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Research Paper

A Technique for Privacy-Preservation of Machine Learning Models using Federated Learning

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ABSTRACT
Privacy preservation has become a critical issue in the age of big data and machine learning, where vast amounts of sensitive information are processed and analysed. Traditional machine learning models often require centralizing data from various sources, which poses significant privacy risks, especially for sensitive domains like healthcare, finance, and personal communications. Unauthorized data access, potential data breaches, and misuse of personal information are major concerns. Moreover, compliance with stringent privacy regulations, such as GDPR, becomes increasingly challenging. This paper presents a federated learning-based privacy-preserving model aimed at enhancing the security of machine learning processes while maintaining the confidentiality of sensitive data. The system demonstrated a high level of accuracy, reaching 98.36% during training and testing phases. Additionally, the system ensures regulatory compliance with modern data privacy laws and enhances its scalability for real-time applications. These results underscore the effectiveness of the proposed model in addressing contemporary privacy challenges while maintaining high predictive performance.

KEYWORDS: *Privacy-Preservation, Machine Learning, Federated Learning, Logistic Regression, Training*

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I. Introduction

Machine Learning (ML) has witnessed an unprecedented surge in utilization across diverse applications, revolutionizing the way we approach problem-solving and decision-making. From healthcare and finance to transportation and entertainment, Machine Learning has become an integral component, offering sophisticated solutions that adapt and evolve based on data patterns. This widespread adoption is fueled by the exponential growth in data availability, computational power, and advancements in Machine Learning algorithms. The increasing reliance on Machine Learning reflects its transformative potential to unlock insights from massive datasets, automate complex tasks, and improve decision accuracy (Jordan & Mitchell, 2015). However, this proliferation of Machine Learning comes with inherent challenges, with one of the foremost concerns being the privacy of sensitive data used in training and deploying Machine Learning models. As Machine Learning applications become more pervasive, the need to address these privacy issues becomes paramount to ensure ethical and responsible use of technology.

Privacy concerns associated with sensitive data used in Machine Learning (ML) models are multifaceted and can have significant ethical and legal implications. Some key privacy concerns include: Data breaches, Re-identification Risk, Bias and Discrimination, informed consent, Algorithmic Transperency, Secondary use of data, Cross-Domain Inference, Model inversion, Homomorphic Attacks, Data Poising etc. Addressing these privacy concerns requires a comprehensive approach that includes robust security measures, ethical data handling practices, transparency in model development, and ongoing efforts to mitigate biases and discrimination in Machine Learning algorithms. It also emphasizes the importance of adhering to privacy regulations and standards to protect individuals' rights and maintain public trust in the use of ML technologies.

Given the importance of preserving privacy in the era of Machine Learning, there is a compelling need for robust and effective privacy-preserving techniques. These techniques should not only ensure the confidentiality of sensitive data but also address the broader ethical considerations associated with ML applications.

Federated Learning (FL) emerges as a promising solution to address the privacy concerns inherent in traditional ML approaches. Unlike conventional centralized training methods, Federated Learning distributes the learning process across decentralized devices or servers. In this paradigm, the training of ML models occurs locally on individual devices, utilizing locally stored data. Only the model updates, rather than raw data, are transmitted to a central server, where they are aggregated to improve the global model.

II. Review of Related Literature

In fields such as healthcare, Machine Learning algorithms analyze patient data to facilitate early disease detection and personalized treatment plans (Obermeyer & Emanuel, 2016). Financial institutions leverage Machine Learning for fraud detection, risk assessment, and optimizing investment strategies (Lipton et al., 2016). Additionally, Machine Learning plays a pivotal role in enhancing the efficiency and safety of transportation systems through predictive maintenance and autonomous vehicle technologies (Goodfellow et al., 2016). Furthermore, the entertainment industry benefits from ML-driven content recommendations, personalized user experiences, and advanced content creation tools (Hu & Wu, 2018). Other researches in this domain are outlined.

Kairouz *et al*. (2019) presented "Privacy-Preserving Credit Scoring with Federated Machine Learning". They explored Federated Learning for credit scoring applications, allowing financial institutions to collaboratively build models without sharing sensitive customer financial information. In their ,methodology, Financial institutions locally train credit scoring models on their datasets. Only model updates are shared and aggregated, ensuring privacy. The result of Federated Learning-based credit scoring models achieve comparable accuracy to centralized models without exposing sensitive financial information.

