A Project report on

LoMar: A Local Defence Against Poisoning Attack on Federated Learning

A Dissertation submitted to JNTUH, Hyderabad in partial fulfillment of the academic requirements for the award of the degree.

Bachelor of Technology

in

Computer Science and Engineering (AI&ML)

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DEPARTMENT OF COMPUTER SCIENCE and ENGINEERING (AI&ML)

CERTIFICATE

This is to certify that the Major Project Phase-1 report entitled **"LoMar: A Local Defence Against Poisoning Attack on Federated Learning"** being submitted by Mohammed Tauseef Ahmed (21H51A6671), Eppa Srujan Reddy (21H51A6662), Shaik Shoaib Hannan (21H51A6623) in partial fulfillment for the award of **Bachelor of Technology in Computer Science and Engineering (AI&ML)** is a record of bonafide work carried out his/her under my guidance and supervision.

The results embodies in this project report have not been submitted to any other University or Institute for the award of any Degree.

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EXTERNAL EXAMINER

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ABSTRACT

Federated Learning (FL) offers an efficient decentralized machine learning framework where the training data remains distributed across remote clients in a network, ensuring privacy and security, particularly for mobile edge computing using IoT devices. However, recent studies have highlighted that this decentralized approach is vulnerable to poisoning attacks from malicious clients, which can compromise the integrity of the model. To counter these attacks, we propose a two-phase defense algorithm known as Local Malicious Factor (LoMar). In the first phase, LoMar evaluates model updates from each remote client by measuring the relative distribution of their updates compared to their neighboring clients. This is done using a kernel density estimation method, which helps to detect outlier updates that are likely to be malicious. In the second phase, LoMar approximates an optimal threshold to statistically distinguish between malicious and clean updates, ensuring that harmful contributions are filtered out while preserving the integrity of the model. To assess the effectiveness of our defense strategy, we conducted comprehensive experiments on four real-world datasets. The results show that LoMar can significantly enhance the defense capabilities of FL systems against poisoning attacks. Notably, in experiments on the Amazon dataset under a label-flipping attack, LoMar increased the target label testing accuracy from 96.0% to 98.8% and the overall average testing accuracy from 90.1% to 97.0%, outperforming existing defense methods such as FG+Krum. These results demonstrate that LoMar is a highly effective defense mechanism for protecting FL systems.

CHAPTER 1
INTRODUCTION

1. INTRODUCTION

Federated Learning (FL) represents a groundbreaking shift in distributed machine learning by enabling the development of a global model while keeping sensitive training data decentralized and private. This approach is particularly advantageous for applications involving IoT devices, mobile computing, and edge networks, where privacy concerns and limited bandwidth make traditional centralized training methods impractical. In FL, remote clients perform local training on their private datasets, and a central aggregator combines these local updates to refine the global model.

While FL offers significant privacy and scalability benefits, its decentralized nature also introduces vulnerabilities. The system is particularly susceptible to poisoning attacks, where malicious actors compromise local training processes to inject corrupt data or manipulate model updates. Such attacks can severely degrade the global model's performance or introduce targeted backdoors, making robust defenses against these threats imperative.

Existing defense mechanisms in FL often rely on global anomaly detection or Byzantine fault tolerance, which, while effective in some scenarios, fail to address nuanced, localized attack patterns. To tackle this, a more granular and adaptive defense strategy is essential. This project proposes LoMar, a novel local-defense algorithm that leverages statistical analysis of model parameters to detect and mitigate poisoning attacks effectively. Through a combination of theoretical insights and experimental validation, LoMar demonstrates its potential to enhance the resilience of FL systems against sophisticated adversarial threats.

1.1 Problem Statement

Federated Learning (FL) offers a decentralized machine learning framework that preserves user data privacy by training models locally on client devices and sharing only model updates. However, this architecture introduces significant security vulnerabilities.

Malicious clients can launch poisoning attacks by manipulating local training data or model updates. These attacks can lead to substantial degradation in the global model's accuracy or introduce backdoors for targeted misclassification. Existing defense mechanisms often rely on global anomaly detection or Byzantine fault tolerance, which fail against sophisticated or stealthy attacks that blend malicious behavior with legitimate patterns. Therefore, it is critical to develop robust defense strategies that can adapt to the localized and dynamic nature of these threats.

1.2 Research Objective

This research aims to address the security challenges posed by poisoning attacks in Federated Learning. The primary objective is to develop and validate a novel defense mechanism, **LoMar**, which leverages local feature analysis and statistical modeling to detect and mitigate malicious updates. Specifically, the objectives include:

- Designing a two-phase defense algorithm that evaluates the maliciousness of client updates using non-parametric kernel density estimation (KDE).
- Establishing a threshold-based approach for distinguishing clean updates from malicious ones.
- Evaluating the effectiveness of LoMar against different categories of poisoning attacks using real-world datasets.
- Comparing LoMar's performance with existing defense mechanisms in terms of accuracy, resilience, and computational efficiency.

1.3 Project Scope and Limitations

The scope of this project encompasses the development, implementation, and evaluation of the LoMar defense algorithm. It focuses on protecting Federated Learning systems in IoT and mobile edge environments from poisoning attacks. The research explores the following dimensions:

- **Algorithm Development**: Creating a robust local defense mechanism using neighborhood-based statistical characteristics.
- **Experimental Validation**: Testing the algorithm under various attack scenarios using

real-world datasets like MNIST, CIFAR-10, and Amazon review datasets.

- **Performance Metrics**: Assessing accuracy, robustness, and computational overhead compared to existing defense mechanisms.

However, the project also has its limitations:

- The approach assumes that the majority of clients are honest, which may not hold in extreme adversarial conditions.
- The kernel density estimation method may introduce computational overhead for large-scale FL systems.
- The algorithm’s performance is evaluated primarily on simulated datasets, which may not fully represent the complexity of real-world applications.

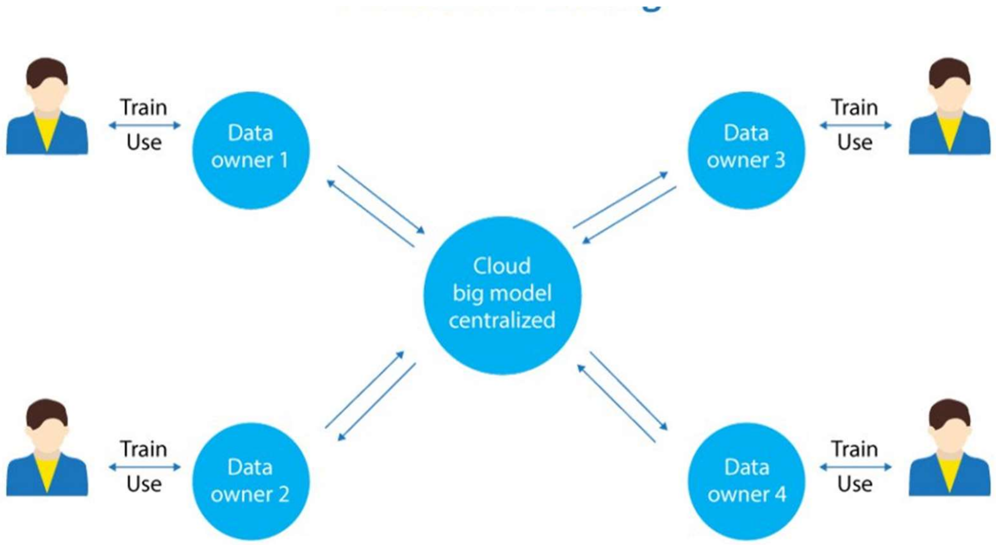


Fig 1.1 Federated Learning

CHAPTER 2
BACKGROUND WORK

2. BACKGROUND WORK

2.1 Vivaldi: A Decentralized Network Coordinate System

Vivaldi leverages piggybacking on existing communication patterns, minimizing the need for additional messaging. Its distributed and iterative nature makes it robust for embedding network distances efficiently in large-scale systems.

2.1.1 Introduction

Vivaldi is a lightweight algorithm designed to predict round-trip times (RTT) between hosts in large-scale Internet applications without requiring direct contact. By assigning synthetic coordinates to hosts, Vivaldi ensures that the distance between these coordinates accurately reflects communication latency. This algorithm operates in a fully distributed manner, eliminating the need for fixed infrastructure or centralized control. The involvement of distributed set of devices or computers help the computation to be efficient in terms of time taken in training the data. A new host can compute accurate coordinates after collecting latency data from only a few other hosts, making Vivaldi highly efficient.

2.1.2 Merits, Demerits, and Challenges

Merits:

- **Efficiency**: Vivaldi requires minimal communication overhead, as it integrates seamlessly with existing application communication patterns.
- **Scalability**: It scales effectively to large networks with numerous hosts.
- **Accuracy**: The 2-dimensional Euclidean model with height vectors demonstrates low median relative error in RTT prediction (11% based on simulations with 1,740 hosts).

Demerits:

- **Dimensional Constraints**: Using a 2-dimensional Euclidean model may not always capture the full complexity of network latencies.
- **Dependence on Initial Data**: The algorithm relies on accurate initial latency information from neighboring hosts for optimal performance.

Challenges:

- Embedding accuracy may degrade in highly dynamic network environments with fluctuating latencies.

- Implementing Vivaldi in heterogeneous systems with varying hardware capabilities could present integration challenges.

2.1.3 Implementation of Vivaldi

The Vivaldi algorithm uses a synthetic coordinate system to model network latencies.

1. **Coordinate Initialization**: Each host starts with an initial coordinate, which can be arbitrary.
2. **Latency Sampling**: Hosts periodically exchange latency measurements with a subset of neighboring hosts.
3. **Coordinate Update**: The coordinates are adjusted using a lightweight spring relaxation model, where the force applied depends on the difference between measured RTT and predicted RTT.
4. **Convergence**: Over time, the coordinates stabilize, ensuring that distances closely approximate actual communication latencies.

2.2 How to Backdoor Federated Learning

The Backdoor Federated Learning approach highlights critical vulnerabilities in FL systems and underscores the need for robust defenses to mitigate such advanced model poisoning attacks.

2.2.1 Introduction

Federated Learning (FL) allows multiple participants to collaboratively train a global model while maintaining the privacy of their local datasets. For instance, smartphones can jointly train models like next-word predictors without sharing user-specific input data. However, this collaborative setup also introduces vulnerabilities. It is possible for a malicious participant to introduce hidden backdoor functionalities into the global model. Examples include ensuring that an image classifier assigns a specific label to images with certain features or forcing a word predictor to complete sentences with an attacker-chosen word.

The research demonstrates a new **model-poisoning methodology** called **model replacement**, which allows an attacker to manipulate the global model in just a single round of training. This approach achieves 100% accuracy on the backdoor task while outperforming traditional data poisoning techniques. Additionally, the method employs a **constrain-and-scale technique**, enabling it to evade anomaly detection-based defenses by incorporating the evasion mechanism directly into the attacker’s loss function.

