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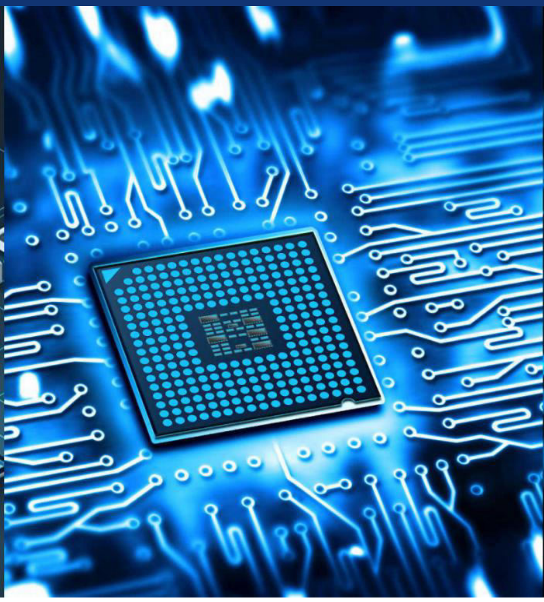


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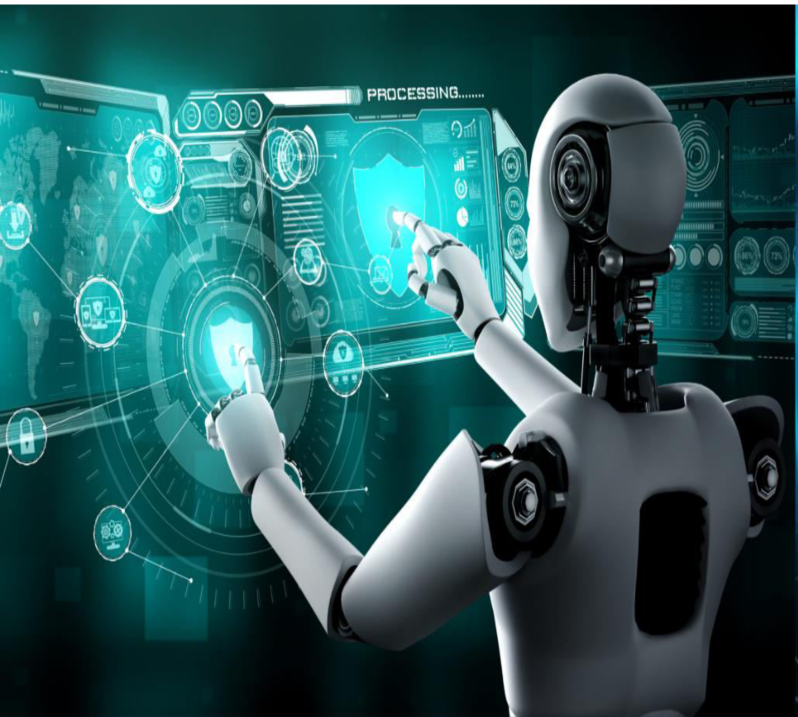

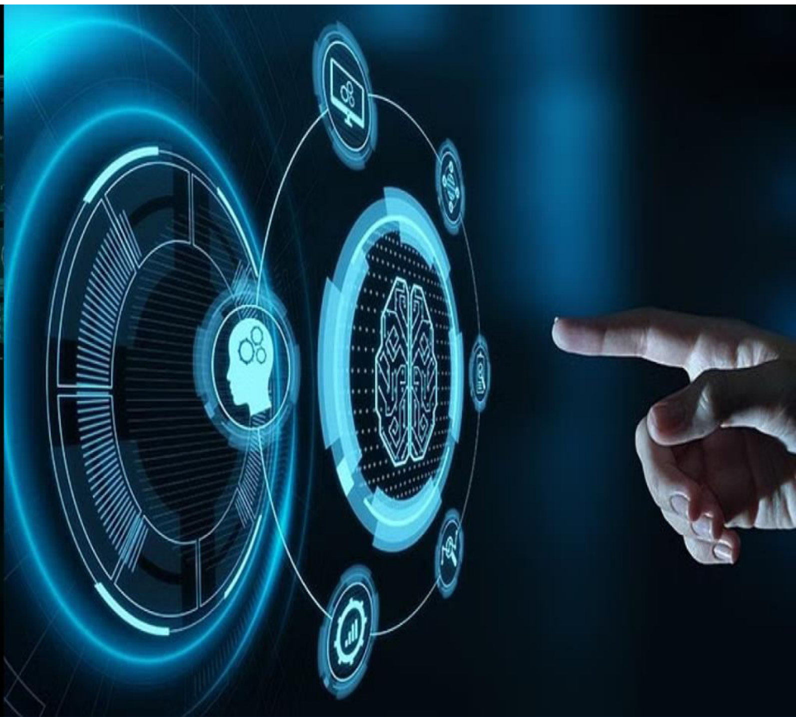

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Resilience in Federated Learning-Based IoMT Applications

