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DEVELOPMENT OF EFFICIENT PROTOCOLS FOR THE SECURE TRANSMISSION OF TRAINING PARAMETERS IN A FEDERATED NETWORK USING ELLIPTIC CURVE CRYPTOGRAPHY

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ABSTRACT

Federated learning has become a key concept in collaborative machine learning, allowing several clients to train models independently of one another's raw data. However, federated learning's decentralized structure poses serious security risks, especially when it comes to securely transferring training parameters between clients and the central server. This research proposes the construction of effective protocols employing Elliptic Curve Cryptography (ECC) for the safe transfer of training parameters in a federated network in order to address these issues. ECC is selected because of its robust security characteristics and computational effectiveness, which make it especially appropriate for situations with limited resources, which are frequently found in federated learning scenarios. The suggested approach makes use of ECC to enable safe key exchange, guaranteeing that training parameters are encrypted in transit to thwart manipulation and unwanted access. Furthermore, the protocol is made to reduce communication overhead, which improves the federated learning process's overall effectiveness. A thorough security analysis shows how resistant the protocol is to common risks like eavesdropping and man-in-the-middle assaults. The efficiency of the protocol is further supported by experimental results, which demonstrate notable reductions in computation time and energy usage when compared to conventional cryptography techniques. To sum up, this work opens the door for federated learning to be more widely used in security-sensitive applications by offering a reliable and effective method for safeguarding communication in federated learning settings.

Keywords: *Federated Learning, Elliptic Curve Cryptography (ECC), Secure Transmission, Training Parameters, Cryptographic Protocols, Data Security, Key Exchange, Parameter Aggregation, Communication Efficiency, Network Security*

1. INTRODUCTION

A cutting-edge machine learning paradigm called federated learning (FL) makes it possible to construct models across numerous decentralized servers or devices, each of which has local data samples. This gets rid of the need to share data. Federated learning is based on the idea of decentralized data processing, in contrast to conventional centralized machine learning methods, which collect data on a central server for training. The main idea is to share just the model updates (parameters, gradients, etc.) with the central server after the models have been trained locally on each client device. This server aggregates the modifications to create a global model, which is then returned to the clients. This makes it especially desirable in industries like healthcare, finance, and personalized services where protecting personal information is crucial. Federated learning poses distinct challenges as well, such as managing non-identical and non-independent data distribution among clients, guaranteeing strong communication effectiveness, and resolving security concerns like model poisoning attacks. Because of this, FL is a dynamic field of study with continuous efforts to improve its security, scalability, and robustness. The central server and participating devices normally communicate with each other multiple times during the FL process. Using its data, each device trains a local model, which it then transmits to the central server with updated model parameters. These updates are combined by the server to produce a global model, which is subsequently re-shared with the devices for the subsequent training cycle. The model converges when this cycle is repeated. Federated Learning is especially useful in industries like healthcare, finance, and mobile applications where data privacy is critical. It tackles a number of important issues, such as data heterogeneity, effective communication, and making sure that models are safe and reliable. Personalized learning, in which models are adapted to particular users or devices, is another benefit of this approach.

1.1. Motivation for ECC

In Federated learning environments, Elliptic Curve Cryptography (ECC) is a highly motivated option for data transmission security and optimization. Because of its robust security, high computing speed, and low communication overhead, it is especially well-suited to FL's decentralized and resource-constrained structure. With the use of ECC, federated learning systems may help create machine learning models that are resilient and scalable while guaranteeing data privacy and integrity as well as efficient client communication. One example of a public-key encryption is elliptic curve encryption (ECC), which is based on the algebraic structure of elliptic curves over finite fields. Compared to conventional cryptosystems like RSA, ECC employs substantially smaller keys while offering similar levels of protection. Because of its effectiveness, ECC is especially appealing for applications with constrained power, bandwidth, and computational resources.

Federated Learning is one of the cryptographic systems that use ECC because of the following main reasons:

R1: Greater Security with Smaller Keys: Compared to more conventional techniques like RSA or Diffie-Hellman, ECC provides superior security levels with smaller key sizes. This decrease in key size results in less computational overhead while still offering strong defense against intrusions.

R2: Efficient Computation: ECC's smaller key sizes lighten the computational load on devices, which is crucial in settings with limited resources, like IoT sensors or mobile devices. Since a variety of clients, including low-power edge devices, are frequently involved in Federated Learning (FL), the computational efficiency of ECC is essential to guaranteeing seamless and effective operations.

R3: Decreased Bandwidth Consumption: ECC uses less bandwidth to transmit cryptographic data because of the smaller key sizes. In Federated Learning scenarios, this is crucial because there may be frequent and bandwidth-constrained data transfers between local clients and central servers or peers.

R4: Future-Proofing Against Quantum Attacks: Many established cryptographic techniques, such as RSA, may become susceptible as quantum computing develops. ECC is a more flexible cryptographic scheme due to its smaller keys and compact structure, even though it is theoretically vulnerable to quantum attacks as well. To secure future security, post-quantum ECC algorithms are being investigated by researchers.