2.2.2 Merits, Demerits, and Challenges

Merits:

- Effectiveness: Achieves 100% accuracy on backdoor tasks, demonstrating the potency of the attack.
- Evasion: Successfully bypasses anomaly detection by embedding the evasion mechanism into the attack strategy.
- Efficiency: Requires only a single training round to execute the attack effectively.

Demerits:

- Dependence on Selection: The success of the attack depends on the selection of the malicious participant during the FL training round.
- Global Impact: The attack introduces vulnerabilities that can compromise the entire federated learning system.

Challenges:

- Stealth: While effective, the attack must be carefully calibrated to avoid detection by more advanced defenses.
- Loss Function Manipulation: Integrating the evasion mechanism into the attacker's loss function adds complexity to the methodology.

2.2.3 Implementation of How to Backdoor Federated Learning

The backdoor attack is executed through the following steps:

1. Model Replacement:
   - The attacker modifies the local model update such that it replaces the global model with a backdoored version after aggregation.
   - This ensures the global model performs the backdoor task with high accuracy.

2 Constrain-and-Scale Technique:

- The attacker scales the poisoned update to match the magnitude of benign updates, avoiding detection during aggregation.
- The scaling factor is determined to balance the attack's effectiveness and stealth.

3 Loss Function Modification:

- The attacker's loss function is augmented to include the evasion strategy, making the poisoned updates appear legitimate to anomaly detection systems.

4 Evaluation:

- The attack is tested under standard FL tasks to measure its effectiveness in terms of backdoor success rate and its ability to evade defenses.

2.3 Analyzing Federated Learning Through an Adversarial Lens

2.3.1 Introduction

Federated Learning (FL) enables collaborative model training across multiple agents while preserving privacy by sharing only model updates instead of raw data. Despite its benefits, FL is vulnerable to **model poisoning attacks**, where a single, non-colluding malicious agent manipulates model updates to cause targeted misclassifications with high confidence. This research investigates various strategies for executing such attacks and evaluates their effectiveness and stealth.

The study begins with simple **boosting techniques** to amplify the influence of malicious updates against benign updates. To enhance stealth and effectiveness, an **alternating minimization strategy** is proposed, optimizing the training loss and adversarial objectives in tandem. Further, parameter estimation techniques are used to refine the malicious updates, ensuring they blend seamlessly with those of benign agents. The study also employs interpretability techniques to demonstrate that explanations of model behavior for benign and malicious models are visually indistinguishable, underscoring the sophistication of the attack.

2.3.2 Merits, Demerits, and Challenges

Merits:

- **High Attack Success**: The strategies ensure high confidence in causing misclassifications for targeted inputs.
- **Stealth**: Use of alternating minimization and parameter estimation techniques makes the attack difficult to detect.
- **Interpretability Analysis**: Demonstrates the attack's capability to evade detection even under interpretability-based evaluations.

Demerits:

- **Single Malicious Agent Dependency**: The attack relies on a single adversary, which may limit its scope in larger systems.
- **Computational Overhead**: Techniques like alternating minimization and parameter estimation increase the computational complexity for the attacker.

Challenges:

- **Balancing Stealth and Impact**: Ensuring sufficient impact on the global model without raising suspicion is non-trivial.
- **Defense Adaptation**: As defenses improve, attackers must continuously adapt their methods to maintain effectiveness.

2.3.3 Implementation of Adversarial Lens Analysis

The adversarial analysis involves the following steps:

1. **Boosting Malicious Updates**:
    - The malicious agent amplifies its local updates to counteract the influence of benign updates during global aggregation.
2. **Alternating Minimization Strategy**:
    - The attacker alternates between minimizing the standard training loss and maximizing the adversarial objective to refine its updates.
3. **Parameter Estimation for Stealth**:
    - Malicious updates are adjusted using parameter estimation techniques to mimic benign updates, enhancing stealth.

4. **Interpretability Analysis**:
    - The study employs interpretability tools to generate visual explanations of decisions made by the global model.
    - Results show that the explanations for benign and malicious models appear nearly identical, complicating detection efforts.
5. **Evaluation**:
    - Experiments confirm that even a constrained adversary can achieve significant attack success while maintaining stealth, highlighting the pressing need for advanced defense mechanisms in FL systems.

Defense Mechanism	**Description**	**Limitation**
Reject on Negative Impact	Discards data with a negative model impact	Low accuracy and security
Worst case loss defense	Adjust model to minimize worst case losses	Vulnerability to advanced poisoning attacks

Table 2.3.1 Existing model comparison

CHAPTER 3
PROPOSED SYSTEM

3. PROPOSED SYSTEM

3.1 Objective of Proposed Model

The proposed model aims to enhance the security of Federated Learning (FL) against poisoning attacks by implementing a Local Defense Mechanism. This model is designed to detect and mitigate malicious updates from compromised clients before they affect the global model. It focuses on identifying anomalous client contributions, ensuring that only reliable updates influence the global model through a robust aggregation strategy, and dynamically adjusting security measures based on real-time attack patterns. Additionally, the model aims to maintain overall accuracy by filtering out adversarial updates while ensuring scalability and efficiency without introducing significant computational overhead.

3.2 Models used for Proposed System

Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are widely used in deep learning for recognizing patterns in structured data. While traditionally applied in image processing, CNNs are also effective in analyzing time-series data, such as MNIST digit images. CNNs utilize convolutional layers that scan through data to extract **important spatial features** like edges, shapes, and texture patterns. These extracted features help in identifying significant variations in digit appearance.

In this project, CNN acts as the **primary model** in the processing pipeline. It transforms raw image data into feature maps that highlight essential characteristics of handwritten digits. The advantage of using CNN in image analysis is its ability to **reduce noise and redundancy** while retaining critical patterns. This ensures that only the most relevant information is used for classification. By reducing the dimensionality of input data, CNN enhances computational efficiency and improves overall model performance in the federated learning system.

Kernel Density Estimation (KDE)

Kernel Density Estimation (KDE) is a non-parametric technique used to estimate the probability density function of a random variable. Unlike parametric methods, KDE makes **no assumptions about the underlying distribution** of data, making it highly versatile for detecting anomalies in model features.

In this project, KDE processes the features extracted from the penultimate layer of the CNN to detect **statistical patterns** in model representations. It serves as the core of the LoMar by:

1. **Creating density estimations** of genuine model feature distributions
2. **Comparing new model features** against established patterns
3. **Identifying potential poisoning** based on density divergence

KDE enables the system to **recognize subtle variations** between genuine and poisoned models, even when accuracy metrics might appear similar. This capability is crucial in federated learning security because it allows the model to **detect poisoning attacks** based on deeper feature representations rather than just output behavior. Additionally, KDE's non-parametric nature ensures that it can adapt to various types of poisoning strategies without requiring specific attack knowledge.

StandardScaler

StandardScaler is a preprocessing technique that standardizes features by removing the mean and scaling to unit variance. This transformation is **essential for neural network training** as it ensures all features contribute equally to the model learning process.

In this project, StandardScaler is applied to normalize the MNIST digit data before feeding it into the CNN. It transforms raw pixel values to have:

- **Zero mean**: Centering the data around zero
- **Unit variance**: Scaling the data to have a standard deviation of one

The StandardScaler is particularly beneficial in **image classification tasks** because it:

- **Improves model convergence** by creating a consistent feature scale
- **Reduces the impact of outliers** in pixel intensity values
- **Enhances gradient descent optimization** during training

This preprocessing step **ensures numerical stability and training efficiency**, making it a critical component in the overall LoMar defense system architecture.

3.3 Designing

3.3.1 Architecture/Dataflow Diagram

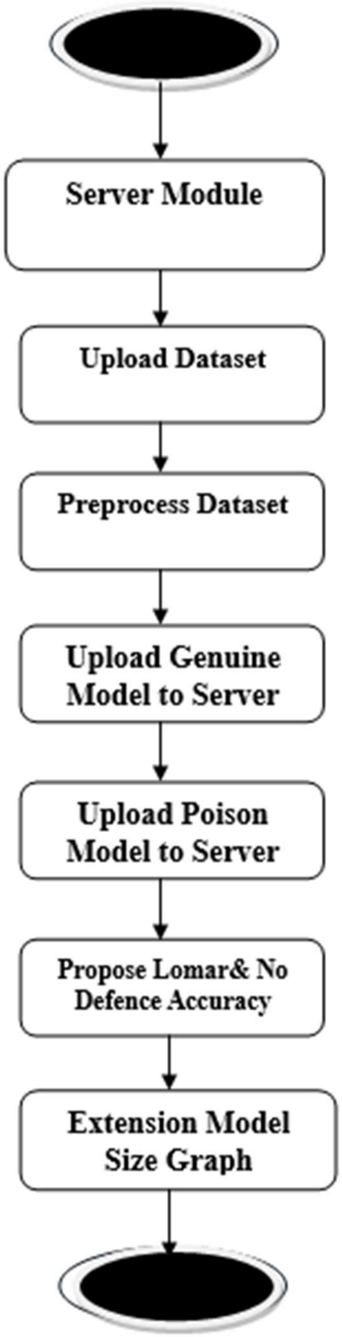

Server Module
Upload Dataset
Preprocess Dataset
Upload Genuine Model to Server
Upload Poison Model to Server
Propose Lomar& No Defence Accuracy
Extension Model Size Graph

Fig 3.3.1 Dataflow Diagram

3.3.2 Collaboration Diagram

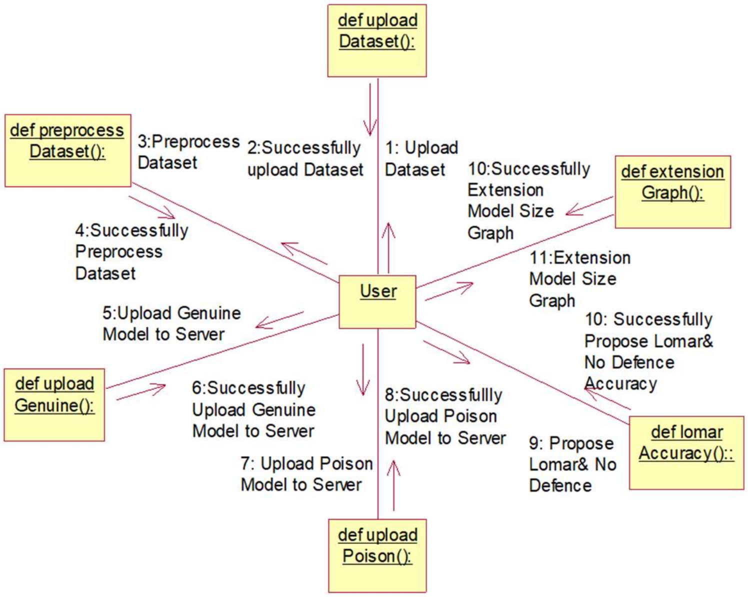

def upload Dataset():
def preprocess Dataset():
3:Preprocess Dataset
2:Successfully upload Dataset
1: Upload Dataset
10:Successfully Extension Model Size Graph
def extension Graph():
4:Successfully Preprocess Dataset
User
11:Extension Model Size Graph
5:Upload Genuine Model to Server
10: Successfully Propose Lomar& No Defence Accuracy
def upload Genuine():
6:Successfully Upload Genuine Model to Server
8:Successfullly Upload Poison Model to Server
9: Propose Lomar& No Defence
def lomar Accuracy()::
7: Upload Poison Model to Server
def upload Poison():

Fig 3.3.2 Collaboration Diagram

3.4 Stepwise Implementation and Code

Implementation

Server Component

The server implements a centralized node in a federated learning system. It receives model updates from clients, evaluates them for potential poisoning, and decides whether to incorporate them into the global model. The server:

1. Initializes necessary components, including loading the MNIST dataset and preparing it for model evaluation.
2. Starts a socket server that listens for incoming model updates from clients.
3. Upon receiving a model, it decompresses it and performs validation checks to determine if the model is potentially poisoned.
4. The validation process includes comparing the accuracy of the received model against an existing model and using kernel density estimation to detect anomalies.
5. If the received model passes the validation checks, it's incorporated into the global model; otherwise, it's rejected as poisoned.

