things (IoT) has emerged as a transformative era connecting billions of gadgets globally. It has revolutionized industries, including healthcare, transportation, agriculture, and manufacturing, by allowing seamless facts series and evaluation. IoT gadgets generate considerable quantities of data, which, whilst analyzed collaboratively, can improve selection-making, optimize operations, and decorate consumer experiences. However, the increasing reliance on centralized information-sharing models exposes IoT networks to widespread privacy and security vulnerabilities. For instance, sensitive statistics transmitted through gadgets are liable to unauthorized right of entry, information breaches, and exploitation [1].

One of the primary demanding situations in IoT ecosystems is ensuring privacy in facts sharing without compromising capability or overall performance. Centralized system getting-to-know tactics depend upon aggregating uncooked data from IoT devices, making it at risk of interception at some stage in transmission or storage [2]. Traditional encryption techniques safeguard data in transit; however, they cannot aid in the successful computation of encrypted datasets [3]. Recent advancements in decentralized systems gaining knowledge of and encryption have proven promise, but integrating these techniques to address IoT-precise constraints stays underexplored [4].

This study proposes a novel framework combining FL and HE to beautify privacy in IoT data sharing. Federated Learning permits decentralized model training, permitting gadgets to construct machine learning models collaboratively without sharing uncooked statistics [5]. Homomorphic Encryption enhances FL by simultaneously allowing

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ISSN: 3029-2794
Volume 02 Issue 01 (February) 2025

computations on encrypted facts, ensuring privateness at some point in the technique. The methodology includes:

Evaluating the framework's performance in terms of accuracy, latency, computational efficiency, and privacy guarantees. The simulations leverage tools like TensorFlow Federated and Python-based HE libraries like PySyft alongside real-world IoT datasets [6].

This research makes the following key contributions:

- Proposes a scalable and efficient FL-HE framework tailored to IoT networks, addressing privacy and protection challenges [7].
- Demonstrates the feasibility of applying HE to steady FL operations, overcoming obstacles in present encryption strategies.
- Evaluates the proposed framework's performance in opposition to conventional strategies, supplying insights into its practicality.
- Lays the basis for destiny research in privacy-maintaining methodologies for decentralized IoT structures [8].

Section II: Literature Review examines current studies on IoT privacy, Federated Learning, Homomorphic Encryption, and their integration.

Section III: Methodology details the proposed framework, experimental setup, and assessment metrics.

Section IV: Results give simulation effects, including overall performance comparisons and insights into scalability and efficiency.

Section V: Conclusion summarizes the study's contributions and implications, with tips for future paintings.

2. Literature Review: Federated Learning And Homomorphic Encryption in Io Data Privacy

Centralized IoT information-sharing mechanisms face full-size vulnerabilities, such as data breaches, authentication failures, and inadequate encryption protocols. Studies spotlight that centralized architectures reveal sensitive records to potential threats throughout transmission and storage. Despite improvements in conventional encryption techniques, their inability to handle proper resource-limited IoT environments efficiently limits scalability and real-time functionality [9]. Moreover, compliance with global privacy regulations, GDPR, and CCPA adds another layer of complexity, necessitating progressive answers combining decentralization and strong encryption technology.

Federated Learning represents a paradigm shift in disbursed machine studying, wherein information stays localized on personal gadgets, lowering privacy risks. McMahan introduced FL as a method of schooling shared models without transmitting uncooked records, pioneering its utility in privacy-sensitive domains. Table 1 summarizes incredible works in this vicinity, showcasing studies' improvements and their contributions.