Hao et al., (2019) presented Federated Learning for Secure and Privacy-Preserving Industrial artificial intelligence, which focuses on applying Federated Learning to secure and privacy-preserving Industrial Internet of Things (IIoT) in smart grids, ensuring efficient energy management without compromising data privacy. They proposed an efficient and privacy-enhanced federated learning (PEFL) scheme for Industrial Artificial Intelligence (IAI). Compared with existing solutions, PEFL is noninteractive, and can prevent private data from being leaked even if multiple entities collude with each other. Moreover, extensive experiments with real-world data demonstrate the superiority of PEFL in terms of accuracy and efficiency.

Bonawitz et al., (2019) designed "Federated Learning for Autonomous Vehicles". The study discusses Federated Learning applications in the context of autonomous vehicles, enabling vehicles to learn from each other's experiences without sharing raw sensor data. In their methodology, Autonomous vehicles locally train models on their sensor data. Model updates, capturing knowledge from various vehicles, are transmitted and aggregated without sharing raw sensor data. The result of their experiment showed that Federated Learning facilitates collaborative learning among autonomous vehicles, improving overall model performance and safety without compromising individual vehicle data.

Rani, et al (2023) in their work "Federated Learning-Based Misbehaviour Detection for the 5G-Enabled Internet of Vehicles", discussed how Vehicular Networks and the Internet of Vehicles (IoV) enable cooperative learning through federated learning. The work proposes a privacy-preserving IoV malware detection framework. According to experiments, the proposed Federated Learning approach detected attacks in IOV networks with a maximum accuracy of 99.72%. In addition to precision, recall, and F1 scores, 99.70%, 99.20%, and 99.26% were achieved. A comparison of the proposed model with the existing model shows that the proposed model is more accurate.

Gu, et al., (2023), proposed an information reporting framework for solving both efficiency and privacy issues. Specifically, messages are probabilistically reported to the server depending on their importance. Furthermore, the DAG-based blockchain ensures that messages reported for a specific event are all gathered in the same ledger. We also present a scheme based on the geo-indistinguishability to protect the location privacy of vehicles. Extensive experiments demonstrate that the proposed framework preserves the location privacy of vehicles and achieves efficiency with acceptable overheads.

Wang *et al*., (2022) proposed a Privacy Protection Scheme for Federated Learning under Edge Computing (PPFLEC). Firstly, they proposed a lightweight privacy protection protocol based on a shared secret and weight mask, which is based on a random mask scheme of secret sharing. It is more accurate and efficient than homomorphic encryption. It can not only protect gradient privacy without losing model accuracy, but also resist equipment dropping and collusion attacks between devices. Second, they designed an algorithm based on a digital signature and hash function, which achieves the integrity and consistency of the message, as well as resisting replay attacks. Finally, they proposed a periodic average training strategy, compared with differential privacy to prove that their scheme is 40 % faster in efficiency than in deferential privacy. Meanwhile, compared with federated learning, they system achieved the same efficiency under the condition of ensuring safety. Therefore, the scheme can work well in unstable edge computing environments such as smart healthcare.

III. Analysis of the Proposed System

The proposed system's architecture shown in figure 1 integrates distributed key management to enhance privacy preservation and scalability within a federated learning framework. Initially, learning clients request both traditional encryption keys and homomorphic encryption keys from a centralized Key Management Center (KMC). However, instead of relying solely on a centralized entity, the distributed key management approach ensures that key generation and distribution tasks are decentralized, potentially across multiple KMC nodes or through a distributed consensus mechanism.

With these keys, clients encrypt their model updates using homomorphic encryption, maintaining data privacy during transmission to the central server. The server, equipped with its own set of decryption keys, performs computations like model aggregation directly on the encrypted updates, eliminating the need for decryption and preserving privacy. Moreover, the KMC's distribution of homomorphic encryption keys for encrypting global model parameters further fortifies privacy protection. By distributing encryption keys and computation tasks, the system mitigates risks associated with centralized key management, such as single points of failure, while enhancing scalability. Additionally, the integration of homomorphic encryption enables secure inference on sensitive data, extending privacy protection beyond training. Overall, the proposed system offers a comprehensive solution for privacy-preservation, ensuring data privacy across diverse and distributed datasets while enabling collaborative model training.