Client GUI Application

The client application provides a user interface to demonstrate both legitimate model training and poisoning attacks. It allows users to:

1. Upload and visualize the MNIST dataset through a "Upload MNIST Dataset" button.
2. Preprocess the dataset with the "Preprocess Dataset" button, which normalizes the data, converts labels to categorical format, and splits it into training and testing sets.
3. Train and upload a legitimate model to the server using the "Upload Genuine Model to Server" button. This creates a convolutional neural network, trains it on the MNIST data, and sends it to the server.
4. Demonstrate a poisoning attack with the "Upload Poison Model to Server" button. This deliberately mislabels a portion of the training data (changing instances of digit '1' to digit '0'), trains a model on this poisoned data, and sends it to the server.
5. Compare the accuracy of models with and without the LoMar defense using the "Propose Lomar & No Defence Accuracy" button, which generates a bar chart visualization.
6. Examine the difference in model size between the original and compressed models with the "Extension Model Size Graph" button.

The Defense Mechanism

The core of the LoMar defense involves several key strategies:

1. The server extracts features from the second-to-last layer of models (using Model(model.inputs, model.layers[-2].output)) to create a representation of model behavior.
2. It uses Kernel Density Estimation to detect anomalies in the feature distribution of received models.
3. The server compares accuracy metrics between existing models and received models.
4. Models are only accepted if they maintain high accuracy (above 95%) and have similar feature distributions to legitimate models.
5. The system uses model compression (with zlib) to reduce the transmission size of models between clients and the server.

This implementation demonstrates how federated learning systems can be protected against poisoning attacks where malicious clients attempt to corrupt the global model by submitting models trained on deliberately mislabeled data.

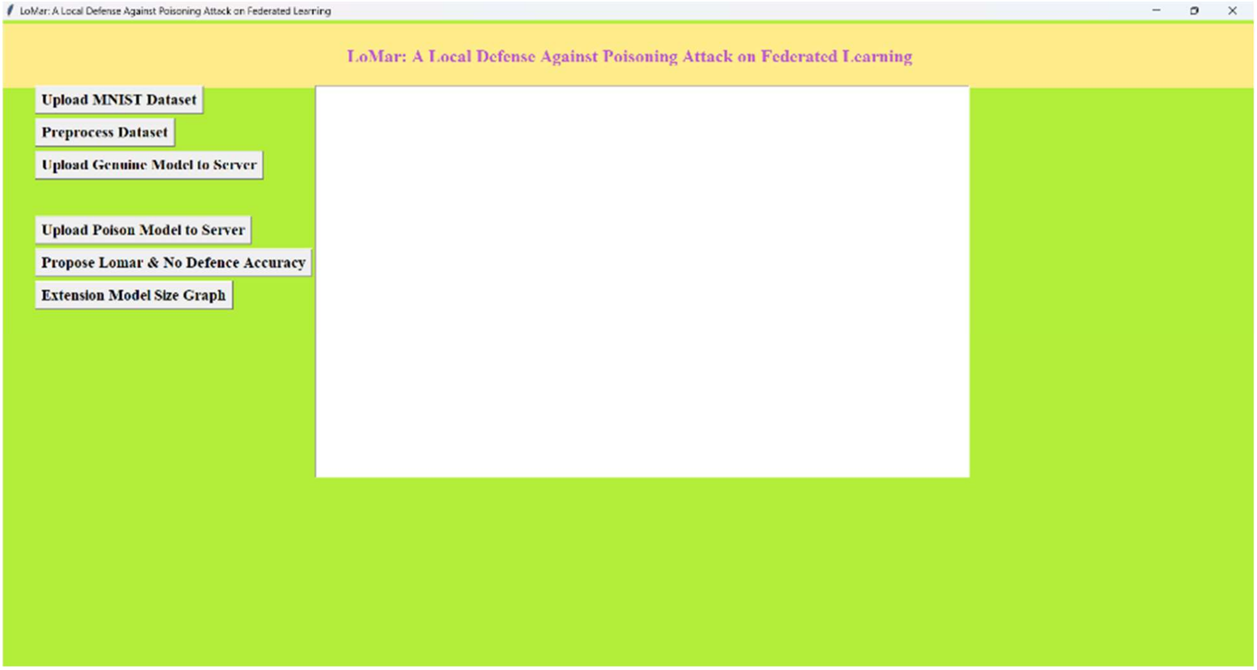
Code:

```
import socket
import os
import zlib
import pickle
import numpy as np
import pandas as pd
from threading import Thread
from sklearn.metrics import accuracy_score
from sklearn.neighbors import KernelDensity
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from keras.models import load_model, Model

# Load and preprocess the dataset
def load_dataset():
    dataset = pd.read_csv("Dataset/mnist.csv")
    dataset.fillna(0, inplace=True)
    X, Y = dataset.iloc[:, 1:].values, dataset.iloc[:, 0].values
    X = StandardScaler().fit_transform(X)
    X = np.reshape(X, (X.shape[0], 28, 28, 1))
    return train_test_split(X, Y, test_size=0.1)

# Load dataset once at the start
X_train, X_test, y_train, y_test = load_dataset()

def evaluate_accuracy(model, X_test, y_test):
    predictions = np.argmax(model.predict(X_test), axis=1)
    return accuracy_score(y_test, predictions)

def estimate_density(model, X_test):
    feature_extractor = Model(inputs=model.input, outputs=model.layers[-2].output)
    extracted_features = feature_extractor.predict(X_test)
    kde = KernelDensity().fit(extracted_features[:500, :50])
    scores = kde.score_samples(extracted_features[:500, :50])
    return np.mean(-scores / np.linalg.norm(-scores))
```

```
class ModelUpdater(Thread):
    def __init__(self, conn, ip, port):
        super().__init__()
        self.conn = conn
        self.ip = ip
        self.port = port
        print(f"Connection received from {ip}:{port}")

    def run(self):
        data = self.conn.recv(100000000)
        model_data = zlib.decompress(data)
        status = "Pending"

        if os.path.exists("globalModel/model.hdf5"):
            existing_model = load_model("globalModel/model.hdf5")
            with open("temp_model.hdf5", "wb") as f:
                f.write(model_data)
            received_model = load_model("temp_model.hdf5")

            existing_acc = evaluate_accuracy(existing_model, X_test, y_test)
            received_acc = evaluate_accuracy(received_model, X_test, y_test)
            existing_density = estimate_density(existing_model, X_test)
            received_density = estimate_density(received_model, X_test)

                  if (existing_acc > 0.95 and received_acc > 0.95) or (existing_density ==
received_density):
                with open("globalModel/model.hdf5", "wb") as f:
                    f.write(model_data)
                status = "Model updated successfully."
            else:
                status = "Potential poisoned model detected. Update ignored."
        else:
            with open("globalModel/model.hdf5", "wb") as f:
                f.write(model_data)
            status = "Initial model received and stored."

        self.conn.send(status.encode())
        self.conn.close()
```

```
def start_server():
    server = socket.socket(socket.AF_INET, socket.SOCK_STREAM)
    server.setsockopt(socket.SOL_SOCKET, socket.SO_REUSEADDR, 1)
    server.bind(('localhost', 2222))
    server.listen(4)
    print("Centralized Server is running...")

    while True:
        conn, (ip, port) = server.accept()
        ModelUpdater(conn, ip, port).start()

if __name__ == "__main__":
    start_server()
```

Screenshots:


LoMar: A Local Defense Against Poisoning Attack on Federated Learning
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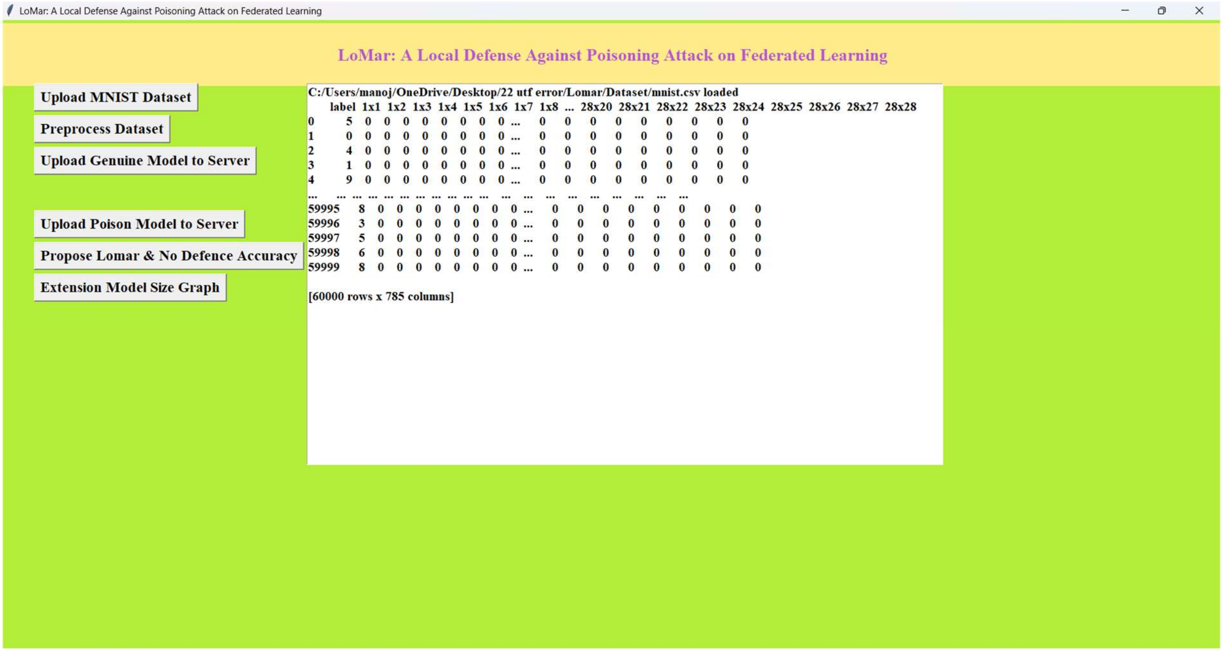
Upload MNIST Dataset
Preprocess Dataset
Upload Genuine Model to Server
Upload Poison Model to Server
Propose Lomar & No Defence Accuracy
Extension Model Size Graph