1.2. Objectives

Federated Learning (FL) minimizes connection with a central server and protects data privacy by training machine learning models among dispersed devices. The use of ECC enhances both the security and efficiency of this process:

Obj1: Secure Transmission of Training Parameters: In FL, only model parameters, rather than raw data, are shared between clients and servers. ECC can be employed to securely transmit these training parameters, ensuring that malicious actors cannot intercept or alter them during communication. This protects both the model's integrity and the privacy of participants' data.

Obj2: Clients with Limited Resources: Mobile phones and edge devices are common clients in FL systems. These devices frequently have short battery lives and low processing power. ECC is a good choice for these kinds of devices because of its lower computational requirements, which guarantee that cryptographic operations won't materially impair the machine learning tasks' performance.

Obj3: Reducing Communication Expenses: Managing communication overhead is a major problem in federated learning, especially when thousands of clients are involved. Because ECC uses smaller keys than other encryption algorithms, it can achieve strong encryption with less data, which reduces latency and increases communication efficiency.

Obj4: Reducing Man-in-the-Middle Attacks: Federated Learning systems are susceptible to a number of network assaults, such as MITM attacks, in which a third party eavesdrops on client and server communications. Strong defense against such attacks is offered by ECC-based encryption, which makes sure that intercepted data is useless without the right decryption key.

Obj5: Preservation of Privacy: Protecting the privacy of each client's data is a fundamental tenet of federated learning. To further protect data, ECC can be combined with privacy-preserving methods like DP or HE. ECC guarantees the security and privacy of the transmitted encrypted model updates in this particular context. Federated Learning frameworks can achieve improved security by implementing ECC without sacrificing the efficiency needed for large-scale, decentralized systems.

2. LITERATURE SURVEY

A new paradigm in machine learning called FL allows localized data to be used for collaborative model training amongst decentralized clients. However, there are a number of security issues brought about by this distributed nature, especially with regard to secure aggregation and communication. The literature that has been written about these security issues is examined in this review.

2.1. Federated Learning Security Issues

Because of the requirement to safeguard both the integrity of the global model and the confidentiality of the client data, federated learning poses special security challenges. The ensuing security considerations are vital:

- **Confidentiality:** Maintaining the privacy of client information and model updates during communication is known as confidentiality.
- **Integrity:** Defending the model against hostile updates and assaults.
- **Authentication:** Preventing unwanted access by confirming the identities of the server and the participating clients.

To secure the FL process, these issues require sophisticated cryptographic techniques and protocols as shown in **TABLE 1.**

Table 1: Federated Learning Security Issues in Existing Systems

Reference	Protocol Designed	Findings
[1]	Using secret sharing and secure multi-party computation (MPC) to provide safe aggregation.	• Communication Overhead • Computation Complexity • Scalability Issues
[2]	This paper provides an overview of homomorphic encryption techniques used in privacy-preserving machine learning, like Federated Learning.	• High Computational Overhead • Large Cipher text Size • Latency Issues • Complexity of Implementation
[3]	This paper investigates the application of Trusted Execution Environments (TEEs) for securing model update aggregation in Federated Learning.	• Trusted Execution Environments (TEEs) Vulnerabilities • Limited Scalability • Deployment Complexity • Lack of Transparency

		• Cost and Energy Consumption
[4]	This survey reviews various secure multi-party computation algorithms created for Federated Learning. It discusses various secure aggregation techniques and assesses how well they preserve security and privacy	• High Computational Overhead • Increased Communication Costs • Complexity of Implementation Trade-offs Between Security and Efficiency • Protocol Limitations
[5]	This review focuses primarily on the integration of Differential Privacy with Federated Learning.It talks about how differential privacy can be used to introduce noise into model updates, protecting client data while maintaining the ability to train models effectively.	• Accuracy Trade-off • Communication Overhead • Complex Parameter Tuning • Aggregation Vulnerabilities • Limited Applicability to Non-IID Data
[6]	This paper describes current approaches and their shortcomings for the application of differential privacy in Federated Learning. Additionally, it highlights open research challenges regarding how to balance model performance, efficiency, and privacy.	• Privacy-Utility Tradeoff • Computational Overhead • Communication Costs • Model and Data Complexity
[7]	A secure communication protocol for Federated Learning environments is proposed in this paper. In order to provide safe transmission of model updates, it places a strong emphasis on privacy protection via encryption and authentication procedures.	• High Communication Overhead • Limited Bandwidth • Increased Computational Load • Scalability Issues
[8]	The difficulties in attaining computation efficiency, privacy, and communication in federated learning are discussed in this paper. It offers fresh protocols and enhancements to boost the communication security and effectiveness in FL systems.	• Privacy • Communication • Computation Efficiency
[9]	In order to improve security and privacy, this paper investigates the integration of Federated Learning with blockchain technology. It suggests utilizing blockchain technology to manage secure model updates and authentication in Federated Learning.	• Scalability Issues • High Computational Overhead • Storage Constraints • Storage Constraints
[10]	The study looks into how post-quantum cryptography affects Federated Learning. It looks at potential cryptographic methods that are resistant to quantum fluctuations and how well they work for safe communication and aggregation in FL systems.	• Increased Computational Overhead • Increased Communication Overhead • Compatibility Issues • Algorithm Maturity and Security