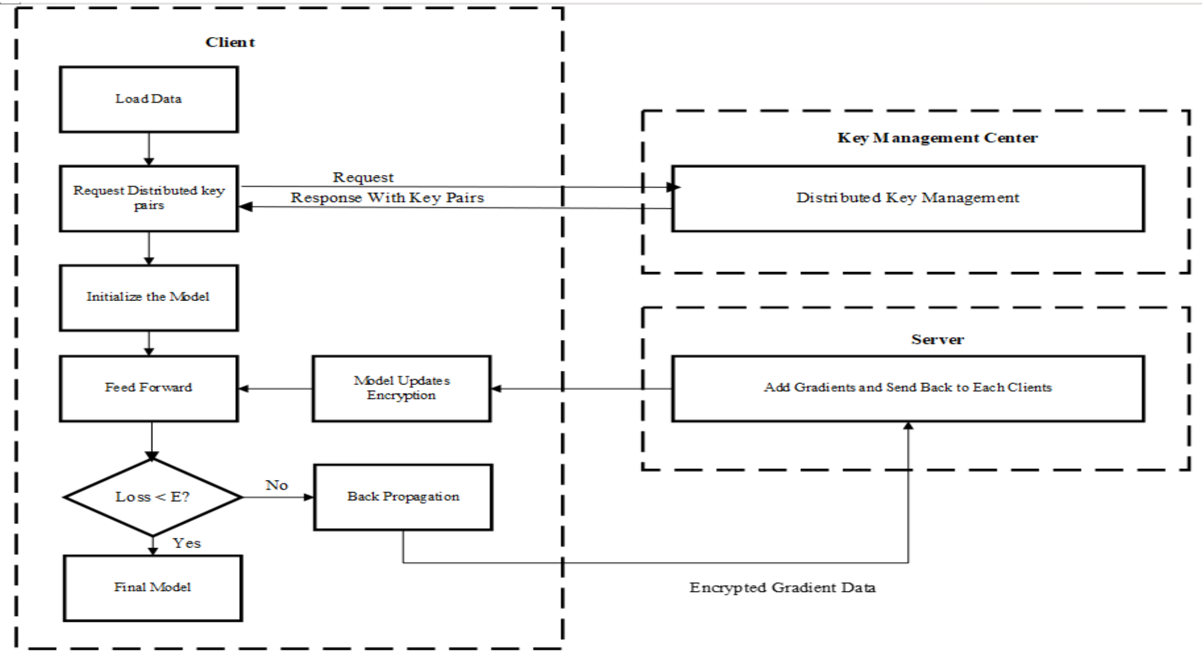


Figure 1: Architecture of the Proposed System

The proposed architecture is grouped into three modules namely, client, key management center and server modules. The details of the components and the process of operations are outlined below.

a. Load Data: The process begins with loading the training data from distributed sources, which may be spread across multiple learning clients. These data sources contain sensitive information that needs to be protected throughout the federated learning process.

b. Request Distributed Key Pairs: Learning clients initiate a request to a centralized Key Management Center (KMC) to obtain distributed key pairs. These key pairs include both traditional encryption keys and homomorphic encryption keys, necessary for securing data and computations in the federated learning process.

c. Key Management Center (Distributed Key Management): The KMC is responsible for generating and distributing key pairs to learning clients securely. It ensures that each client receives the necessary encryption keys to protect their data and enable secure computations during model training and aggregation.

d. Initialize the Model: Once equipped with encryption keys, learning clients initialize their local models using the training data available to them. This step prepares the models for training and eventual aggregation with contributions from other clients.

e. Model Updates Encryption with Encryption: As training progresses, learning clients encrypt their model updates using the encryption keys obtained from the KMC. Additionally, homomorphic encryption is applied to these updates, allowing computations to be performed directly on the encrypted data without decryption, thus preserving privacy.

f. **Server (Add Gradients and Send Back to Each Clients)**: The central server receives the encrypted model updates from learning clients and performs aggregation using homomorphic operations. It adds the aggregated gradients to each client's encrypted model updates and sends them back for further training iterations.

g. **Feed Forward**: Learning clients receive the aggregated model updates from the server and continue training by incorporating these updates into their local models. This process iterates until convergence criteria are met.

h. **Loss < E? (YES) -> Final Model**: At each iteration, the system evaluates whether the loss function falls below a predefined threshold (E). If the condition is satisfied, indicating convergence, the final global model is derived from the aggregated parameters across all clients.

i. **Loss < E? (NO) -> Back Propagation**: If the convergence criteria are not met, backpropagation occurs, and the process continues with another iteration of model updates, encryption, aggregation, and training until convergence is achieved.