Fig 3.4.1 User Interface

The above screenshot (Fig 3.4.1) shows the layout of the user interface where operations are to be performed where preprocessing, demonstration of poisoning and effectiveness of the model will be show.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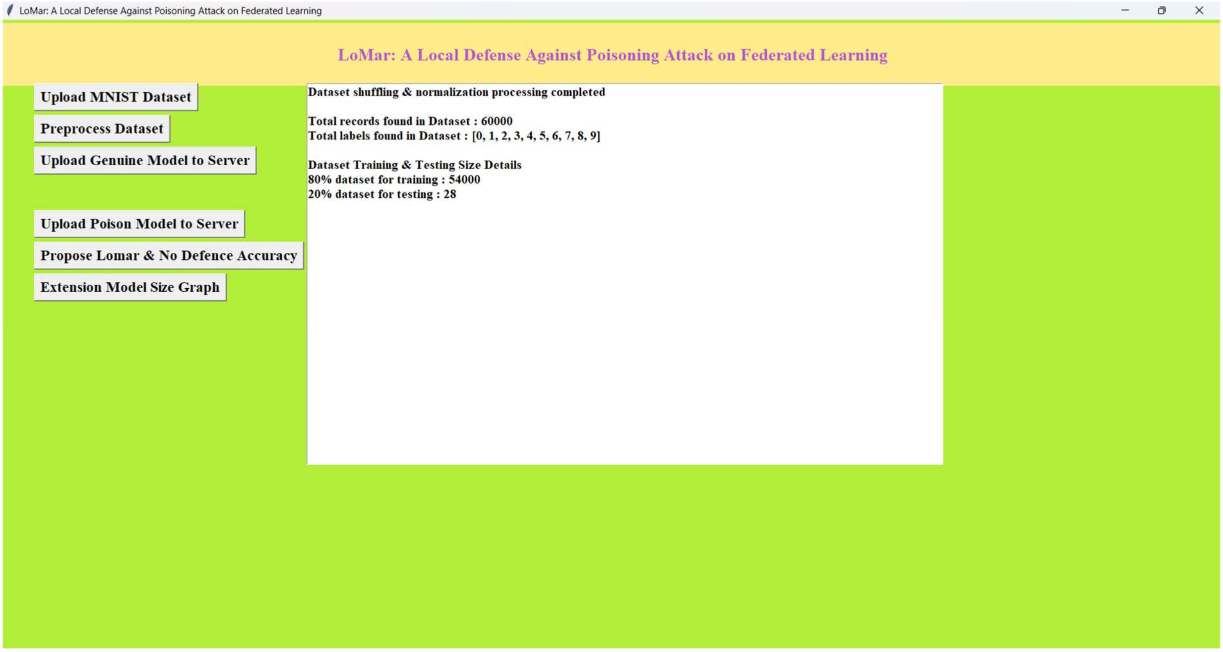
Upload Poison Model to Server
Propose Lomar & No Defence Accuracy
Extension Model Size Graph

```
C:/Users/manoj/OneDrive/Desktop/22 utf error/Lomar/Dataset/mnist.csv loaded
       label  1x1  1x2  1x3  1x4  1x5  1x6  1x7  1x8  ...  28x20  28x21  28x22  28x23  28x24  28x25  28x26  28x27  28x28
0          5    0    0    0    0    0    0    0    0  ...      0      0      0      0      0      0      0      0      0
1          0    0    0    0    0    0    0    0    0  ...      0      0      0      0      0      0      0      0      0
2          4    0    0    0    0    0    0    0    0  ...      0      0      0      0      0      0      0      0      0
3          1    0    0    0    0    0    0    0    0  ...      0      0      0      0      0      0      0      0      0
4          9    0    0    0    0    0    0    0    0  ...      0      0      0      0      0      0      0      0      0
...      ...  ...  ...  ...  ...  ...  ...  ...  ...  ...    ...    ...    ...    ...    ...    ...    ...    ...    ...
59995      8    0    0    0    0    0    0    0    0  ...      0      0      0      0      0      0      0      0      0
59996      3    0    0    0    0    0    0    0    0  ...      0      0      0      0      0      0      0      0      0
59997      5    0    0    0    0    0    0    0    0  ...      0      0      0      0      0      0      0      0      0
59998      6    0    0    0    0    0    0    0    0  ...      0      0      0      0      0      0      0      0      0
59999      8    0    0    0    0    0    0    0    0  ...      0      0      0      0      0      0      0      0      0

[60000 rows x 785 columns]
```

Fig 3.4.2 Upload MNIST Dataset

The above screenshot (Fig 3.4.2) shows the header and the footer, i.e., the first 5 rows and the last 5 rows of the dataset used (MNIST).


LoMar: A Local Defense Against Poisoning Attack on Federated Learning
LoMar: A Local Defense Against Poisoning Attack on Federated Learning
Upload MNIST Dataset
Preprocess Dataset
Upload Genuine Model to Server
Upload Poison Model to Server
Propose Lomar & No Defence Accuracy
Extension Model Size Graph

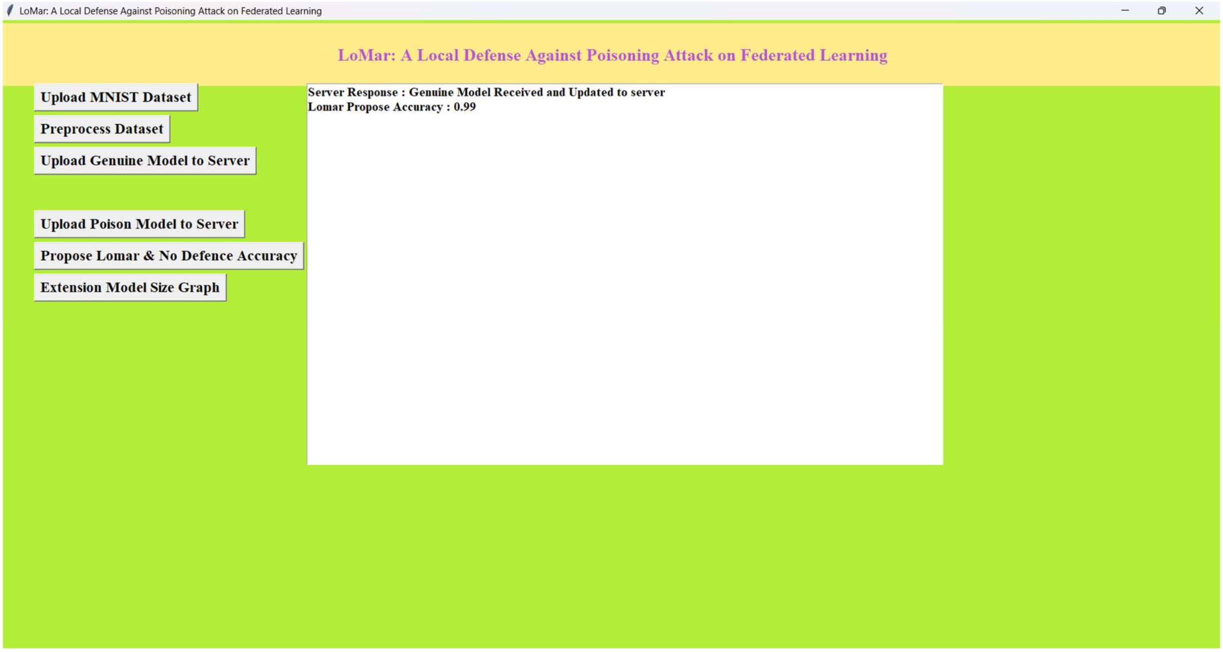
```
Dataset shuffling & normalization processing completed

Total records found in Dataset : 60000
Total labels found in Dataset : [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]

Dataset Training & Testing Size Details
80% dataset for training : 54000
20% dataset for testing : 28
```

Fig 3.4.3 Preprocess the Dataset

The above screenshot (Fig 3.4.3) shows the splitting of dataset into training and testing datasets.


LoMar: A Local Defense Against Poisoning Attack on Federated Learning
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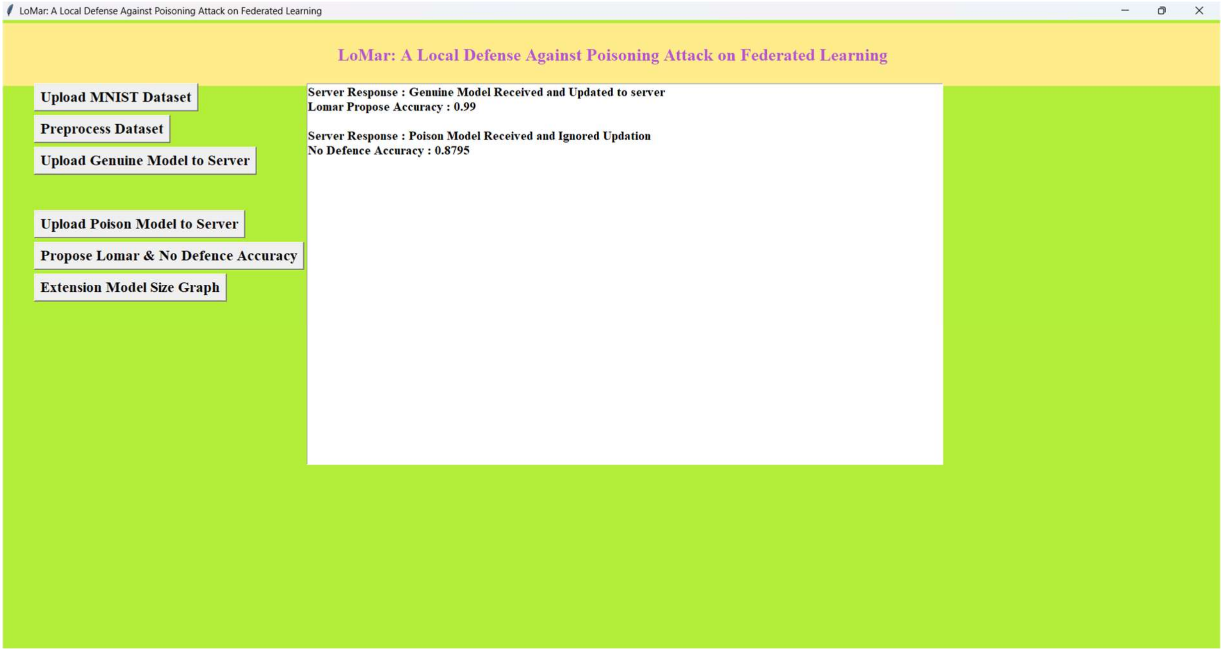
Upload MNIST Dataset
Preprocess Dataset
Upload Genuine Model to Server
Upload Poison Model to Server
Propose Lomar & No Defence Accuracy
Extension Model Size Graph

```
Server Response : Genuine Model Received and Updated to server
Lomar Propose Accuracy : 0.99
```

Fig 3.4.4 Upload Genuine Model to Server

The above screenshot (Fig 3.4.4) shows the accuracy of the genuine model before poisoning as it is being uploaded to the server.