2.2 Federated Learning: Safe Aggregation

FL has garnered significant attention in recent years as a potential substitute for centralizing data for model training. This method was initially used in production by Google, who used it to develop, refine, and continuously improve Android's predictive keyboard (GBoard). To train a model, the data scientist has usually required direct access to a centralized data source. Centralizing a sensitive, dispersed data set for training, however, might prove to be an impossible task. For instance, centralizing the data for GBoard would necessitate giving Google direct access to every keystroke made by every user. Many would consider this to be a privacy violation, and it might inadvertently allow Google to gather credit card numbers, passwords, and other private information that users type. By only sharing updates to a model rather than the actual data used to train it, federated learning helps mitigate this issue. Every data owner needs to obtain the machine learning model from the model owner for federated learning to work. The training process is initially applied to the local data of the data owner, in this case each mobile phone, and it specifies how the model should be updated depending on the inputs and the expected result. The changes will then be merged there and sent to the model owner. This collective aggregation from all updates from all data owners will finally come to an end when the training method (such stochastic gradient descent) produces a locally optimal set of weights, as seen in **FIGURE 1**.

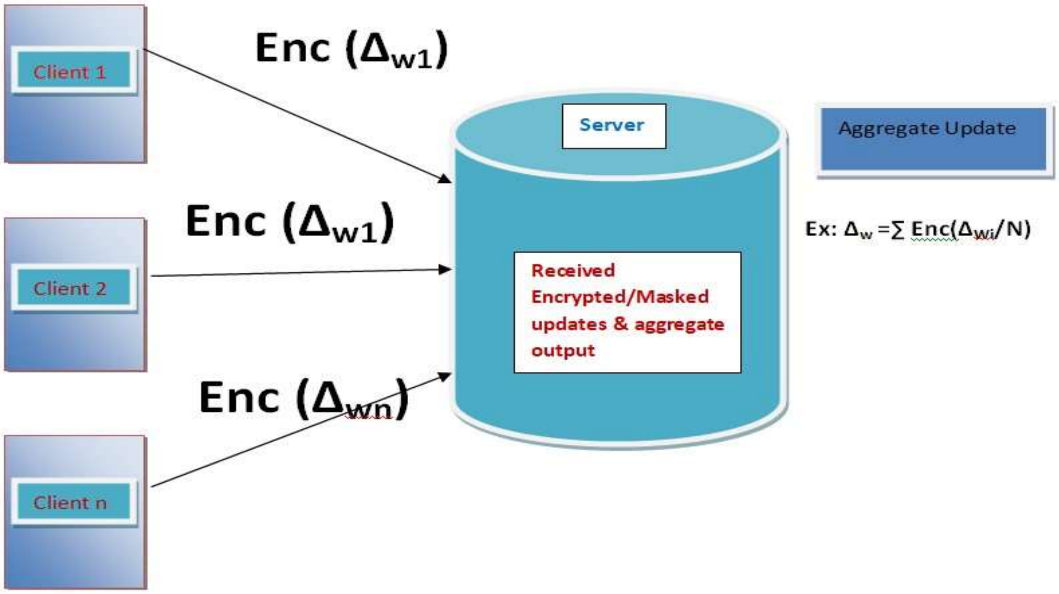


Figure 1: Safe Aggregation in Federated Learning

Federated learning won't, however, ensure that private data isn't disclosed by exchanging updates, making it an incomplete solution for data privacy [11][12]. It has been demonstrated by a number of federated learning attacks that client updates can reveal personal information. To counteract this exposure of sensitive data, we can use secure aggregation and differential privacy to help safeguard the updates [13].