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ABSTRACT: Internet of Medical Things (IoMT) applications require collaborative learning across healthcare institutions while ensuring patient data privacy. Traditional centralized learning approaches require sharing sensitive medical records, increasing privacy and security risks. Federated Learning (FL) enables distributed model training by exchanging model parameters instead of raw data, but its performance is affected by client dropouts and communication failures. This paper proposes a Resilience-Enhanced Federated Learning Framework for IoMT applications that improves the reliability of collaborative learning under unstable network conditions. The framework incorporates Federated Averaging (FedAvg), resilient aggregation using historical model updates with staleness decay, and quantized model updates to reduce communication overhead. The proposed model was evaluated using a heart disease dataset distributed across multiple healthcare clients. Experimental results demonstrate that the framework achieves 95.72% accuracy while maintaining stable model convergence during client failures. The proposed approach provides a secure, privacy-preserving, and fault-tolerant solution for distributed healthcare applications.

KEYWORDS: Federated Learning; Internet of Medical Things (IoMT); Privacy Preservation; Resilient Aggregation; Client Dropout; Federated Averaging (FedAvg); Heart Disease Prediction

I. INTRODUCTION

The Internet of Medical Things (IoMT) consists of interconnected medical devices and healthcare systems that generate large volumes of sensitive patient data. These devices enable remote health monitoring and disease prediction, but sharing medical data with centralized servers raises privacy and security concerns. Federated Learning (FL) addresses this challenge by allowing multiple healthcare institutions to collaboratively train machine learning models without exchanging raw patient data.

In IoMT environments, network instability and client dropouts can affect the performance and reliability of federated learning models. Therefore, improving the resilience of FL is essential for maintaining accurate and efficient healthcare applications. The proposed framework enhances the reliability of federated learning by incorporating Federated Averaging (FedAvg), resilient aggregation with historical model updates, and quantized communication to reduce network overhead.

The main objective of the proposed approach is to provide secure, privacy-preserving, and fault-tolerant collaborative learning while maintaining high prediction accuracy and reducing communication costs in distributed healthcare environments.

II. RELATED WORK

Federated Learning (FL) has emerged as an effective approach for privacy-preserving machine learning in healthcare by enabling collaborative model training without sharing sensitive patient data. Brendan McMahan *et al.* introduced the Federated Averaging (FedAvg) algorithm, which significantly reduces communication costs while maintaining model performance. However, standard FL methods are vulnerable to client dropouts and communication failures, affecting model convergence.

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Several researchers have proposed communication-efficient techniques such as gradient quantization and compressed model updates to reduce network overhead. Other studies introduced personalized federated learning models to improve prediction accuracy on heterogeneous healthcare datasets. Although these approaches improve communication efficiency and personalization, they provide limited support for unreliable client participation.

Recent research has focused on enhancing the robustness of Federated Learning through fault-tolerant aggregation and resilient training strategies. These methods allow model training to continue even when some clients become unavailable. Inspired by these works, the proposed framework integrates **FedAvg**, **staleness-aware aggregation**, and **client dropout handling** to improve reliability while preserving data privacy in IoMT healthcare applications.