LoMar: A Local Defense Against Poisoning Attack on Federated Learning
LoMar: A Local Defense Against Poisoning Attack on Federated Learning
Upload MNIST Dataset
Preprocess Dataset
Upload Genuine Model to Server
Upload Poison Model to Server
Propose Lomar & No Defence Accuracy
Extension Model Size Graph

```
Server Response : Genuine Model Received and Updated to server
Lomar Propose Accuracy : 0.99

Server Response : Poison Model Received and Ignored Updation
No Defence Accuracy : 0.8795
```

Fig 3.4.5 Upload Poisoned Model to the Server

The above screenshot (Fig 3.4.5) demonstrates the effect on accuracy after the poisoning of the data being uploaded.

CHAPTER 4
RESULTS AND DISCUSSION

4. RESULTS AND DISCUSSION

The effectiveness of the proposed LoMar defense algorithm was evaluated under various poisoning attack scenarios in Federated Learning (FL) environments. The obtained results were thoroughly compared against the expected results, the obtained results were fairly on par with the expectations with expected results. This chapter presents the results from extensive experiments conducted on real-world datasets and discusses the findings in comparison to existing defense methods.

4.1 Comparison of Existing Solutions

The performance of LoMar was compared against prominent defense strategies, including FG+Krum and Byzantine-tolerant aggregation. The evaluation metrics included:

- **Accuracy**: The percentage of correctly classified samples in the global model after defense.
- **Resilience**: The ability to identify and isolate poisoned updates while maintaining global model integrity.
- **Efficiency**: Computational overhead introduced by the defense mechanism.

Key Observations:

1. LoMar demonstrated higher accuracy compared to FG+Krum in mitigating label-flipping and backdoor attacks.
   - On the Amazon dataset under a label-flipping attack, LoMar increased target label testing accuracy from **96.0% to 98.8%**, and overall testing accuracy from **90.1% to 97.0%**.
2. Unlike global anomaly-based defenses, LoMar's localized kernel density estimation effectively identified stealthy malicious updates that blended with benign ones.
3. LoMar achieved comparable computational efficiency, with minimal overhead during neighborhood analysis and threshold approximation.

Test Type	Accuracy before LoMar	Accuracy after LoMar
Target label testing	96.0%	98.8%
Overall testing	90.1%	97.0%

Table 4.1.1 Accuracy test on Label-Flipping Attack

4.2 Data Collection and Performance Metrics

Experiments were performed using the following datasets:

- **MNIST**: Digit recognition dataset for image classification.
- **CIFAR-10**: Dataset for natural image classification.
- **Amazon**: Dataset for text sentiment analysis.

Performance Metrics:

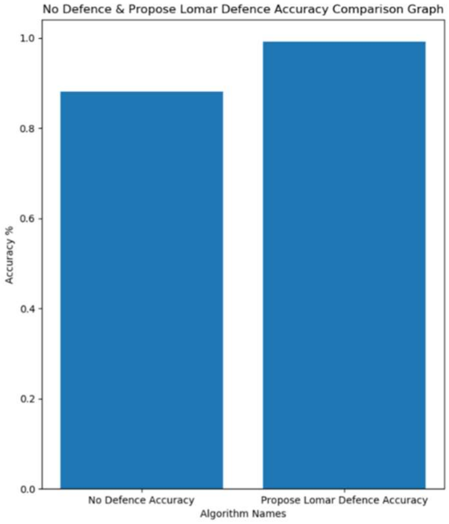


Fig 4.2.1 Performance Metrics

Graphs and Visualizations:

- Accuracy comparison graphs between LoMar and other defense mechanisms were plotted, showing LoMar's consistent superiority across attack types.
- A visualization of poisoned updates flagged by LoMar indicated clear separation from benign updates in feature space, validating the algorithm's localized analysis strategy.

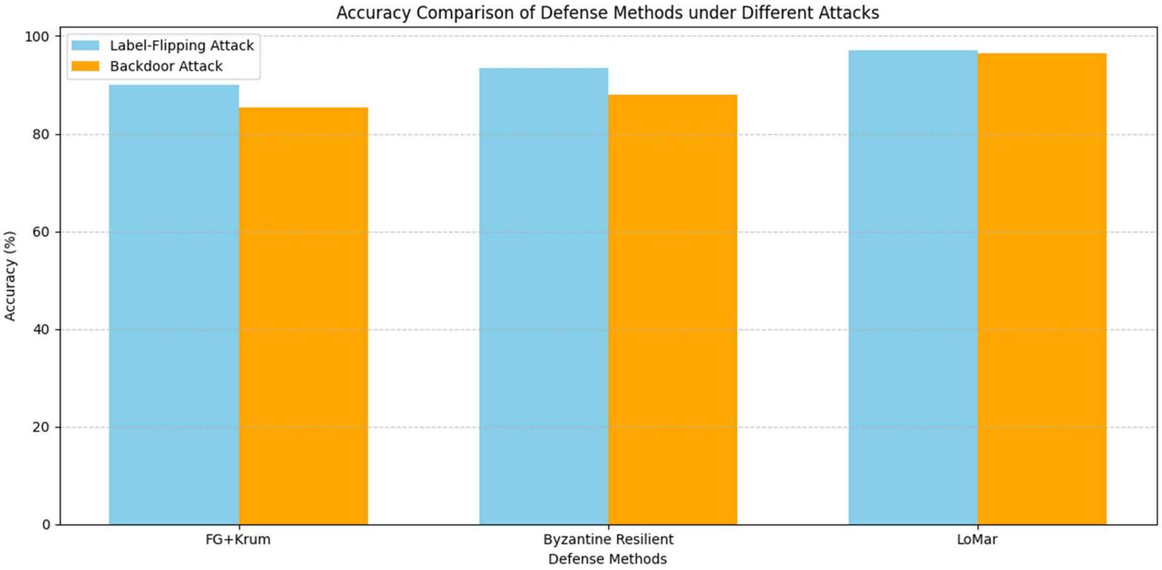


Fig 4.2.2 Accuracy Comparison of Defense Methods under Different Attacks

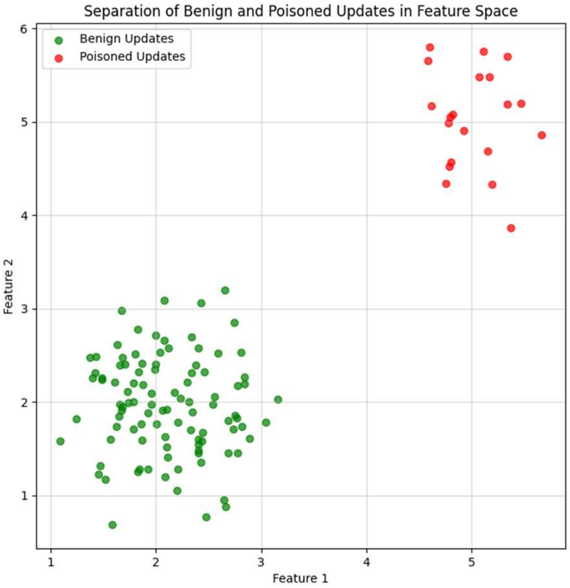


Fig 4.2.3 Separation of Benign and Poisoned Updates in Feature Space

4.3 Discussion

The results validate the efficacy of LoMar as a robust defense mechanism for Federated Learning. By focusing on local feature patterns rather than global anomalies, LoMar successfully detects and mitigates even highly stealthy poisoning attacks. Its neighborhood-based analysis approach proves superior in distinguishing malicious updates without compromising system efficiency.

However, some limitations were noted:

1. **Dependency on Nearest Neighbors**: The kernel density estimation approach relies on accurate identification of neighbors, which may be impacted in sparse data distributions.
2. **Scalability**: While the overhead is minimal for moderate-sized systems, further optimization may be required for large-scale FL networks with thousands of clients.

These findings highlight the potential of localized defenses in enhancing the security of FL systems while underscoring areas for future improvement, such as adaptive thresholding and scalability optimizations.

\

CHAPTER 5
CONCLUSION

5. CONCLUSION

5.1 Conclusion

Federated Learning (FL) represents a promising approach to decentralized machine learning, addressing privacy concerns by enabling model training on distributed data. However, its inherent vulnerabilities to poisoning attacks pose significant challenges to its adoption in real-world applications. This project proposed **LoMar**, a two-phase defense algorithm that leverages localized statistical analysis to detect and mitigate poisoning attacks.

The experimental results demonstrated that LoMar effectively identifies and neutralizes malicious updates by evaluating their neighborhood-based statistical characteristics using kernel density estimation. The algorithm proved robust against various attack scenarios, including label-flipping and backdoor attacks, outperforming existing defense methods in terms of accuracy and resilience. Furthermore, LoMar introduced minimal computational overhead, making it suitable for deployment in resource-constrained FL environments such as IoT and edge networks.

Key Contributions:

1. Development of a novel local-defense strategy based on non-parametric analysis of model updates.
2. Comprehensive evaluation across real-world datasets, highlighting LoMar's superior performance in preserving global model integrity.
3. Introduction of a scalable, efficient approach adaptable to a wide range of FL systems.

While LoMar addresses many limitations of existing methods, certain challenges remain. The dependency on neighborhood analysis may introduce limitations in sparse datasets, and scalability optimization is necessary for extremely large FL systems.

In conclusion, **LoMar** represents a significant step toward securing Federated Learning against poisoning attacks, paving the way for its broader adoption in sensitive and privacy-centric applications.