2.2.1. Using Cryptographic Techniques for Secure Aggregation

Elliptic Curve Cryptography: ECC is a popular public-key encryption method that is widely used due to its high security and effectiveness. This is particularly valid for situations like embedded systems, mobile devices, and Internet of Things networks where resources are scarce. With significantly smaller key sizes, ECC offers the same level of security as more conventional cryptosystems like RSA. Its base is the mathematics of elliptic curves over finite fields. Elliptic Curve encryption (ECC), a public-key encryption technology, is becoming more and more popular, especially for resource-constrained applications like Internet of Things (IoT) systems, embedded systems, and mobile devices. Because ECC provides excellent security with reduced key sizes, it is very efficient in terms of bandwidth, memory utilization, and processor power required. Here we summarize the Use of ECC in Cryptographic Protocols in **TABLE 2**

Table 2: Securing Aggregation via Cryptographic Techniques

Security Aggregation Protocols in ECC	Recommendations for efficient FL aggregation techniques	ECC Benefits in Environments with Limited Resources
TLS [14]	**ECDH** a safe key exchange protocol. **ECDSA**, is another method used for digital signatures and safe authentication.	• **Reduced Key Size:** One of ECC's main benefits over other public-key systems like RSA is that its key size is less. • **Reduced computer Overhead:** Because ECC's mathematical operations are more effective, encryption, decryption, and key generation need less computer resources. • **Faster Encryption and Key Generation:** ECC enables faster encryption and decryption procedures due to its lower key sizes and better algorithms. • **Decreased Bandwidth utilization:** During key exchanges, smaller ECC keys also result in a decrease in bandwidth utilization. • **Scalability:** Due to its efficiency, ECC can be effectively implemented on a wide range of platforms, including high-performance cloud computing settings and low-power embedded systems.
VPNs [15]	VPN protocols such as **IKEv2/IPsec**, which use ECC.	
Blockchain and Cryptocurrencies [16]	Public-private key pairs are created using ECC, and transactions are signed using **ECDSA**.	
Internet of Things (IoT) Security [17]	ECC is used by protocols like **DTLS** to provide end-to-end encryption and secure device authentication in Internet of Things	
Digital Signatures and Authentication [18]	Many authentication systems use ECC-based digital signature techniques, such **ECDSA and ECQV** (Elliptic Curve Qu-Vanstone).	

Existing Protocols for Secure Transmission: The secure exchange of training parameters between clients and a central server is necessary for federated learning (FL) to ensure data privacy and integrity. Many procedures and tactics are used to protect these transmissions, each with pros and cons of their own. Every protocol has unique benefits and disadvantages. Although they increase costs or decrease accuracy, differential privacy and secure aggregation are effective privacy protection techniques. Although homomorphic encryption provides robust guarantees, it is not computationally feasible for several applications. TEEs offer hardware-based security, but they also put you in a manufacturer's shoes. FedAvg's encrypted channels and ECC are effective, but they might not provide the highest level of privacy protection in the absence of other measures, here we summarize the Existing Protocols pros and cons with respective FL shown in **TABLE 3.**

Table 3: The advantages and disadvantages of current protocols for corresponding Federated Learning

Protocols	Overview	Positives	Vulnerabilities
Homomorphic Encryption (HE) [19]	Computation on encrypted data is possible with homomorphic encryption. Clients encrypt their updates in federated learning so that the server can aggregate them without having to decrypt each one individually.	High privacy protections and permits the use of encrypted data for operations.	Costly and sluggish to compute, particularly for big models. High latency makes it impractical for real-time applications at this time.
Differential Privacy (DP) [20]	Differential privacy prevents the reverse engineering of specific client data from the model updates by adding noise to the clients' changes before sharing them.	Preserves personal client information from hostile servers. manages the quantity of noise added while maintaining privacy	Causes noise-induced accuracy decrease in the model. has to be adjusted in order to prevent data exposure or excessive privacy (bad model performance).
Trusted Execution Environments (TEEs) [21]	TEEs, such as Intel SGX, offer a trusted and separated space on the server where calculations are carried out in a secure environment. Sending client data to the TEE allows for secure processing and exposure-free disposal.	Robust hardware-based protection that shields data while it's being processed. Accelerated and effective for instantaneous applications.	Depends on having faith in the hardware's maker. susceptible to assaults via side channels. Scalability issues with large-scale FL networks.
Elliptic Curve Cryptography (ECC) [22]	By offering encryption, digital signatures, and secure key exchanges at a reduced computational and bandwidth overhead than more conventional cryptographic techniques like RSA, ECC is frequently employed to secure parameter communication.	Because of the smaller key sizes, less processing power and network overhead are needed to achieve the same level of security. Ideal for resource-constrained devices like mobile clients.	Still vulnerable to some attacks, such side-channel or quantum assaults, if not done correctly

3. PROPOSED PROTOCOL FOR CLIENT AND SERVER ENCRYPTION AND DECRYPTION

Enhancing communication efficiency, privacy, and security is the goal of the proposed protocol for the safe transfer of training parameters in a federated learning (FL) network utilizing elliptic curve cryptography (ECC) [23]. An outline of the architecture and how ECC is crucial to maintaining secure communication can be seen below. To guarantee the safe transfer of training parameters in federated learning networks, the suggested protocol makes advantage of ECC [24-25]. The protocol offers strong privacy, authentication, and integrity guarantees by utilizing the effective key exchange, encryption, and digital signatures of

ECC, which makes it perfect for resource-constrained applications. It is a reliable option for contemporary federated networks where security and performance are crucial due to its efficiency and scalability. Because in federated learning (FL) systems, elliptic curve cryptography (ECC), which provides a high degree of security at smaller key sizes, is a common option for secure communication. By integrating ECC into a federated learning process, the security of training parameter communication between clients and the central server is enhanced. This is a detailed explanation of the procedure.