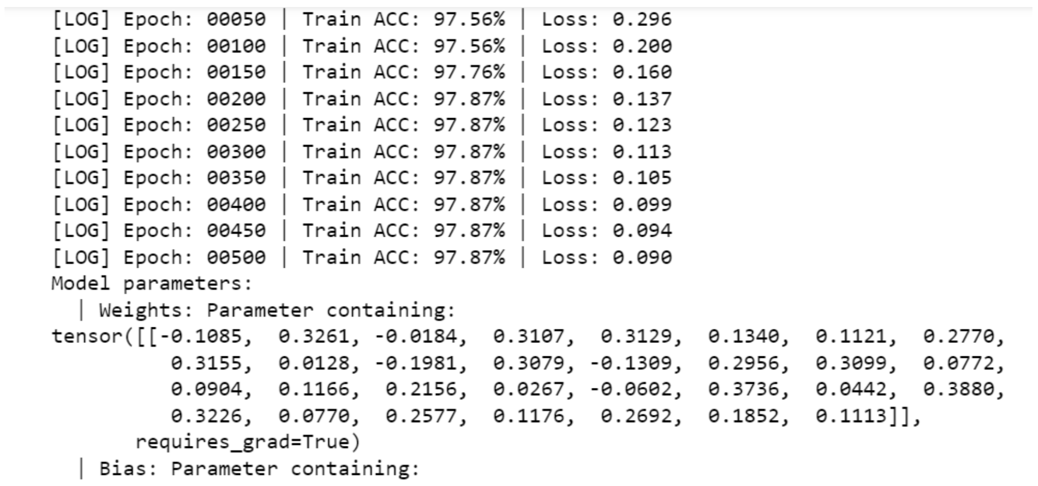
IV. Experimental Setup and Results

The experiments implements a simplified federated learning scenario using PyTorch. It is structured into several main components, with key functionality detailed below:

First, during the **Data Preprocessing stage,** three datasets (dataset1.csv, dataset2.csv, dataset3.csv) are loaded into the system. For each dataset, it performs feature scaling using StandardScaler to standardize the features. It also uses RandomOverSampler to balance class distributions by oversampling the minority class when needed. After preprocessing, the data is converted into PyTorch tensors for use in the model training. Next, the basic **logistic regression model** built using PyTorch's torch.nn. Module, is used as the neural network architecture in this implementation. It consists of a single linear layer with weights initialized to zero. The forward pass uses the sigmoid activation function to map the output to a probability, as logistic regression is well-suited for binary classification problems. Furthermore, the federated learning scenario known as the client class, which involves multiple clients, each of which independently trains a local model on its own dataset is implemented. Each client performs the following:

1. **Preprocessing:** Each client preprocesses its dataset by scaling and splitting it into training and testing sets. The labels in the dataset are also modified, replacing categorical values with binary ones (e.g., "M" for malignant, and "B" for benign in a diagnostic column).
2. **Training:** The client trains its local logistic regression model using a stochastic gradient descent (SGD) optimizer and binary cross-entropy (BCE) loss function. The training loop runs for a specified number of epochs, and at each epoch, the client updates the model weights based on the loss calculated from predictions and true labels.
3. **Model Encryption**: After training, the client encrypts the model's parameters (weights and bias) using a custom encryption function encrypt_weights(). The encrypted parameters are saved locally for future aggregation.
4. Evaluation: Each client evaluates its local model by calculating its accuracy on the test dataset. The accuracy is derived by comparing the predicted outputs with the actual test labels.
5. **Plotting:** Clients can visualize the training process by plotting graphs for training accuracy and loss over iterations.
6. **Server Role:** In this federated learning setup, after the local models have been trained, the server is responsible for aggregating the model weights from all clients to create a global model. This global model represents the combined knowledge learned from all the clients' local datasets. The script hints at the future implementation of the federated aggregation step but currently focuses on training each client independently.
7. **Final Execution:** Three client objects are created, each initialized with its respective dataset. The script then proceeds to train each client's local model for 500 iterations. After training, the script evaluates and prints the model performance, displaying both accuracy and loss metrics. The models' weights can later be aggregated in the server for federated learning.