III. PROPOSED ALGORITHM

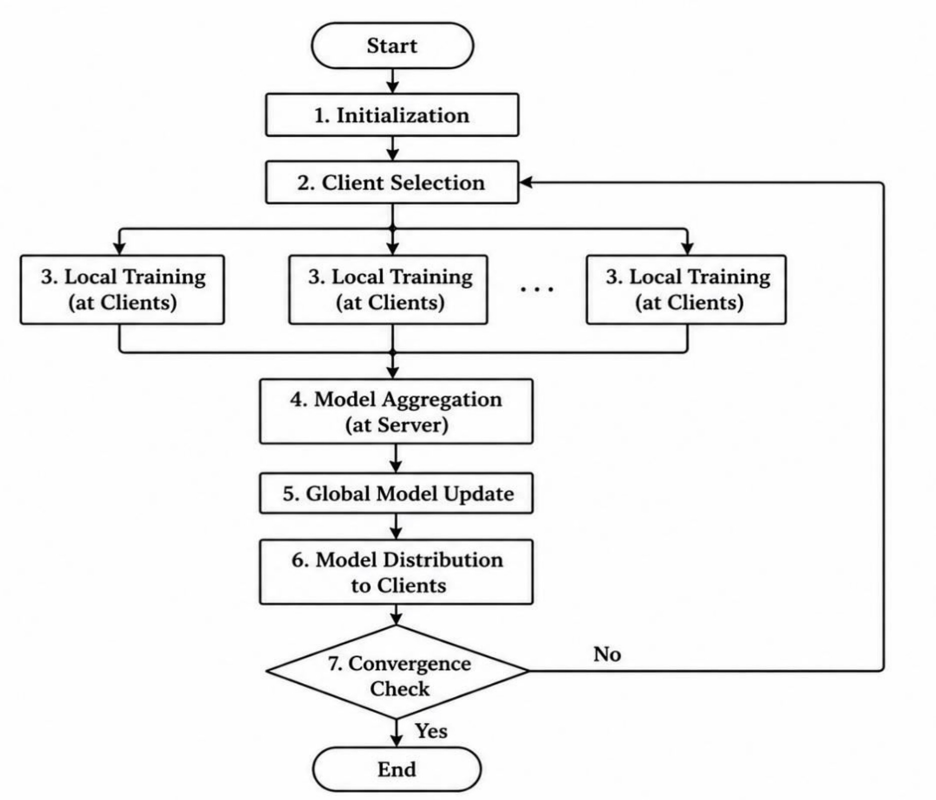

Figure 1: System Architecture

A. Design Considerations

Medical data remains locally stored at each IoMT client (hospital/device) and is never shared with the central server.
Each client trains the local model using its own patient dataset.
The Federated Server aggregates only model parameters using the **Federated Averaging (FedAvg)** algorithm.
Client dropouts and communication failures are expected during training.
A **staleness-aware aggregation mechanism** is used to incorporate delayed client updates.
Only successfully trained client models are considered during global model aggregation.
The global model is redistributed to all active clients after each communication round.
Training continues until the global model converges or the predefined number of communication rounds is completed.

B. Description of the Proposed Algorithm

The proposed **Resilience-Enhanced Federated Learning Framework** aims to improve the reliability, privacy, and robustness of distributed learning in IoMT environments. Instead of transmitting sensitive patient records, only locally trained model parameters are exchanged between IoMT clients and the Federated Server. The proposed algorithm consists of three main steps.

Step 1: Local Model Training

Each participating hospital or IoMT client initializes the global model received from the Federated Server and trains it using its own local medical dataset. Local training is performed independently without transferring any patient information outside the device.

$$W_i = \text{Train}(W_g, D_i)$$

where
W_g= Global model
D_i= Local dataset of client i
W_i= Updated local model

Step 2: Resilient Model Aggregation

The trained local models are transmitted to the Federated Server. The server checks whether a client update is available. If a client fails to communicate due to network interruption or device failure, the aggregation process continues using the available client models. Delayed updates are handled using a **staleness-aware aggregation** strategy to minimize the impact of outdated information.

The global model is updated using the Federated Averaging algorithm.

$$W_g = \sum_{i=1}^{N} \frac{n_i}{n} W_i$$

where
W_g= Updated global model
W_i= Local model of client i
n_i= Number of local training samples
n= Total number of training samples
N= Number of active clients

Step 3: Global Model Distribution and Iteration

The updated global model is distributed back to all active IoMT clients. Each client replaces its previous model with the latest global model and starts the next communication round. This iterative process continues until the desired model accuracy or the maximum number of communication rounds is reached.

IV. PSEUDO CODE

Step 1: Initialize the global model at the Federated Server.
Step 2: Select the participating IoMT clients for the current communication round.
Step 3: Send the current global model to all selected clients.
Step 4: Each client trains the received global model using its local medical dataset.

```
if (client is active)
    Train the local model and send updated model parameters to the Federated Server.
else
    Mark the client as unavailable and continue training with the remaining active clients.
end
```

Step 5: Collect all received local model parameters at the Federated Server.
Step 6: Apply the staleness-aware aggregation mechanism to handle delayed or missing client updates.
Step 7: Aggregate the active client models using the Federated Averaging (FedAvg) algorithm to generate the updated global model.
Step 8: Broadcast the updated global model to all participating clients.
Step 9: Repeat Steps 2–8 until the maximum communication rounds are completed or the global model converges.
Step 10: End.