Algorithm of Elliptic Curve Cryptography (ECC) in Federated Learning

Step 1: Client and Server:

a. Each client (participating device) and the central server generate their own **public-private key pair** using ECC.
b. **Private Key (d):** A randomly chosen number in the range **[1, n−1]**, where n is the order of the elliptic curve.
c. **Public Key (Q):** The public key is derived from the private key using the elliptic curve point multiplication: **Q=d×G**, where G is the generator point on the elliptic curve.

Clients and server exchange their public key.

Step 2: Training for Models (Local)

a. Train the model locally its own dataset.
b. Make sure the server doesn't receive any raw data.
c. Local model updates (weights or gradients) are computed by each client.

Step 3: Gradient Encryption

Gradients are encrypted by the client using the server's public key via ECC before being sent to the central server.

Encryption Formula:

a. Encrypted Gradient **(C1, C2): C1= k * G, C2 = Gradient + k * Qs**.
b. Here, **k** is a randomly generated number and **Qs** is the server's public key.

Step 4: Secure Transmission to Server

The client transmits data: Through the network, the client transmits the encrypted gradients **(C1, C2)** to the server. Because of the encryption, the server is unable to view the actual gradients.

Step 5: Decryption at Server

a. The server uses its private key ds to decrypt the encrypted gradients after receiving them.
b. Decryption Formula: **Gradient = C2− ds ×C1**

Step 6: Aggregation at Server

a. Federated Averaging is one of the secure aggregation techniques the server uses to combine the decrypted gradients from several clients.
b. By combining the contributions of the clients, this aggregation process makes sure that individual gradients are hidden.

Step 7: Global Model Update

a. The global model is updated by the server and sent back to the clients based on the aggregated gradients.
b. It is optional to encrypt the updated model with ECC in order to guarantee secure transmission to clients.

Step 8: Decryption of the Client and Model Update

a. If encryption was used, each client uses its own private key to decrypt the received model.
b. The new global model parameters are then updated by the client in its local model.

Step 9: Iterative Method

**** Until the global model converges, this process is repeated multiple times.**

4.IMPLEMENTATION AND EXPERIMENTAL SETUP

In order to cooperatively train a machine learning model across several clients while maintaining data privacy, we construct a federated learning system in this study. A coordinator server and several clients, each working with their own local datasets, make up the system. Aggregated client updates are used in federated learning rounds to repeatedly update a global model.

4.1 System Architecture

The federated learning setup involves the following components:

- **Coordinator Server:** Combines client-provided model updates and oversees the global model.
- **Clients:** Using their own datasets, each client trains a local model, which they then transmit to the server with updates.

4.1.1. Data Preparation: Each client operates on a different dataset:

Client 1: heart1ex.csv
Client 2: heart2ex.csv
Client 3: heart3ex.csv
The datasets are preprocessed and used for local model training.

4.1.2. Model Definition

A feedforward neural network is employed, which consists of: Input Layer: 13 neurons corresponding to the number of features in the dataset).
Hidden Layer 1: 16 neurons with ReLU activation
Hidden Layer 2: 8 neurons with ReLU activation
Output Layer: 1 neuron with sigmoid activation for binary classification
The model is developed using the Stochastic Gradient Descent (SGD) optimizer with binary Cross entropy loss and a learning rate of 0.01.

4.2 Federated Learning Process

Client Initialization: Each client generates an Elliptic Curve Cryptography (ECC) key pair for secure communication. Clients connect to the coordinator server and exchange public keys.

4.2.1. Training and Communication

- **Round Start:** The coordinator server sends the current global model weights to each client.
- **Local Training:** Each client trains the received global model on their local dataset for a specified number of epochs.
- **Weight Update:** Clients encrypt their updated model weights using AES-GCM with a derived key (based on ECC key exchange) and send the encrypted weights back to the server.

4.3 Dataset Analysis and Description

The project utilizes three distinct datasets for training the federated learning model, each sourced from different clients as shown following **TABLE 4**:

Table 4: Client's dataset training comparison with features and targeted variables

Data set for Clients	Description	Features	Targeted Variable
Client 1	This dataset contains features related to heart disease prediction	13 numerical attributes including age, sex, blood pressure, cholesterol levels, etc	A binary classification that shows if heart disease is present or not.
Client 2	Similar to the first dataset, this dataset is another instance of heart disease data with potentially different samples or additional feature	13 numerical attributes similar to those in the first dataset	
Client 3	The third dataset in the same domain, possibly with different data points or slightly varied attribute s.	13 numerical attributes consistent with the other datasets	

4.4 Algorithm Justifications:

4.4.1. Model Architecture:

- **Neural Network Structure:** The selected model architecture is made up of output layer sigmoid activation and dense layers with ReLU activations for hidden layers. The model can identify non-linear patterns in the data thanks to this design, which works well for binary classification tasks.