The overall workflow mimics the federated learning process where data remains decentralized (clients do not share raw data) but models are trained locally, and the learned knowledge (model weights) is shared securely. This approach enhances privacy and security, especially for sensitive data such as medical diagnostics. The training results of the federated learning model for the clients are shown in the Figures 1 to 9.



```
[LOG] Epoch: 00050 | Train ACC: 97.56% | Loss: 0.296
[LOG] Epoch: 00100 | Train ACC: 97.56% | Loss: 0.200
[LOG] Epoch: 00150 | Train ACC: 97.76% | Loss: 0.160
[LOG] Epoch: 00200 | Train ACC: 97.87% | Loss: 0.137
[LOG] Epoch: 00250 | Train ACC: 97.87% | Loss: 0.123
[LOG] Epoch: 00300 | Train ACC: 97.87% | Loss: 0.113
[LOG] Epoch: 00350 | Train ACC: 97.87% | Loss: 0.105
[LOG] Epoch: 00400 | Train ACC: 97.87% | Loss: 0.099
[LOG] Epoch: 00450 | Train ACC: 97.87% | Loss: 0.094
[LOG] Epoch: 00500 | Train ACC: 97.87% | Loss: 0.090
Model parameters:
  | Weights: Parameter containing:
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          0.3155,  0.0128, -0.1981,  0.3079, -0.1309,  0.2956,  0.3099,  0.0772,
          0.0904,  0.1166,  0.2156,  0.0267, -0.0602,  0.3736,  0.0442,  0.3880,
          0.3226,  0.0770,  0.2577,  0.1176,  0.2692,  0.1852,  0.1113]],
       requires_grad=True)
  | Bias: Parameter containing:
```

Figure 1 Training of the federated learning model using logistic regression for client 1

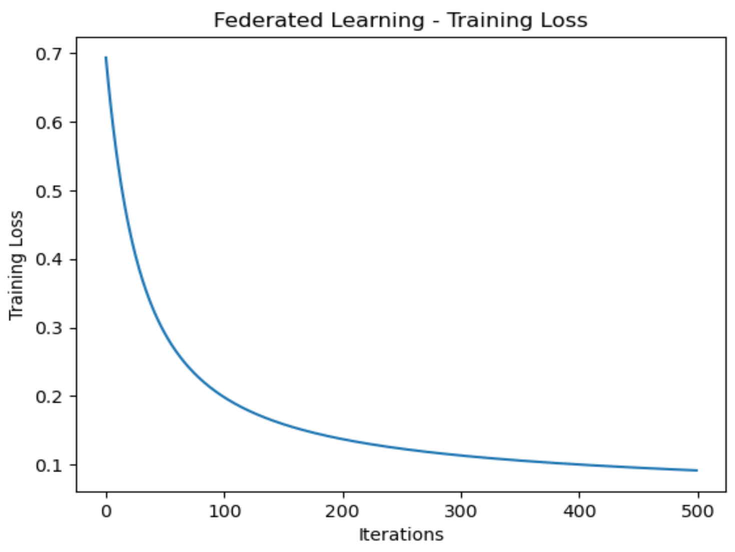


Figure 2 Training loss of the federated learning model using logistic regression on client 1

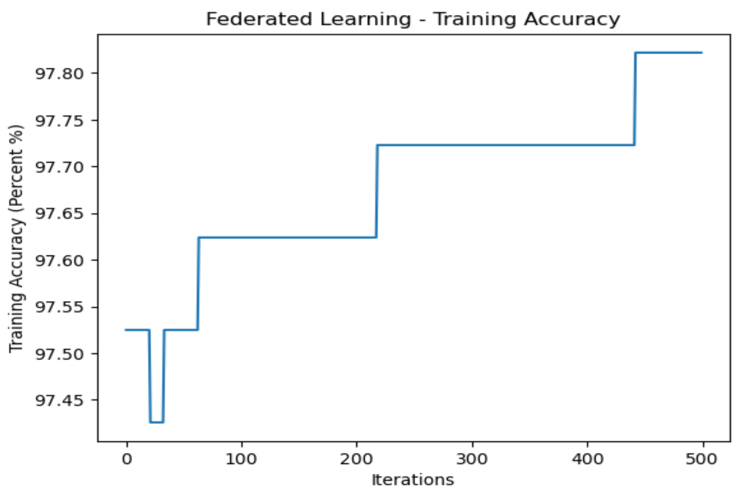
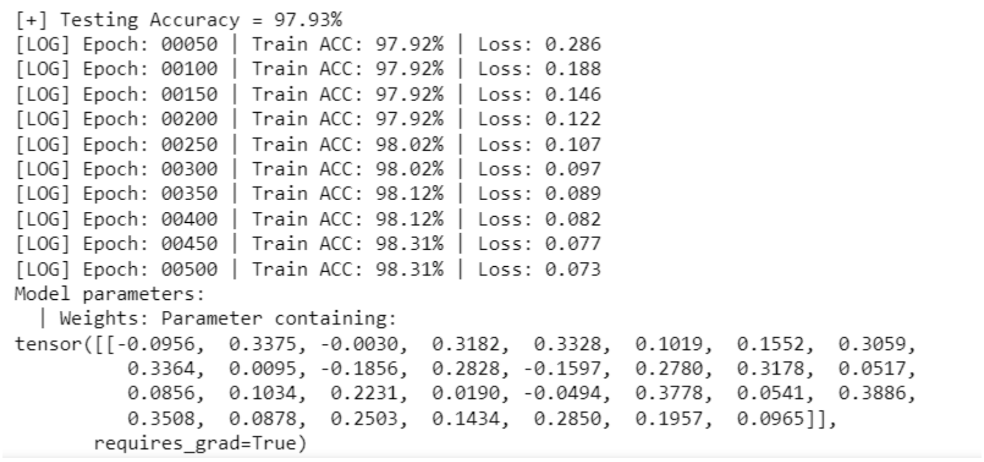