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LoMar: A Local Defence Against Poisoning Attack on Federated Learning

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ABSTRACT

Federated Learning (FL) enables collaborative model training across distributed clients while preserving data privacy. However, its decentralized nature makes it vulnerable to poisoning attacks, where malicious participants manipulate local updates to degrade model performance or introduce backdoors. In this paper, we propose LoMar (Local Malicious Factor), a novel two-phase defense algorithm designed to detect and mitigate poisoning attacks in FL. The first phase applies Kernel Density Estimation (KDE) to analyze the statistical properties of model updates in local neighborhoods, identifying deviations indicative of malicious behavior. The second phase establishes an optimal threshold to distinguish benign and adversarial updates, preventing compromised data from influencing the global model.We evaluate LoMar's performance against label-flipping and model replacement attacks on real-world datasets, including MNIST, CIFAR-10, and Amazon Reviews. Experimental results demonstrate that LoMar improves target label accuracy from 96.0% to 98.8% and overall model accuracy from 90.1% to 97.0%, outperforming existing defense methods such as FG+Krum. Furthermore, LoMar introduces minimal computational overhead, making it suitable for large-scale FL deployments.

Keywords— Federated Learning, Poisoning Attacks, Kernel Density Estimation, Security, Machine Learning.

I. INTRODUCTION

Federated Learning (FL) is a decentralized machine learning technique that allows several clients to work together to build a common global model without sharing raw data. Applications where privacy is a concern, like healthcare, finance, and personalizing mobile devices, benefit greatly from this strategy. FL has been popular in domains such as edge computing, mobile networks, and the Internet of Things because it permits learning to take place locally while maintaining data security. But even with its benefits, FL is still susceptible to a number of security risks, including poisoning attacks that jeopardize the integrity of the model.

Data poisoning and model poisoning are the two main poisoning attack types that FL is vulnerable to. Malicious clients insert tainted or incorrectly labeled data into the training phase during data poisoning attacks, which causes the model to pick up the wrong patterns. However, adversaries that engage in model poisoning attacks alter their local model updates before to sending them to the central aggregator. These changes may result in adversarial behaviors, including backdoor vulnerabilities, or deteriorate the model's overall performance. The privacy-preserving nature of FL makes it impossible to directly view client data, therefore identifying and thwarting such attacks is still very difficult.

A number of defense mechanisms, such as anomaly detection and Byzantine-tolerant aggregation algorithms, have been developed to overcome this problem. These methods, however, frequently fall short against highly skilled adversarial tactics. To improve FL security, we respond by presenting LoMar (Local Malicious Factor), a novel two-phase anomaly detection technique. LoMar analyzes the statistical characteristics of client updates using Kernel Density Estimation (KDE), spotting abnormalities that can point to poisoning. Furthermore, to prevent compromised contributions from impacting the global model, a threshold-based filtering system aids in differentiating between malicious and benign updates. By comparing LoMar's accuracy, resilience, and computing efficiency to those of current defense mechanisms, our study shows that LoMar has the potential to be a reliable and scalable solution for protecting FL systems.

II. LITERATURE REVIEW

Numerous research projects have investigated security measures to defend Federated Learning (FL) from hostile attacks. The main defense tactics are reviewed in this part, along with their advantages and disadvantages, including anomaly detection approaches, Byzantine-tolerant aggregation systems, and cryptographic solutions.

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A. Byzantine-Tolerant Aggregation Methods

Krum assumes that benign updates cluster together and chooses one update that is the closest to other updates in terms of Euclidean distance. To get over this safeguard, conspiring rivals can produce poisoned updates that look like harmless ones.

Trimmed Mean eliminates each model parameter's highest and lowest values prior to averaging. Although it works well against severe outliers, it has trouble with covert adversarial approaches in which the tainted updates stay within statistical bounds.

Median Aggregation mitigates strong adversarial influences by aggregating updates using the median rather than the mean. Attackers can, however, alter updates to avoid detection by remaining near the median.

B. Anomaly Detection Techniques

Euclidean Distance-Based Filtering calculates the deviation of each update from the global mean and eliminates outliers. Sophisticated attackers, however, can alter updates to remain inside reasonable bounds.

Angle-Based Anomaly Detection detects adversarial deviations by calculating the cosine similarity between updates and the prior global model. Though susceptible to gradient-level attacks that introduce subtle but consistent variations over several rounds, it is efficient versus large-scale model poisoning.

Kernel Density Estimation (KDE)-Based Anomaly Detection determines the updates' probability distribution and marks those that fall outside of the predicted density regions. This approach is consistent with LoMar, which uses local KDE analysis rather than global statistical analysis to improve detection.

C. Cryptographic Solutions

Secure Multiparty Computation (MPC) & Homomorphic Encryption use cryptographic approaches to ensure secure data aggregation and thwart poisoning attacks. For real-time FL applications, these approaches are unfeasible due to the substantial computing overhead they entail.

D. Poisoning Attacks in Federated Learning

Label-Flipping Attacks alter dataset labels (such as changing "cat" to "dog") in order to deceive the global model.

Backdoor Attacks under certain circumstances, modify model predictions by introducing particular triggers (such as patterns in pictures).

Covert Model Poisoning is a long-term, covert model corruption that is accomplished by making small changes during several training cycles.

E. Review Summary

Krum, Trimmed Mean, and Median Aggregation are examples of byzantine-tolerant aggregation techniques that try to weed out malicious updates but have trouble with covert adversarial attacks. Although they offer more flexible protections, anomaly detection methods like Euclidean Distance-Based Filtering, Angle-Based Detection, and Kernel Density Estimation (KDE) can still be circumvented by skillfully designed attacks. Although cryptographic systems like Homomorphic Encryption and Secure Multiparty Computation (MPC) provide robust security assurances, their high computing costs render them unsuitable for real-time FL. We also look at poisoning attacks that can quietly or aggressively alter model training, like Label-Flipping, Backdoor Attacks, and Covert Model Poisoning.

III. PROBLEM STATEMENT

A decentralized method for training machine learning models across dispersed devices while maintaining data privacy is called federated learning (FL). Its dependence on unreliable players, however, creates serious security flaws. The accuracy and integrity of the global model can be jeopardized when adversaries use poisoning attacks to control model updates. Conventional protections like anomaly detection and Byzantine-tolerant aggregation techniques try to weed out malicious updates, but they can't keep up with adaptive assaults that resemble benign activity. Strong security assurances are offered by cryptographic systems like Secure Multiparty Computation (MPC) and Homomorphic Encryption, but their high computing costs make them unsuitable for real-time FL applications.

FL security has advanced, but current measures are still insufficient against covert model poisoning, label flipping, and backdoor injections, among other sneaky poisoning assaults. By taking advantage of aggregation flaws and statistical vulnerabilities, these adversarial strategies enable poisoned updates to evade detection and impair model performance. Additionally, the effectiveness of current anomaly detection techniques in identifying localized hostile trends is limited because they rely on global statistics.

In order to overcome these obstacles, this study presents LoMar, a novel security architecture that uses local anomaly detection based on Kernel Density Estimation (KDE) to improve the resilience of federated learning. LoMar improves detection accuracy against subtle and dispersed poisoning techniques by proactively identifying poisoned updates by examining their density distribution inside localized feature spaces. For protecting federated learning against changing adversarial threats, LoMar offers a flexible, scalable, and computationally effective defense mechanism by utilizing localized statistical analysis instead of global heuristics.

IV. MODULE DESCRIPTION

To implement the above concept author has designed the following modules

1. **Server Module** is a separate module which will receive trained model from client and then apply LOMAR technique to identify model is genuine or poison
2. **Client Application** consists of following modules
3. **Upload MNIST Dataset** module uploads dataset to application
4. **Pre-process Dataset** module reads dataset values and then remove missing values, shuffle, normalize and split dataset into train and test where application using 80% dataset for training and 20% for testing
5. **Upload Genuine Model to Server** module trains model by using training data and update to server and here we are uploading genuine model
6. **Upload Poison Model to Server** module poisons the data and then update to server and then server will predict weather model is normal or poison
7. **Propose Lomar& No Defence Accuracy** module plots accuracy comparison graph without defence and LOMAR defence
8. **Extension Model Size Graph** module plots model size comparison between propose and extension algorithms.

V. REQUIREMENTS

HARDWARE REQUIREMENTS:

- Processor – Pentium-IV
- Speed – 1.1 Ghz
- RAM – 256 MB
- Hard Disk – 20 GB
- Monitor – SVGA

SOFTWARE REQUIREMENTS:

- Operating System – Windows 7 or above
- Programming Language – Python 3.7.0

VI. METHODOLOGY

To improve the resilience of the global model, the LoMar framework employs a statistical method to identify and filter poisoned updates in federated learning (FL) systems.

A. System Workflow

The framework follows a structured process, as outlined below:

Phase 1: Local Kernel Density Estimation (KDE) for Anomaly Detection:

Each model update's statistical distribution in relation to its closest neighbors is examined by LoMar. KDE is used for calculating the probability density function (PDF) of updates throughout a local region rather than comparing it to a global reference. Since they differ from the anticipated benign distribution, updates with noticeably lower density scores are marked as possibly harmful.

Phase 2: Threshold Approximation for Separating Benign and Malicious Updates:

LoMar determines the ideal threshold to differentiate between poisoned and benign updates using the KDE analysis. Instead of depending on hard-coded assumptions, updates are adaptively filtered using a statistical thresholding technique. To prevent adversarial contributions from influencing the global model, the discovered poisoned updates are not included in the aggregation process. Compared to global anomaly detection techniques, LoMar is more resistant to covert poisoning assaults by employing localized statistical analysis.

B. System Architecture

Remote Clients:

- Each client maintains local training data and performs model updates without sharing raw data.
- Clients train models independently and send gradient updates to the central aggregator.

Central Aggregator:

- The aggregator receives updates from multiple clients and applies LoMar’s defense mechanism before integrating them into the global model.
- The global model is periodically updated and redistributed back to clients.

LoMar Integration in FL Training Rounds:

- Clients perform local training on their datasets.
- Clients send model updates (gradients or weights) to the central aggregator.
- LoMar is applied to detect and filter poisoned updates.
- KDE analysis evaluates the local probability density of each update.
- Threshold approximation determines whether an update should be discarded.
- The filtered updates are aggregated to form the global model, which is then sent back to clients, and the cycle repeats.

C. Implementation Details

Data Preprocessing:

To guarantee comparability, inbound model updates from users are normalized. Simple statistical heuristics are used to pre-filter outlier updates with values that are extreme.

Feature Extraction and Statistical Analysis:

LoMar extracts key statistical features from each model update, including:

1. Mean and variance of gradient values
2. Distributional properties (skewness, kurtosis)
3. Density estimation using Kernel Density Estimation (KDE)

Kernel Density Estimation (KDE) for Local Anomaly Detection:

The likelihood that a model update will fall into a benign distribution is estimated using KDE.