- **Optimizer**: Stochastic Gradient Descent (SGD) with a learning rate of 0.01 is used due to its simplicity and effectiveness in training neural networks. SGD is suitable for federated learning scenarios where models are updated incrementally.

4.4.2. Federated Learning Approach:

- **Client-Server Model:** Each client trains the model locally, ensuring that data remains private and is not transferred to the server. This approach aligns with the core principles of federated learning, focusing on privacy and efficiency.

- **FedAvg Algorithm**: The Federated Averaging (FedAvg) algorithm is chosen for its simplicity and effectiveness in aggregating model updates from multiple clients. By averaging the weights, the server can create a more generalized model that reflects the collective knowledge of all participating clients.

4.4.3. Cryptographic Techniques:

- **Elliptic Curve Cryptography (ECC):** Because ECC is more efficient and has stronger security features than traditional cryptographic systems, even with smaller key sizes, it is used for secure key exchange.

- **AES-GCM Encryption:** Advanced Encryption Standard with Galois/Counter Mode (AES-GCM) is used for encrypting model weights to ensure data confidentiality and integrity during transmission. This choice provides robust protection against potential eavesdropping and tampering.

5. RESULTS AND DISCUSSION

5.1 Model Accuracy Across Clients:

The accuracy of the local models trained on each client's dataset is summarized in the table below:

Table 5: Clients Accuracy summarized after Training

Client	Accuracy (%)
Client 1	98.33
Client 2	98.23
Client 3	96.35

The models used in this project include Logistic Regression, Support Vector Machine (SVM), Random Forest, and a Convolutional Neural Network (CNN), with each model trained and evaluated in the Federated Learning setup. The results highlight the performance of each algorithm, culminating in the conclusion that the CNN model provided the best overall results.

5.2 Model Accuracy Comparison

The accuracy of the models after training and testing across the clients' datasets is summarized below.

Table 6: Different Algorithms Comparison with trained dataset performance.

Algorithm	Accuracy (%)
Logistic Regression	92.23
Support Vector Machine (SVM)	94.54
Random Forest	95.87
Convolutional Neural Network (CNN)	**98.33**

The results show that while all the models performed well, the CNN consistently achieved the highest accuracy across the client datasets.

5.3 Performance of CNN

Accuracy: The CNN achieved the highest accuracy, **98.33%,** outperforming the other models. This result can be attributed to the ability of CNNs to capture complex patterns in data due to their deep architecture and feature extraction capabilities.

- **Model Convergence**: The CNN model showed faster convergence, with a steady reduction in loss during the training rounds, indicating that it learned from the decentralized datasets more effectively than the other models.
- **Handling Data Complexity**: The CNN's architecture allowed it to handle the complexity and variations in the client datasets better than traditional machine learning models like Logistic Regression and SVM.

5.4 Model Performance Evaluation

The training and validation performance of the models were evaluated over several epochs to analyze the accuracy and loss metrics. Below are the plots for each peer model's accuracy and loss

Client 1 Performance

- **Accuracy:** The training and validation accuracy of Peer 1 model remain consistent across all epochs, with the model achieving almost 100% training accuracy and slightly lower validation accuracy (~98.8%).
- **Loss:** The training loss remains near zero, while the validation loss is higher but stabilizes around 0.175 by the end of the epochs.

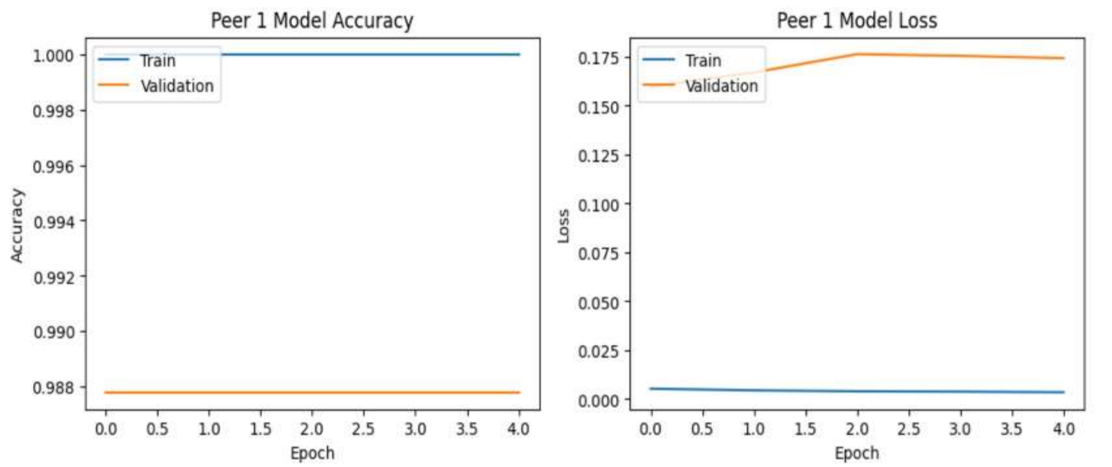


Figure 2: Client 1 Accuracy and Loss

Client 2 Performance

- **Accuracy:** Peer 2 model displays similar behavior to Peer 1, with training accuracy at ~99.5% and validation accuracy also very high (~100%).