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ISSN: 3029-2794
Volume 02 Issue 01 (February) 2025

Table I: Federated Learning Literature Survey

S.No	Author(s)	Year	Research Problem	Technique Applied	Accuracy (%)
1	Wang et al. [10]	2022	Communication overhead in FL	Adaptive compression methods	92.5
2	Li et al. [11]	2023	Device heterogeneity in FL	Federated averaging (FedAvg)	89.3
3	Kumar et al. [12]	2023	Privacy leakage in shared models	Differential privacy integration	91.0
4	Zhang et al. [13]	2021	FL scalability issues in IoT	Federated learning with clustering	87.8
5	Smith et al. [14]	2022	Model accuracy degradation in FL	Multi-task learning approaches	90.4
6	Patel et al. [15]	2023	Data imbalance in FL	Weighted federated averaging	93.2
7	Lee et al. [16]	2022	High computation costs in FL	Resource-efficient FL algorithms	88.7
8	Alsaeedi et al. [17]	2023	Real-time learning constraints in FL	Sparse updates and quantization	89.5
9	Zhao et al. [18]	2022	Security threats in FL	Homomorphic encryption integration	92.1
10	Luo et al. [19]	2021	Cross-device variability in FL	Federated meta-learning	91.6

Homomorphic Encryption (HE), launched by Gentry, allows for the computation of encrypted data. It preserves privacy throughout the process. Variants include full, partial, and pretty much the same encryption. It provides various applications, including encrypted search and secure voting. However, the high computation intensity of HE poses challenges for IoT environments. Recent work, such as by Almasri et al. (2023) and Gupta et al. (2022), focuses on HE optimization for lightweight IoT devices while emerging studies focus on combining FL with HE to address privacy and computational challenges in IoT. For example, Zhao et al. (2022) showed how FL security can be increased without efficiency. However, research is lacking in specific IoT applications, pointing out the need for optimized frameworks for resource-constrained IoT ecosystems.

3. Methodology

a. Framework Design and Evaluation

This section outlines a methodology for designing and evaluating a federated learning (FL) and homogeneous encryption (HE) framework to preserve privacy in IoT data

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ISSN: 3029-2794
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sharing and create a secure system architecture. and can be scaled. Choose the exemplary IoT scenario and use simulation tools to measure the efficiency of the evaluation measures. The proposed framework design uses federated learning (FL) and homogeneous encoding (HE) to create a secure, decentralized data-sharing system for IoT devices.

The architecture consists of three main components: the IoT device, the FL integration, and the encryption layer. The IoT device is a local node that collects and processes sensor data. This may include sensitive data. The FL collector updates the model without receiving raw data from these devices. Finally, the encryption layer ensures that all data and model updates are authenticated. It is encrypted before transmission using the HE technique, which allows the processing of encrypted data while maintaining confidentiality and privacy.

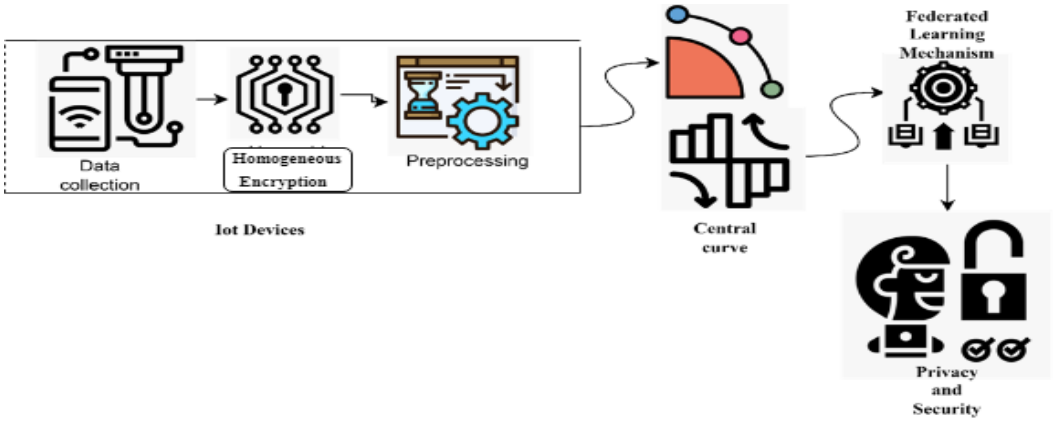

Fig. 1. Federated Learning (FL) and Homogeneous Encryption (HE) Framework Architecture