Figure 3 Training accuracy of the federated learning model using logistic regression on client 1



```
[+] Testing Accuracy = 97.93%
[LOG] Epoch: 00050 | Train ACC: 97.92% | Loss: 0.286
[LOG] Epoch: 00100 | Train ACC: 97.92% | Loss: 0.188
[LOG] Epoch: 00150 | Train ACC: 97.92% | Loss: 0.146
[LOG] Epoch: 00200 | Train ACC: 97.92% | Loss: 0.122
[LOG] Epoch: 00250 | Train ACC: 98.02% | Loss: 0.107
[LOG] Epoch: 00300 | Train ACC: 98.02% | Loss: 0.097
[LOG] Epoch: 00350 | Train ACC: 98.12% | Loss: 0.089
[LOG] Epoch: 00400 | Train ACC: 98.12% | Loss: 0.082
[LOG] Epoch: 00450 | Train ACC: 98.31% | Loss: 0.077
[LOG] Epoch: 00500 | Train ACC: 98.31% | Loss: 0.073
Model parameters:
  | Weights: Parameter containing:
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          0.0856,  0.1034,  0.2231,  0.0190, -0.0494,  0.3778,  0.0541,  0.3886,
          0.3508,  0.0878,  0.2503,  0.1434,  0.2850,  0.1957,  0.0965]],
       requires_grad=True)
```

Figure 4. Training of the federated learning model using logistic regression for client 2

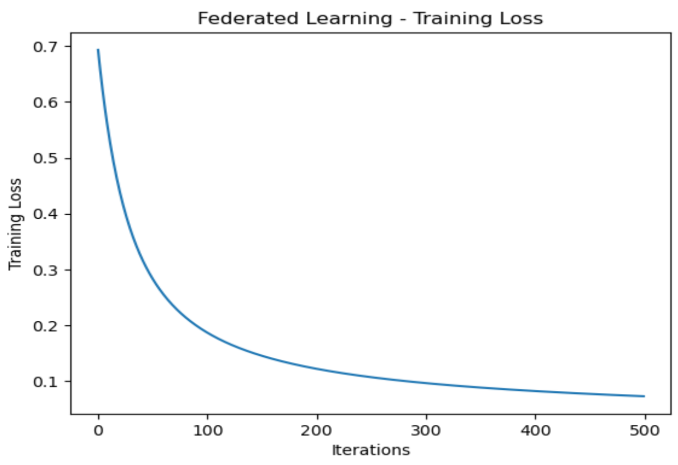


Figure 5: loss of the federated learning model using logistic regression for client 2