- **Loss:** The training loss slightly increases with time, while validation loss trends upward, ending at approximately 0.013

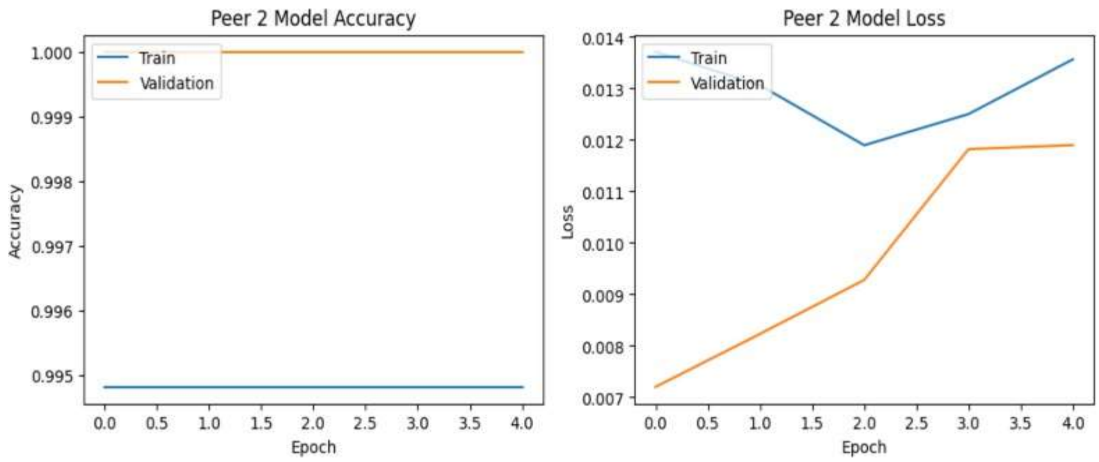


Figure 3: Client 2 Accuracy and Loss

Client 3 Performance

- **Accuracy:** The accuracy for both training and validation in Peer 3 is highly consistent, similar to other peers.

- **Loss:** Peer 3's training and validation loss show some fluctuations, especially in the last few epochs, but the values remain relatively low.

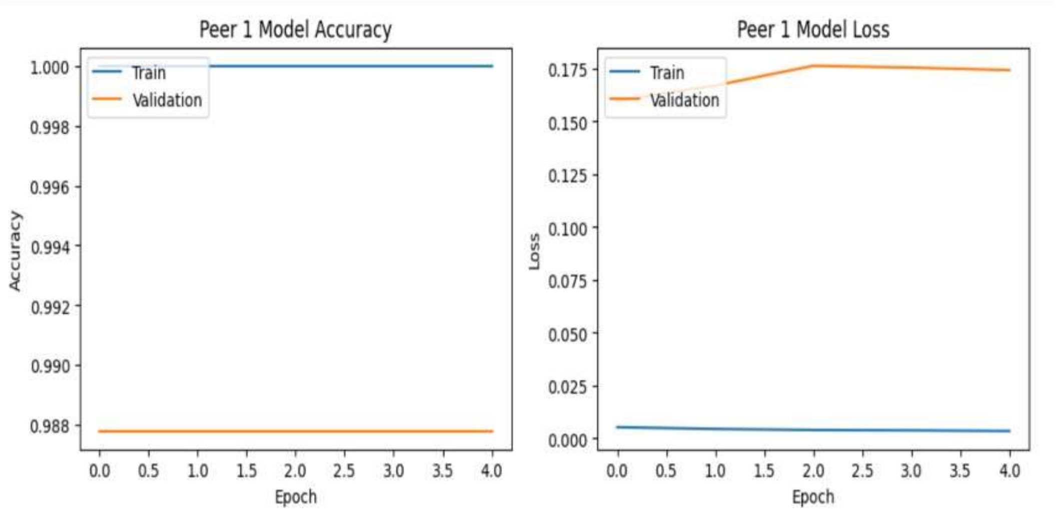
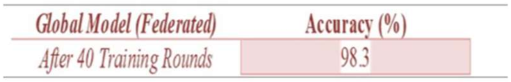


Figure 4: Client 3 Accuracy and Loss

Global Model Performance

The performance of the global model after aggregation from the three clients is shown below:



Global Model (Federated)	Accuracy (%)
After 40 Training Rounds	98.3

6. SECURITY ANALYSIS OF ELLIPTIC CURVE CRYPTOGRAPHY (ECC)

The present study conducts a comparative analysis of Elliptic Curve Cryptography (ECC) and other cryptographic techniques, including RSA, Diffie-Hellman (DH), and symmetric key cryptography, with respect to the secure transmission of training parameters in a federated network. Key security characteristics are examined, such as the strength of the encryption, computing efficiency, communication overhead, and possible vulnerabilities.