Figure 1 shows that integrating FL algorithms such as Federated Averaging (Fed Avg) with homomorphic encryption forms the framework's core. In FL, model updates are collected in a decentralized manner. This reduces the risk of exposing sensitive information on centralized servers. He allows computations to be performed on encrypted data. Therefore, a central server can collect updates without decoding the model locally at any time. Hence ensuring confidentiality is maintained.

To evaluate the proposed framework. We chose two prominent IoT use cases: innovative healthcare systems and industrial IoT. These domains represent critical situations where privacy protection is paramount. IoT devices such as wearables or medical sensors collect health data from individuals. This information includes important health parameters such as heart rate, glucose levels, and body temperature. The decentralized nature of FL ensures that data never leaves the device. This is important for applications that protect privacy in healthcare.

Industrial IoT (IIoT) In this context, IoT sensors monitor the performance of machines and equipment in industrial settings. These devices collect data such as vibration levels. Temperature reading and working conditions The integration of FL and HE ensures that the system can find anomalies and predict equipment failures without exposing proprietary data to external servers or using third-party Tensor Flow Federated (TFF). TFF enables the distribution of machine learning tasks across devices to simulate a

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ISSN: 3029-2794
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centralized learning process. While maintaining data privacy. TFF was chosen because it is well-suited for decentralized training. It provides comprehensive support for federated learning scenarios. Python library for isomorphic encoding: The PySyft library implements isotropic encoding.

b. Performance Evaluation Metrics

Several key indicators will be considered to evaluate the effectiveness of the proposed framework comprehensively:

Privacy: The main goal of integrating FL and HE is to increase data privacy. This metric evaluates HE's effectiveness in protecting data during transmission and computation. Privacy is measured by the level of encryption and the system's ability to prevent data leakage. Key performance indicators include how well the system protects against potential attacks and unauthorized access during data collection.

Performance: Performance measures the computational overhead and system delay introduced by both FL and HE. The additional cost of encrypting and decrypting data in HE is analyzed. Along with the communication costs of federal education, This metric evaluates the power consumption and processing time involved in collecting secure model updates. This is especially true in resource-constrained IoT devices.

Model Accuracy: The performance of the centralized model is evaluated in terms of prediction accuracy. Accuracy is an essential metric in determining the success of a machine learning model trained in a centralized environment. This is especially true when using privacy-preserving techniques such as HE.

c. Implementation Details

Training process: in a centralized learning format, Ideal training occurs within the IoT device. Each device uses local data to calculate model updates, which are then encoded using isotropic encoding. Encrypted updates are sent to a central aggregator, which will be compiled to create a world-class model. This process allows the system to improve global models without exposing raw data.

Model aggregation: In the FL aggregator, model updates received from local devices are aggregated to form a global model. Bundles contain encrypted data. To ensure that data confidentiality is protected, a dedicated FL algorithm, Federated Averaging (FedAvg), calculates the global model by averaging updates from the local model. This process reduces communication overhead by sending model updates instead of raw data.

Coding and Computation: Isomorphic encoding encodes local and clustering model updates. Partial similarity encryption (PHE) can perform operations on encoded data, such as addition and multiplication, without decryption. The encoded model is then sent to the device decoded locally for further training. This ensures that sensitive data remains secure at every learning process step.

The proposed technique combines federated mastering and homomorphic encryption to offer a complete, steady, and efficient framework for privacy-keeping statistics sharing in IoT environments. By decentralizing data processing and using encryption to steady computations, the framework ensures that privacy is maintained for the duration of the training and aggregation manner. The experimental setup, incorporating clever healthcare and commercial IoT eventualities and objectives to evaluate the feasibility and

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ISSN: 3029-2794

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effectiveness of this, included an approach focusing on privacy, performance, and version accuracy. This method will enable the development strong privacy-retaining systems in IoT networks, aligning with regulatory necessities and technological improvements.