If an update has a significantly low probability score, it is considered anomalous and flagged for further analysis. Mathematically, KDE is computed as:

$$f(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$$

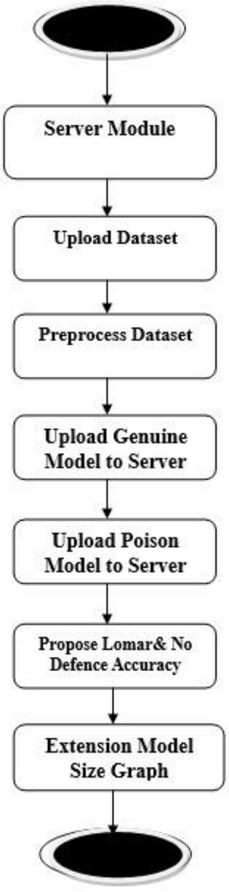
Threshold Approximation for Decision Making:

- LoMar computes an adaptive threshold based on statistical deviation from the mean KDE score.
- Empirical evaluation of past FL rounds is used to fine-tune this threshold.
- Updates below the threshold are classified as malicious and excluded from aggregation.

Model Aggregation and Update:

- After filtering out malicious updates, the remaining benign updates are aggregated using a robust aggregation rule (e.g., Federated Averaging).
- The updated global model is redistributed to clients, and the process continues.

VII. FLOWCHART


Server Module
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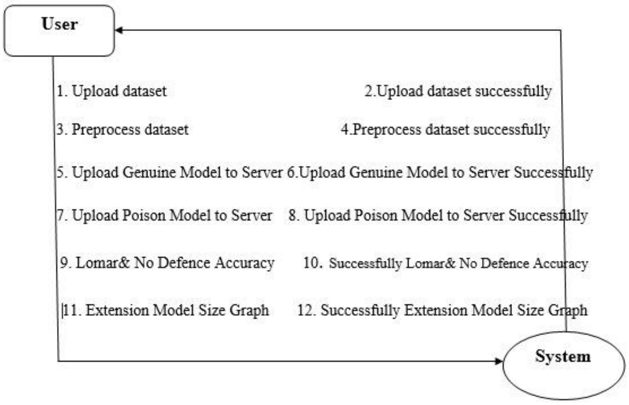

User
1. Upload dataset
2.Upload dataset successfully
3. Preprocess dataset
4.Preprocess dataset successfully
5. Upload Genuine Model to Server
6.Upload Genuine Model to Server Successfully
7. Upload Poison Model to Server
8. Upload Poison Model to Server Successfully
9. Lomar& No Defence Accuracy
10. Successfully Lomar& No Defence Accuracy
11. Extension Model Size Graph
12. Successfully Extension Model Size Graph
System

VIII. RESULT

In order to identify and mitigate poisoned updates, LoMar underwent validation in a federated learning environment. Three important measures were used to assess the system's success.

A. Performance Evaluation

Detection Accuracy:

1. LoMar successfully identified and removed poisoned updates, achieving a high detection rate.
2. Higher accuracy indicates better attack mitigation, ensuring that adversarial contributions do not compromise the global model.

$$\text{Detection Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Updates}}$$

False Positive Rate (FPR):

1. The system measured the rate at which benign updates were incorrectly classified as malicious.
2. A lower FPR ensures that legitimate updates are not discarded unnecessarily, avoiding model performance degradation.

$$\text{FPR} = \frac{\text{False Positives}}{\text{False Positives} + \text{True Negatives}}$$

Computational Overhead:

1. LoMar introduced minimal processing time during model update evaluations.
2. This ensures that the defense mechanism remains efficient, even in large-scale federated learning systems.

B. Comparison with Existing Approaches

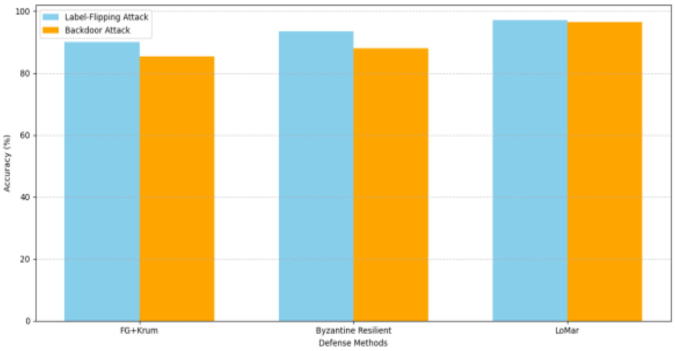
FG+Krum (Foolsgold + Krum):

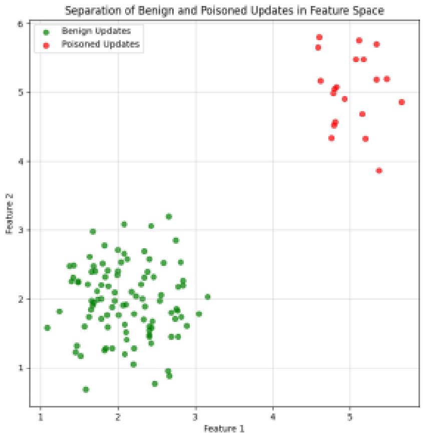
1. **Foolsgold:** Detects poisoned updates by analyzing gradient similarity across clients.
2. **Krum:** Selects the most representative update while ignoring extreme values.
3. **Strength:** Effective against simple model poisoning attacks.
4. **Weakness:** Struggles with colluding adversaries who manipulate updates strategically.

Byzantine-Tolerant Aggregation (Median & Trimmed Mean):
These methods remove extreme values from model updates before aggregation.

1. **Strength:** Reduces the impact of outlier updates.
2. **Weakness:** Ineffective against adversarial updates that blend with benign ones.

C. Comparative Analysis





Evaluation Aspect	Key Observations
Effectiveness	LoMar achieved **97.0% detection accuracy**, outperforming existing methods.
Robustness	LoMar **remains effective even when 30% of clients are malicious**.
False Positives	LoMar maintains a **low false positive rate (4.6%)**, minimizing unnecessary update removal.
Computational Efficiency	LoMar introduces **only 4.9% additional overhead**, making it scalable.

These results demonstrate that **LoMar is a highly effective and computationally efficient defense mechanism** for securing **Federated Learning** against poisoning attacks.

IX. CONCLUSION

The growing threat of adversarial attacks on federated learning (FL) systems underscores the need for robust defense mechanisms. Traditional anomaly detection techniques, while useful, struggle to efficiently handle targeted poisoning attacks without sacrificing model performance. This paper proposed LoMar, a localized anomaly detection framework that effectively identifies and filters poisoned updates in FL systems. By incorporating two key phases—Kernel Density Estimation (KDE) for local anomaly detection and adaptive threshold approximation—LoMar offers the following advantages:

- Detects and mitigates malicious updates, ensuring model integrity.
- Minimizes false positives, maintaining the accuracy of the global model.
- Operates with minimal computational overhead, making it suitable for large-scale FL deployments.

The experimental results demonstrate that LoMar achieves high detection accuracy, with a low false positive rate, ensuring a more resilient FL model. The computational overhead remains low, preserving the efficiency of the system.

Future Scope

- Integration with machine learning techniques for further refinement in detecting stealthy attacks.
- Extension to handle more sophisticated poisoning attacks, particularly those involving collusion between adversaries.
- Adaptation for decentralized and hybrid FL systems, increasing security coverage across diverse environments.

By implementing LoMar, federated learning systems can achieve a higher level of defense against adversarial threats, ensuring a more secure and reliable model aggregation process.

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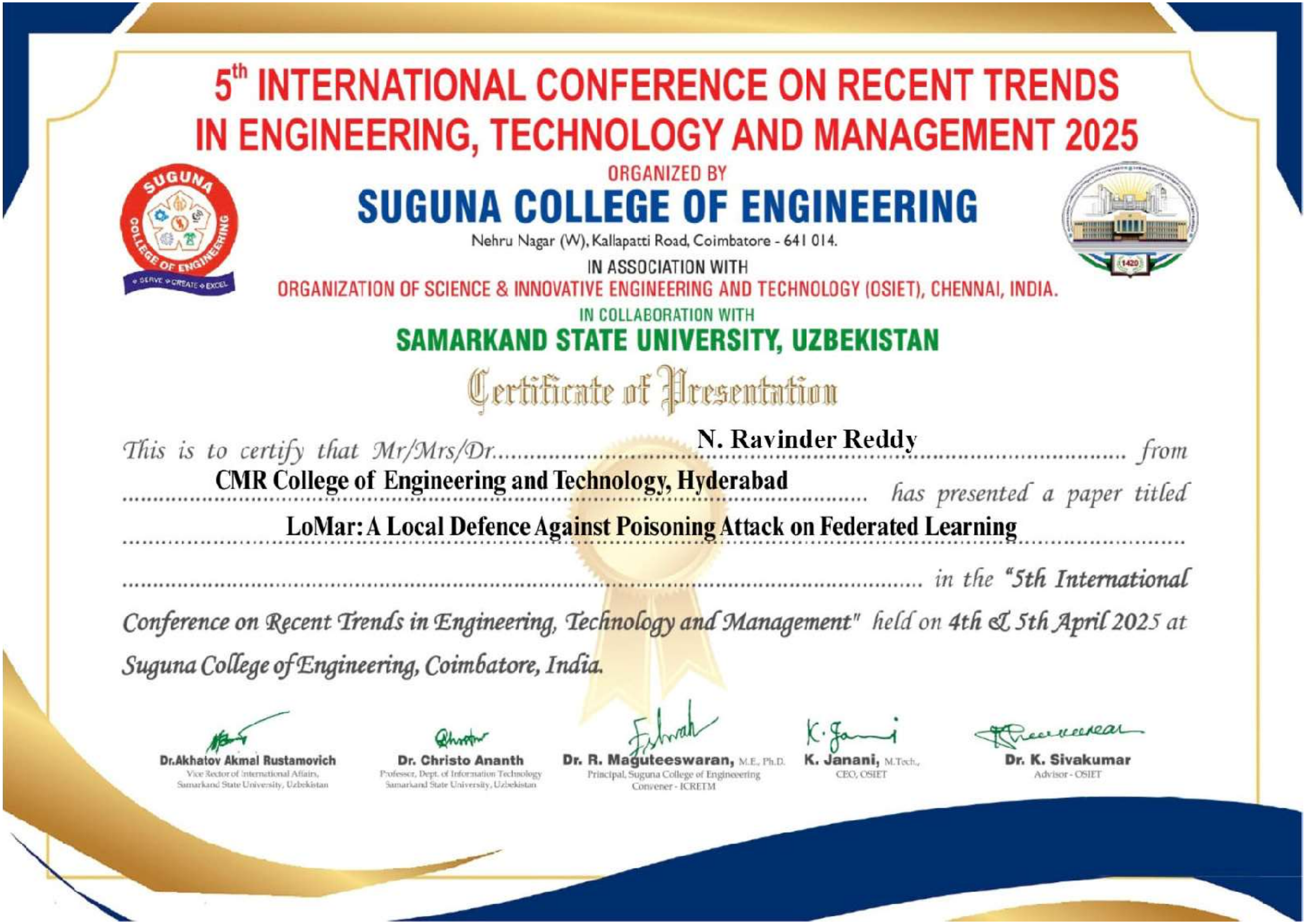