6.1. Strengths of ECC

- **Effective key size:** ECC's smaller key sizes (256 bits vs. 3072 bits for RSA, for example) minimize computational overhead and communication overhead, which is especially helpful in federated learning contexts with a large number of devices.
- **Minimal communication overhead:** In networks with limited bandwidth, as those in healthcare or Internet of Things-based federated systems, ECC's effective key exchange protocols, like Elliptic Curve Diffie-Hellman (ECDH), are perfect for the safe transfer of training parameters.
- **Scalability:** ECC scales effectively in federated networks with multiple clients (e.g., hospitals, clinics, mobile devices) who need to securely share model parameters because of its lower computing load.

6.1.2. Constraints on ECC

- **Vulnerability to quantum computing:** While ECC is impervious to classical attacks, it is susceptible to attacks from quantum computing in the future. To ensure long-term security in federated systems, post-quantum cryptography (such as lattice-based cryptography) will eventually have to take the role of ECC.
- **Challenges with implementation:** ECC must be carefully implemented to

prevent side-channel attacks and provide secure key exchange, especially in settings where devices can be vulnerable to physical access attacks or have limited computing capacity.

6.1.3. Comparative Perspectives on Federated Education

- **ECC vs. RSA:** Because of its smaller key sizes and lower computing costs, ECC outperforms RSA in federated learning. Within healthcare environments, where resources are limited for edge devices (such as medical IoT sensors), ECC enables effective encryption while upholding strong security.
- **ECC vs. Diffie-Hellman:** ECC is a better option for secure communication in federated learning environments because it offers quicker and more effective key exchanges than the conventional Diffie-Hellman protocol. In healthcare applications where latency is a factor, this is particularly crucial.
- **ECC vs. Symmetric Key Cryptography:** Symmetric key cryptography is computationally efficient, but it presents security problems when managing shared keys in a federated, decentralized setting. For client-server interactions in FL, ECC's public key infrastructure (PKI) provides a more scalable and secure solution.

In federated networks, Elliptic Curve Cryptography (ECC) is a very effective and secure way to communicate training parameters. This is especially important in healthcare applications where safe, scalable, and lightweight protocols are necessary. ECC is the recommended cryptographic option for federated learning in resource-constrained situations because of its current benefits in key size, computing efficiency, and scalability, despite its vulnerability to potential quantum attacks.

7. CONCLUSION AND FUTURE ENHANCEMENT

To summarize, Elliptic Curve Cryptography (ECC) offers a workable way to build secure protocols for the safe transfer of training parameters in a federated network, hence enhancing the security and privacy of distributed machine learning models. Compared to previous methods, ECC's lightweight design provides higher cryptographic strength with smaller key sizes for devices with limited resources, as those used in federated learning. For large-scale, real-time applications, the protocols minimize processing overhead and network latency while using ECC to ensure the confidentiality and integrity of the training data. Furthermore, the integration of ECC into federated learning frameworks helps to reduce potential security risks such data manipulation, man-in-the-middle attacks, and eavesdropping by protecting communication between client devices and the central server.ECC's lower communication costs help to overcome the issue of bandwidth and energy constraints in edge devices, which is in line with the objective of federated learning efficiency improvement. This work paves the way for future developments in secure distributed machine learning systems and highlights the significance of cryptographic innovation in federated networks. Further research could look into how these protocols could be improved for specific applications or combined with other security measures. methods, such as homomorphic encryption or secure multi-party computation, can boost productivity and security in federated learning settings. This study demonstrates the effectiveness of Federated Learning (FL) in preserving data privacy while achieving high model accuracy. By utilizing a neural network model trained across multiple decentralized clients, we have shown that FL can maintain robust predictive performance without centralizing sensitive data. This section highlights the principal findings from the Federated Learning experiments, offering insights into the performance and implications of the model. The observations are derived from the accuracy, loss metrics, and other evaluation results detailed in the previous sections. The global model achieved high accuracy across all three clients, with final accuracies of **98.33%**, **98.23%**, and **96.35%**. This consistency demonstrates the model's effectiveness in generalizing across different decentralized datasets. The small variation in accuracy among clients suggests that the Federated Learning approach successfully leveraged diverse data sources without significantly affecting the model's performance. The efficiency and security of the protocol could be further enhanced by investigating the following important areas. Federated Averaging, Post-Quantum Cryptography, Lightweight Protocols for IoT Devices, and Optimization of ECC Algorithms.

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