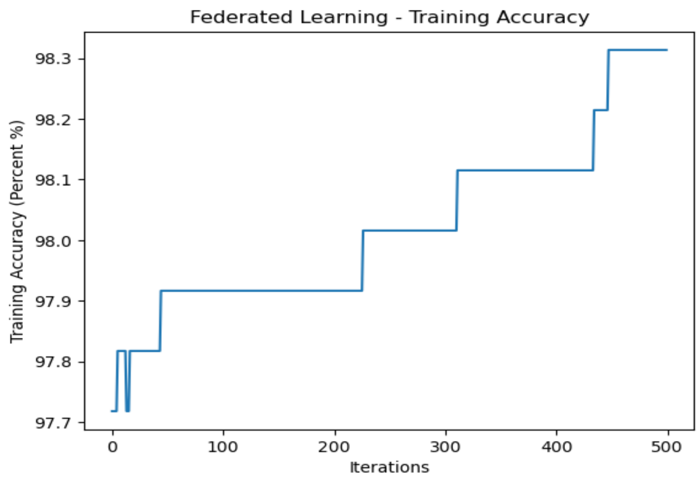
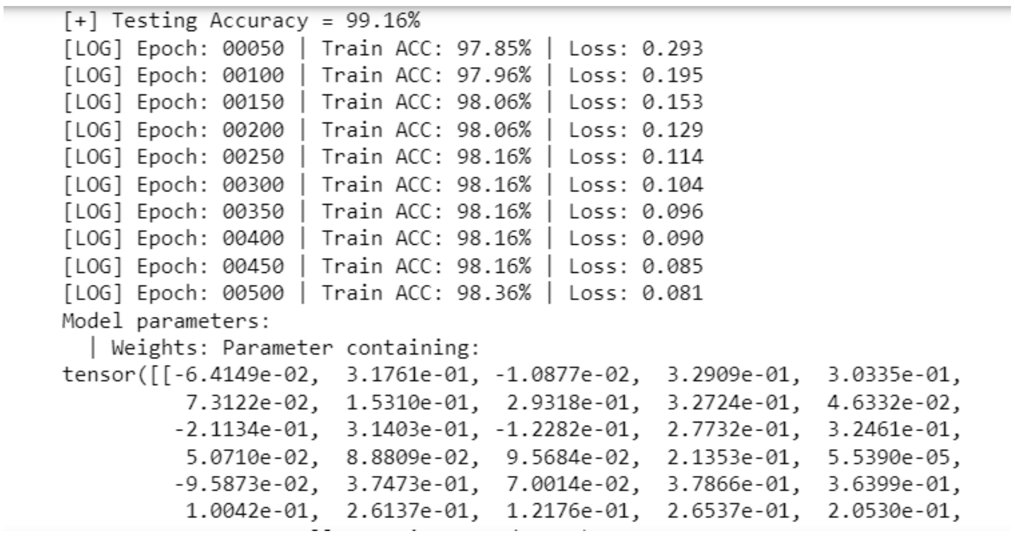


Figure 6: accuracy of the federated learning model using logistic regression for client 2



```
[+] Testing Accuracy = 99.16%
[LOG] Epoch: 00050 | Train ACC: 97.85% | Loss: 0.293
[LOG] Epoch: 00100 | Train ACC: 97.96% | Loss: 0.195
[LOG] Epoch: 00150 | Train ACC: 98.06% | Loss: 0.153
[LOG] Epoch: 00200 | Train ACC: 98.06% | Loss: 0.129
[LOG] Epoch: 00250 | Train ACC: 98.16% | Loss: 0.114
[LOG] Epoch: 00300 | Train ACC: 98.16% | Loss: 0.104
[LOG] Epoch: 00350 | Train ACC: 98.16% | Loss: 0.096
[LOG] Epoch: 00400 | Train ACC: 98.16% | Loss: 0.090
[LOG] Epoch: 00450 | Train ACC: 98.16% | Loss: 0.085
[LOG] Epoch: 00500 | Train ACC: 98.36% | Loss: 0.081
Model parameters:
  | Weights: Parameter containing:
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         -2.1134e-01,  3.1403e-01, -1.2282e-01,  2.7732e-01,  3.2461e-01,
          5.0710e-02,  8.8809e-02,  9.5684e-02,  2.1353e-01,  5.5390e-05,
         -9.5873e-02,  3.7473e-01,  7.0014e-02,  3.7866e-01,  3.6399e-01,
          1.0042e-01,  2.6137e-01,  1.2176e-01,  2.6537e-01,  2.0530e-01,
```

Figure 7: Training of the federated learning model using logistic regression for client 3

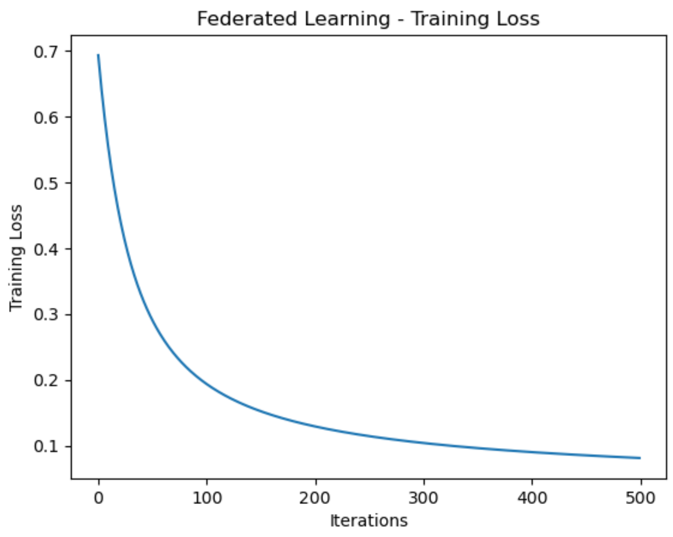

Figure 8: loss of the federated learning model using logistic regression for client 3