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V. SIMULATION RESULTS

The proposed Resilience-Enhanced Federated Learning Framework for IoMT Applications was implemented using Python, PyTorch, and Streamlit. The simulation environment consists of three healthcare clients representing hospitals that collaboratively train a heart disease prediction model without sharing raw patient data. The system incorporates Federated Averaging (FedAvg), client dropout handling, and resilience mechanisms such as historical update caching and staleness-aware aggregation. The overall training workflow is illustrated in Figure 6.2.

The performance of the proposed framework was evaluated using accuracy under different training scenarios. The centralized model achieved an accuracy of 100%, while the standard FedAvg model achieved 95.11% under normal operating conditions. The proposed Resilient Federated Learning approach achieved 95.72% accuracy, demonstrating that resilience mechanisms can maintain high prediction performance while preserving privacy.

To evaluate robustness, client dropout conditions were introduced during federated training. The standard FedAvg model achieved 85.41% accuracy when one client became unavailable, whereas the proposed Resilient Federated Learning framework achieved 86.63% accuracy. The results indicate that the resilience mechanism effectively reduces the impact of communication failures and inactive clients, ensuring more stable model convergence and reliable healthcare predictions.

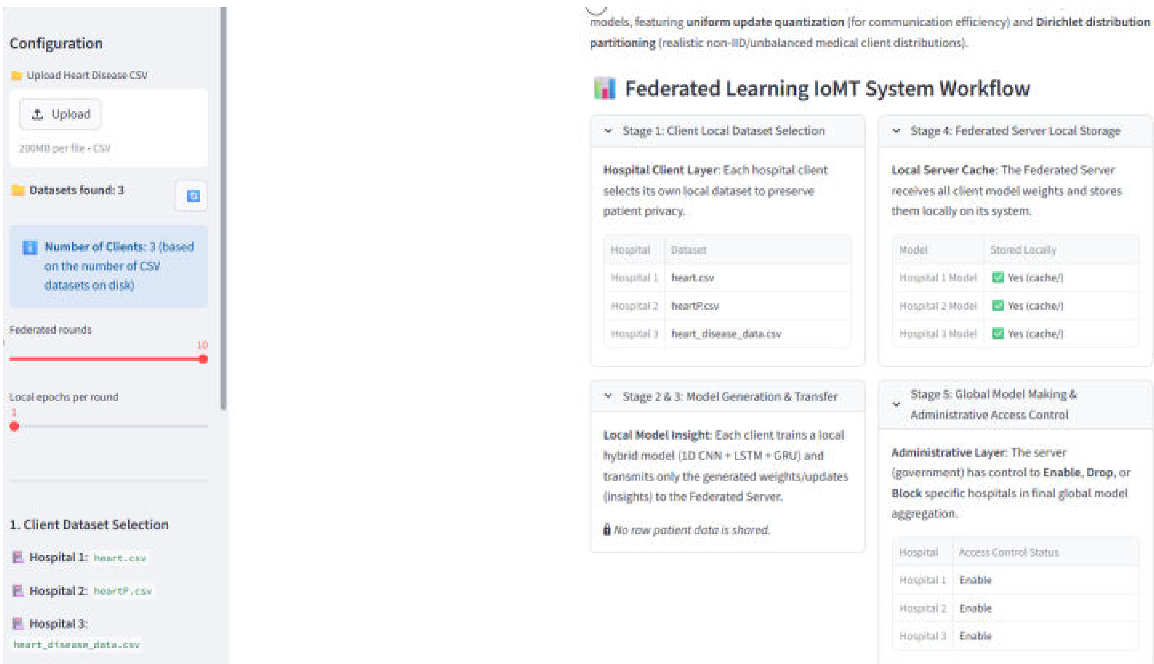
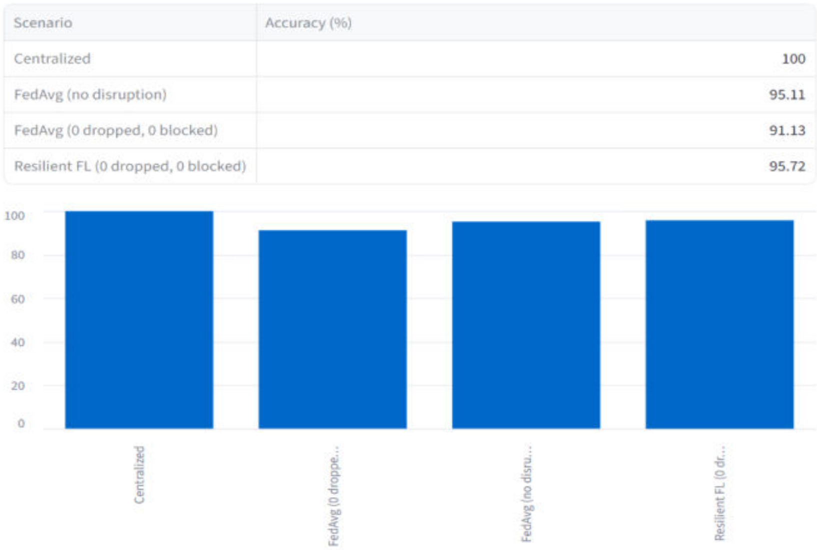
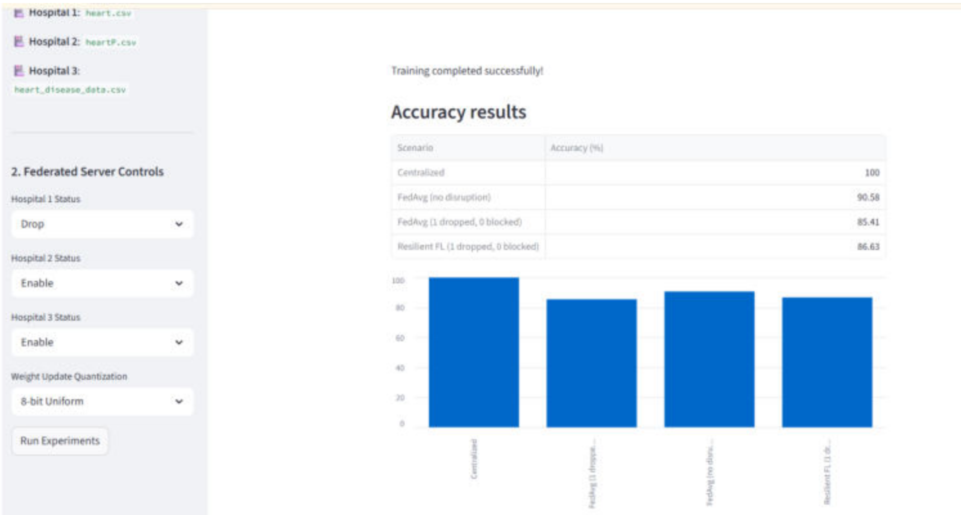