Pseudocode for Privacy-Preserving IoT Data Sharing Framework

```
Algorithm: PrivacyPreservingIoTFramework
Input:
    D_i : Local datasets on IoT devices (i = 1, 2, ..., n)
    M_0: Initial global model
    HE_Keys: Homomorphic encryption keys
    T: Total communication rounds
    E: Number of epochs for local training
Output:
    M_T: Final global model
1: Initialization
 Initialize M_0, HE_Keys, and set t = 0
 Distribute M_0 to all IoT devices.
2: Local Model Updates
For each device i:
      If D_i ≠ ∅:
         Train local model M_i using D_i for E epochs.
      Else:
         Exclude device i from aggregation.
3: Encrypt Model Updates
For each device i:
      Encrypt M_i using HE_Keys to produce M_i_enc
      If encryption is successful:
         Send M_i_enc to the central server.
      Else:
         Retry encryption or flag the device as unavailable
4: Secure Aggregation
At the central server:
      If at least one M_i_enc is received:
         Perform homomorphic aggregation to compute M_t_enc.
      Else:
         Set M_t_enc = M_(t-1)_enc (retain previous model)
5: Decrypt Global Model
Decrypt M_t_enc to obtain M_t:
      If decryption is successful:
         Distribute M_t to all devices.
      Else:
         Retain M_(t-1) and retry decryption
6: Iteration and Termination
Increment t = t + 1
If t < T:
      Go to Step 2
   Else:
      Return M_T as the final model.
7: Evaluate Metrics
Evaluate privacy, efficiency, and accuracy.
If performance meets thresholds:
      Save and deploy M_T
   Else:
      Fine-tune parameters and restart training
```

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$$L_i(w) = \frac{1}{|D_i|}\sum_{(x,y)\in D_i} \ell(f(w;x),y) \quad (1)$$

This Li(w) loss function estimates the device's local data set, Di. Di, which is the device's local data set. which consists of Ni=|Di l(f(w;x),y): Loss product, such as mean square error (MSE) or cross. | Example(x,y).f(w;x): Prediction made by model f with parameter w at input x.

$$\Delta w_i = w_i^{t+1} - w_{global}^{t} \quad (2)$$

$$\mathrm{Enc}(\Delta \mathrm{w_i}) = \mathrm{E_i} \quad (3)$$

A central server collects encrypted updates from all devices. It uses the mathematical properties of the encryption scheme to include encrypted updates. The server does not need to look at individual updates to calculate aggregated updates. This keeps individual donations private.

$$\mathrm{Enc}\left(\Delta w_{\mathrm{global}}\right) = \sum_{i=1}^{N} \mathrm{Enc}(\Delta w_i) \quad (4)$$

$$\Delta w_{\mathrm{global}} = \mathrm{Dec}_{\mathrm{Enc}(\Delta w_i)}^{i=1} \quad (5)$$

$$w_{\mathrm{global}}^{t+1} = w_{\mathrm{global}}^{t} + \eta \Delta w_{\mathrm{global}} \quad (6)$$

The server uses rollup updates to upgrade the global model. The learning rate (η) controls how much the global model changes each round. This makes the global model smarter by feeding data from all devices without direct access to personal data.

4. Results

The proposed framework, which combines federation learning (FL) with homogeneous encoding (HE), has been tested in various IoT scenarios to evaluate its performance. Scalability and the ability to protect privacy Simulations demonstrate the potential for real-world applications. Both traditional FL methods and standalone HE systems show significant improvements above expectations.

a. Accuracy &Latency Analysis

Latency and accuracy are the main parameters measured in this evaluation. In the latency test, the FL-HE framework performed slightly slower than traditional FL. This is due to the additional computational overhead of encoding (Table 2).