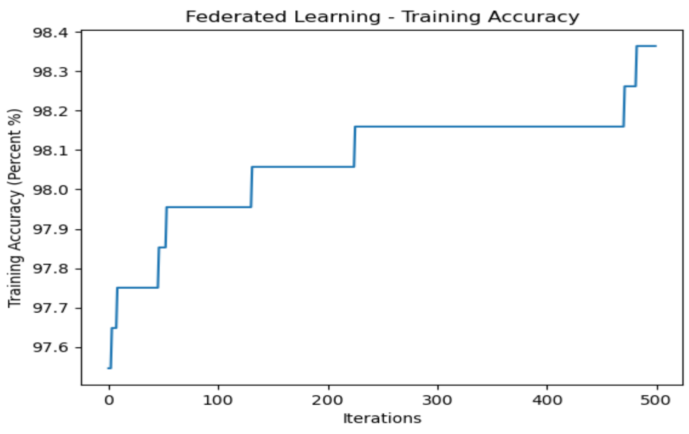

Figure 9: accuracy of the federated learning model using logistic regression for client 3

V. Discussion of Results

From the experiment conducted, Figures 1, 4 and 7 indicate the training progress of a logistic regression model over 500 epochs. The training accuracy (Train ACC) improves rapidly and stabilizes around 97.87%, 97.93% and 99.16% respectively by epochs 250 in each training, indicating that the model has effectively learned from the training data. The loss, which measures the difference between the predicted and actual values, decreases consistently from 0.296, 0.286 and 0.293 respectively in the early epochs to 0.090,0.073 and 0.081 by the 500th epoch, reflecting a gradual improvement in the model's performance. The displayed model parameters, including the weights and bias, are the learned coefficients after training, which will be used to make predictions. The stable accuracy and decreasing loss suggest that the model is well-trained without overfitting.

Figures 2, 5 and 8 depict the training loss over 500 iterations in a federated learning setting. The training loss starts relatively high, near 0.7, and decreases sharply during the initial iterations, indicating that the model is quickly learning to minimize the difference between predicted and actual values. As training progresses, the loss continues to decline but at a slower rate, eventually approaching a value close to 0.1. This behaviour suggests that the model is effectively learning and converging towards a minimum loss, indicating good performance and potentially effective training under the federated learning framework. The steady decrease in loss without significant oscillations also suggests that the learning process is stable.

Figures 3, 6 and 9 shows the training accuracy over 500 iterations in a federated learning environment. The accuracy starts around 97.50%, 97.92% and 98.36% respectively and exhibits a general upward trend with slight fluctuations. There are noticeable step increases in accuracy at various points, particularly around 100, 200, and 400 iterations, ultimately reaching a peak accuracy of approximately 97.87%, 98.31% and 98.36% respectively. The gradual improvement in accuracy indicates that the model is effectively learning from the data and becoming better at making correct predictions as training progresses. The final accuracies same as the peak accuracies for each training suggests that the model has achieved a high level of performance. The small fluctuations early in the training suggest some initial adjustments, but the overall trend indicates successful model convergence.

VI. Conclusion

In this paper, we have demonstrated that Federated Learning offers a robust framework for building machine learning models in a privacy-preserving manner. The principles and mechanisms of Federated Learning were effectively analyzed, a system for privacy preservation was designed and implemented, and the impact on privacy was thoroughly assessed. This study not only highlights the potential of Federated Learning in protecting user data but also sets the stage for future research into more advanced privacy-preserving techniques and their integration into FL systems. Future work could explore optimizing communication efficiency, enhancing model performance on non-IID data, and further strengthening the privacy guarantees through the integration of differential privacy or homomorphic encryption.

Thus, this paper uniquely contributes to the field by integrating Federated Learning with advanced privacy-preserving techniques, specifically tailored to environments with varying communication constraints, this dissertation emphasizes practical implementation, demonstrating how to optimize communication efficiency and enhance privacy protections in real-world scenarios. The approach not only advances the understanding of Federated Learning's mechanisms but also provides a scalable, privacy-centric framework applicable across diverse domains, setting it apart from existing studies.

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