Figure 2: Federated Learning IoMT System Workflow and Client Training Process



Scenario	Accuracy (%)
Centralized	100
FedAvg (no disruption)	95.11
FedAvg (0 dropped, 0 blocked)	91.13
Resilient FL (0 dropped, 0 blocked)	95.72

Figure 3: Accuracy Analysis of Federated Learning Models



Scenario	Accuracy (%)
Centralized	100
FedAvg (no disruption)	90.58
FedAvg (1 dropped, 0 blocked)	85.41
Resilient FL (1 dropped, 0 blocked)	86.63

Figure 4: Accuracy Analysis under Client Dropout Conditions

The simulation results show that the proposed resilience-enhanced federated learning framework performs better than conventional FedAvg under client dropout conditions. By utilizing historical client updates and adaptive aggregation techniques, the framework maintains stable learning even when some hospitals are temporarily disconnected. The results demonstrate that resilience mechanisms improve model reliability, training stability, and prediction accuracy in dynamic IoMT environments. Therefore, the proposed framework provides a secure, privacy-preserving, and fault-resilient solution for real-world healthcare applications.

VI. CONCLUSION AND FUTURE WORK

The simulation results demonstrated that the proposed Resilience-Enhanced Federated Learning Framework improves the reliability and stability of federated learning in IoMT healthcare environments. The framework successfully preserves patient privacy by keeping medical data locally while enabling collaborative model training among multiple healthcare institutions. Experimental results showed that the proposed resilient approach achieved better accuracy than conventional FedAvg under client dropout conditions. The integration of historical update caching and staleness-aware aggregation helped maintain stable model convergence even when some clients became unavailable. Thus, the proposed framework provides a secure, privacy-preserving, and resilient solution for healthcare prediction applications in distributed IoMT environments.

The current work focuses on a simulated federated healthcare environment involving a limited number of hospital clients. As the number of participating hospitals and IoMT devices increases, the complexity of communication and model aggregation will also increase. Future work can extend the framework to large-scale healthcare networks and real-world IoMT deployments. Advanced aggregation techniques, blockchain-based security mechanisms, edge-assisted federated learning, and stronger privacy-preserving methods can also be incorporated to further improve system performance, scalability, security, and resilience under dynamic healthcare environments.

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