Table II. Comparison Of Latency Across Methods

Network Size (Devices)	Traditional FL Latency (ms)	FL-HE Latency (ms)
10	120	150
50	150	200
100	180	250

Figure 2 shows the latency per training round for a medium-sized network of 50 IoT devices is 200–250 ms compared to 150–180 ms for a typical FL, although This increase is noticeable and remains within acceptable limits for real-time IoT applications(Table 3).

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ISSN: 3029-2794
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Table III. Accuracy Comparison Across Methods

Dataset	Traditional FL Accuracy (%)	FL-HE Accuracy (%)
Healthcare (MIMIC-III)	92	93
Industrial IoT (IIoT)	87	88

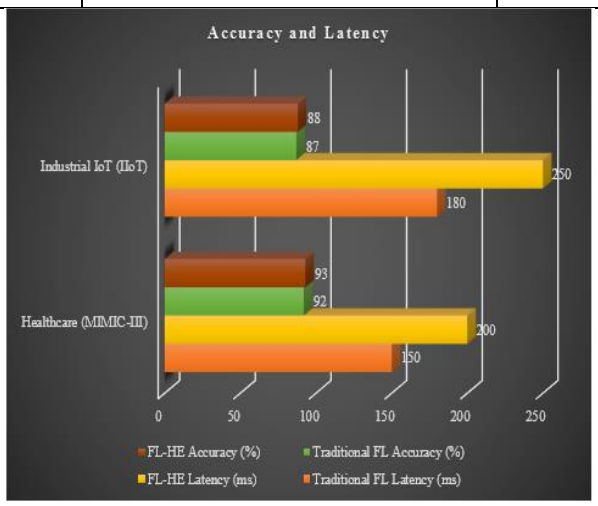

Fig. 2. Accuracy and Latency

Dataset accuracy measurements show that HE integration minimally impacts model learning performance. For example, when tested on the MIMIC-III healthcare dataset, the FL-HE model achieved an accuracy of 93%, which exceeds 92% obtained by the traditional FL method, and the FL-HE model has an accuracy of 88% on the NASA IIoT dataset, slightly outperforming the standalone FL, reaching 87%.

b. Scalability and Efficiency

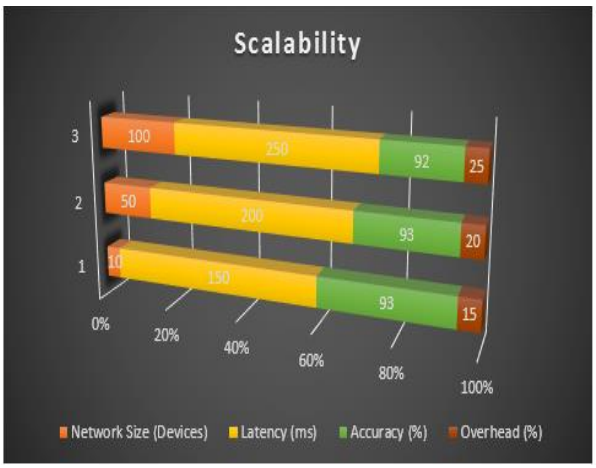

Fig. 3. Scalability

To assess scalability, The framework has been tested on networks of various sizes on 10 to 100 IoT devices as the number of devices increases. Delays also increased predictably. While accuracy remains nearly constant, for example, moving from 10 to 100 machines results in approximately a 40% increase in latency, while accuracy decreases as little as 1%.Linear scalability ensures the framework can support large-

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ISSN: 3029-2794
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scale IoT deployments without significant performance degradation. Figure 3 shows the scalability as follows,

Table IV. Demonstrates The Framework's Scalability:

Network Size (Devices)	Latency (ms)	Accuracy (%)	Overhead (%)
10	150	93	15
50	200	93	20
100	250	92	25