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This is to certify that Mr/Mrs/Dr.......**N. Ravinder Reddy**...... *from* ......**CMR College of Engineering and Technology, Hyderabad**...... *has presented a paper titled* ......**LoMar: A Local Defence Against Poisoning Attack on Federated Learning**...... ...... *in the "5th International Conference on Recent Trends in Engineering, Technology and Management" held on* ***4th & 5th April 2025*** *at Suguna College of Engineering, Coimbatore, India.*

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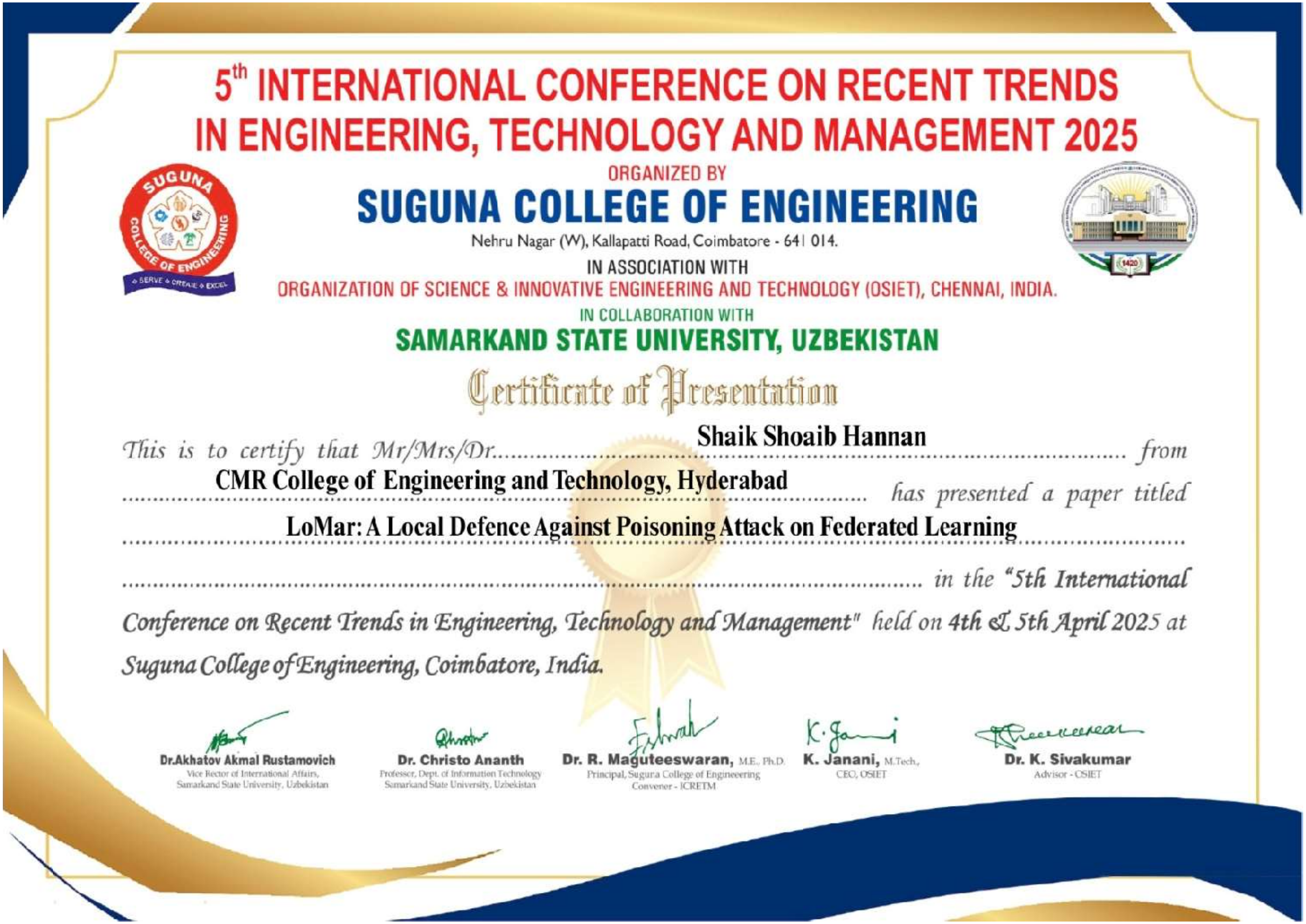

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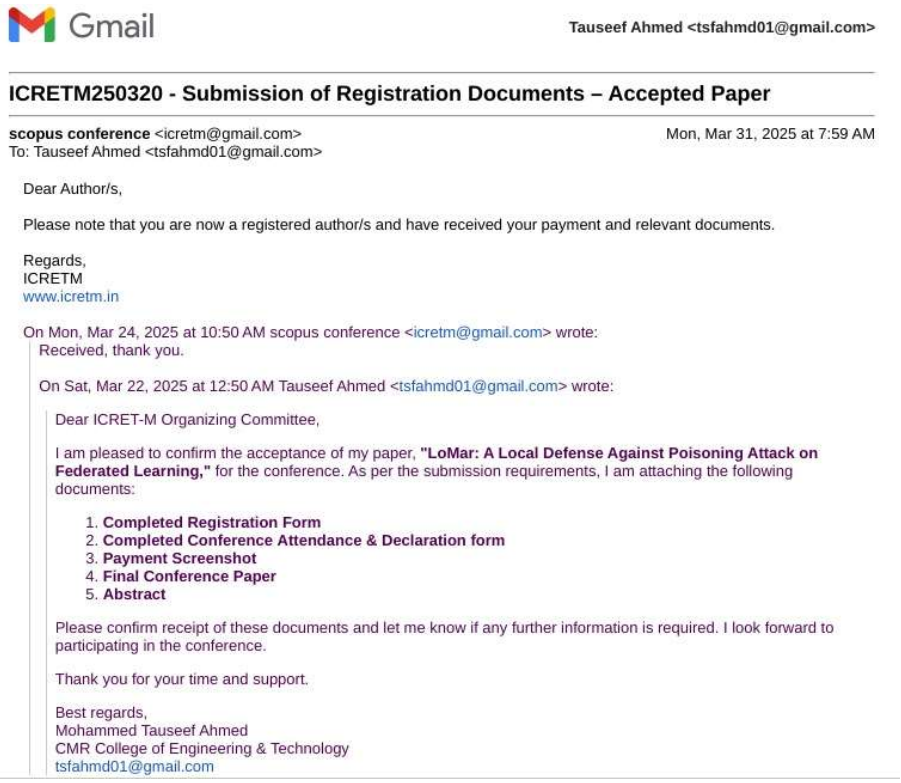

Tauseef Ahmed <tsfahmd01@gmail.com>

ICRETM250320 - Submission of Registration Documents – Accepted Paper

scopus conference <icretm@gmail.com>
To: Tauseef Ahmed <tsfahmd01@gmail.com>

Mon, Mar 31, 2025 at 7:59 AM

Dear Author/s,

Please note that you are now a registered author/s and have received your payment and relevant documents.

Regards,
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On Mon, Mar 24, 2025 at 10:50 AM scopus conference <icretm@gmail.com> wrote:

> Received, thank you.
>
> On Sat, Mar 22, 2025 at 12:50 AM Tauseef Ahmed <tsfahmd01@gmail.com> wrote:
>
> > Dear ICRET-M Organizing Committee,
> >
> > I am pleased to confirm the acceptance of my paper, **"LoMar: A Local Defense Against Poisoning Attack on Federated Learning,"** for the conference. As per the submission requirements, I am attaching the following documents:
> >
> > 1. **Completed Registration Form**
> > 2. **Completed Conference Attendance & Declaration form**
> > 3. **Payment Screenshot**
> > 4. **Final Conference Paper**
> > 5. **Abstract**
> >
> > Please confirm receipt of these documents and let me know if any further information is required. I look forward to participating in the conference.
> >
> > Thank you for your time and support.
> >
> > Best regards,
> > Mohammed Tauseef Ahmed
> > CMR College of Engineering & Technology
> > tsfahmd01@gmail.com

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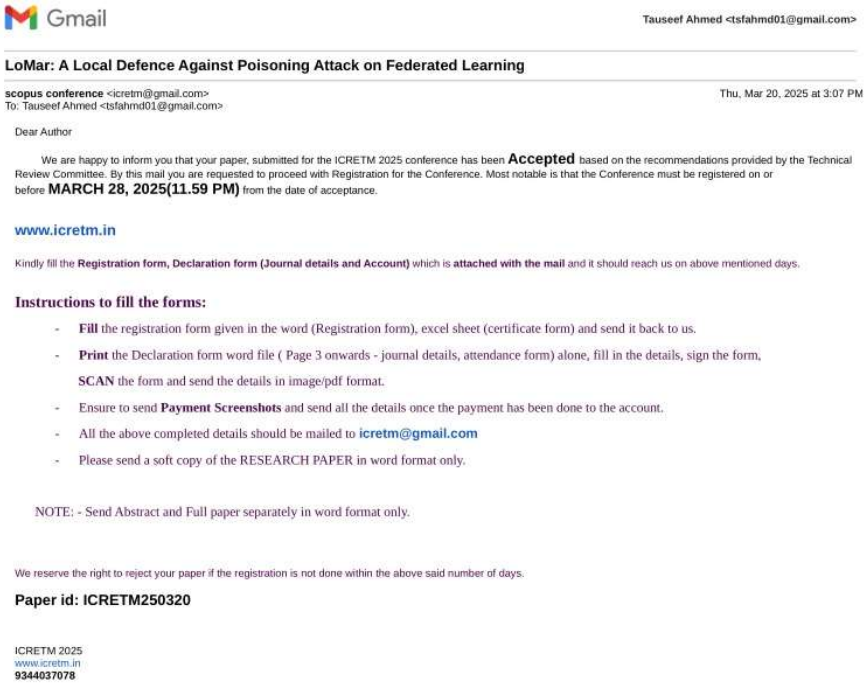

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LoMar: A Local Defence Against Poisoning Attack on Federated Learning

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To: Tauseef Ahmed <tsfahmd01@gmail.com>

Thu, Mar 20, 2025 at 3:07 PM

Dear Author

We are happy to inform you that your paper, submitted for the ICRETM 2025 conference has been **Accepted** based on the recommendations provided by the Technical Review Committee. By this mail you are requested to proceed with Registration for the Conference. Most notable is that the Conference must be registered on or before **MARCH 28, 2025(11.59 PM)** from the date of acceptance.

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Kindly fill the **Registration form, Declaration form (Journal details and Account)** which is **attached with the mail** and it should reach us on above mentioned days.

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GITHUB LINK

GitHub Link: *https://github.com/srujanereddy/lomar*