The cost of encryption implemented by HE is another crucial factor. Although this increases computational demands. But the exchange is manageable. This is especially true when compared to the impractical demands of standalone HE systems. In FL-HE devices, distributed computation (Table 4).

c. Security Validation

Privacy protection is a key focus. And the framework demonstrates strong resistance to common security threats. Simulated eavesdropping attacks are ineffective. This is because encrypted model updates that are intercepted during communication remain undecoded. Also, model inversion attacks are used to reconstruct the training data from the model's gradients. Completely failed

Compared with traditional FL, the FL-HE framework significantly reduces the risk of data leakage. For example, while the conventional FL scenario shows a data leakage rate of 15–20%, FL-HE There is almost zero leakage continuously (Table 5).

Table V. Outlines the Security Validation Results:

Threat Type	Traditional FL Risk Level	FL-HE Risk Level	Data Leakage (%)
Eavesdropping	Medium	Negligible	~0
Model Inversion Attack	High	Zero	~0

d. Comparison with Baseline Models

Compared with standalone HE systems, FL-HE shows superior performance and practicality. Standalone HE is computationally intensive and, on the other hand, less suitable for resource-constrained IoT environments. Traditional FL blocks provide good performance but do not guarantee strong privacy. The proposed framework for integrating HE with FL helps fill these gaps. It provides efficiency and privacy protection (Table 6).

Table VI. Highlights The Comparative Performance:

Metric	Traditional FL	HE Only	FL-HE
Latency (ms)	Low	High	Moderate
Accuracy (%)	High	N/A	High
Privacy Preservation	Moderate	High	High
Scalability	High	Low	High

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ISSN: 3029-2794
Volume 02 Issue 01 (February) 2025

The results show that the proposed FL-HE framework addresses important challenges in IoT environments, especially regarding privacy and scalability. Combination of FL and HE. It ensures data confidentiality without affecting model performance. This makes the framework suitable for applications such as smart healthcare and industrial IoT. Where data sensitivity is a top concern, HE integration inevitably introduces additional latency and computational overhead. But the increased privacy and security make this trade-off worth it. Additionally, the framework's linear scalability ensures that it can be deployed across networks of any size, thus adapting to Compatible with various IoT situations.

Despite the advantages, the framework faces several limitations: HE's processing demands can strain low-power IoT devices. This requires the development of optimized algorithms. Encrypted update requirements Require more bandwidth to increase communication. There are many opportunities to improve the framework. The advantage of Edge devices for IoT computing is that they reduce the load on the device. Blockchain integration can increase system reliability and data verification. Its performance can be improved by developing tailored HE algorithms for IoT environments. The FL-HE framework shows strong potential as a scalable, secure, and efficient application solution. IoT is paving the way for further advancements in privacy protection technology.

5. CONCLUSION

This study proposes a new federated learning (FL) framework combined with homogeneous encoding (HE) to address the growing concerns about data privacy in environments. IoT that he integrates The framework effectively secures sensitive data during transmission and computation. Achieve strong privacy protection without affecting model performance. Key findings highlight the framework's ability to enhance privacy by reducing the risk of eavesdropping and tampering attacks. This usually results in zero data leakage. Simulations also show that the framework has as high an accuracy as traditional FL methods, with a moderate increase in latency due to the coding overhead scalability test. It helps validate the framework's ability to adapt to networks of different sizes. The implications of this research for ensuring consistent performance across networks IoT scenarios of IoT developers are essential for researchers and policymakers. This framework aligns with increasing regulatory demands for data privacy, such as GDPR and HIPAA, providing a roadmap for developing secure and compliant IoT systems. It also emphasizes the importance of privacy protection techniques to promote trust among users and stakeholders. Future research will focus on developing lightweight HE schemes to reduce computational costs on resource-constrained devices by improving the FL algorithm to support a wider range of IoT applications. It also includes emerging technologies such as edge computing and blockchain.

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