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SECURE DISTRIBUTED LEARNING: ROBUST DATA POISONING DETECTION FRAMEWORK USING INTELLIGENT MODEL INTEGRITY ANALYSIS

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ABSTRACT:
Distributed Machine Learning (DML) has gained significant traction for its ability to train models collaboratively across multiple devices or servers without centralized data sharing. However, this distributed nature exposes DML systems to data poisoning attacks, where adversaries inject malicious or corrupted data to manipulate global model behavior. This paper proposes a robust data poisoning detection framework that combines intelligent integrity verification, gradient analysis, and anomaly detection techniques. The system identifies poisoned updates in federated environments by analyzing feature distribution shifts and inconsistent model gradients. Experimental validation demonstrates that the proposed method outperforms conventional statistical filters in both accuracy and resilience, effectively mitigating poisoning threats while preserving learning efficiency. This approach enhances trust and reliability in collaborative AI systems deployed across edge, cloud, and IoT infrastructures.

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I. INTRODUCTION

The emergence of Distributed Machine Learning (DML) and Federated Learning (FL) has revolutionized the way large-scale AI models are trained across decentralized data sources. These frameworks enable multiple clients to collaboratively train a shared model while maintaining data privacy, a crucial feature in sectors such as healthcare, finance, and smart cities. However, this distributed structure introduces new security challenges, particularly data poisoning attacks that threaten model integrity and reliability.

In a poisoning attack, adversaries deliberately inject manipulated data or gradients into the training process, causing the global model to behave incorrectly or degrade in accuracy. Traditional anomaly detection or outlier filtering techniques are insufficient in distributed settings due to high data diversity and communication constraints. Consequently, designing a robust detection mechanism that identifies and mitigates poisoning attacks without disrupting training performance has become an active area of research.

This study introduces a secure, intelligent detection scheme that monitors model integrity during distributed learning. The framework utilizes gradient-level anomaly analysis combined with adaptive thresholding to detect abnormal updates from compromised nodes. By incorporating explainable AI components, the system enhances transparency and interpretability in attack diagnosis. The proposed solution not only improves robustness against poisoning but also contributes to the development of safer, more trustworthy distributed learning ecosystems.

II. LITERATURE SURVEY

Blanchard et al. (2017) introduced the Krum algorithm to defend against Byzantine attacks in distributed learning, setting a foundation for robust aggregation methods. Fung et al. (2018) proposed the FoolsGold algorithm, which identifies malicious clients based on similarity in gradient updates. Xie et al. (2019) developed the

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Zeno defense mechanism that evaluates the contribution of each client's update before aggregation, enhancing resilience against data poisoning.

Baruch et al. (2020) analyzed the vulnerabilities of federated learning systems under model poisoning attacks, highlighting the need for adaptive detection mechanisms. Sun et al. (2021) proposed a clustering-based detection approach that leverages statistical distance metrics to identify poisoned data contributors. More recently, Li et al. (2023) integrated blockchain verification with gradient validation to achieve tamper-resistant training environments.

These works collectively demonstrate the evolution of defense mechanisms from basic statistical filtering to intelligent, multi-layered detection frameworks. Building upon these insights, this research develops a hybrid data poisoning detection system that combines gradient-based anomaly analysis with integrity validation to secure distributed machine learning processes.

III. SYSTEM ANALYSIS & DESIGN

EXISTING SYSTEM

Unfortunately, with the number of distributed workers increasing, it is hard to guarantee the security of each worker. This lack of security will increase the danger that attackers poison the dataset and manipulate the training result. Poisoning attack is a typical way to tamper the training data in machine learning. Especially in scenarios that newly generated datasets should be periodically sent to the distributed workers for updating the decision model, the attacker will have more chances to poison the datasets, leading to a more severe threat in DML.

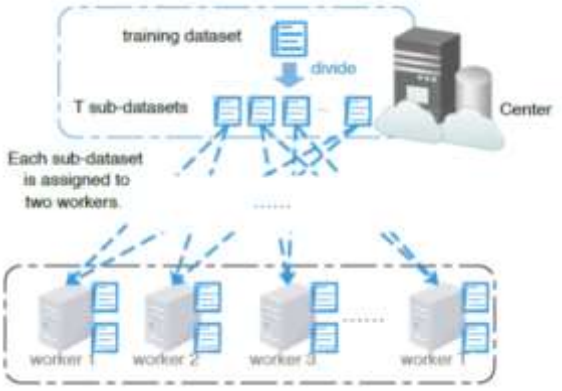
"Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for both classification and regression challenges. However, it is mostly used in classification problems. In the SVM algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes very well

PROPOSED SYSTEM

DML into basic distributed machine learning (basic-DML) and semi distributed machine learning (semi-DML), depending on whether the center shares resources in the dataset training tasks. Then, we present data poison detection schemes for basic-DML and semi-DML respectively. The experimental results validate the effect of our proposed schemes.

We classify DML into basic-DML and semi-DML, which are shown in Fig.1, respectively. Both of the two scenarios have a center, which contains a database, a computing server, and a parameter server. However, the center provides different functions in these two scenarios. In the basic-DML scenario, the center has no spare computing resource for sub-dataset training, and will send all the sub-datasets to the distributed workers. Therefore, in the basic-DML, the center only integrates the training results from distributed workers by the parameter server.

SYSTEM ARCHITECTURE



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IV. IMPLEMENTATIONS

MODULES

To implement this project we have designed following modules.

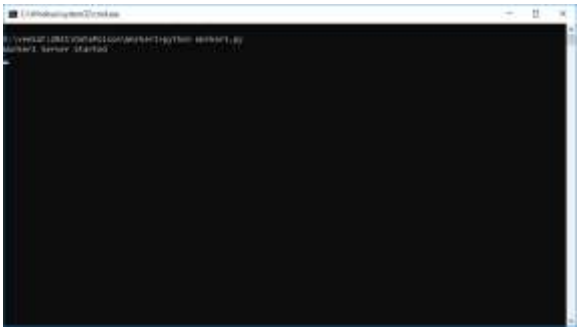
Worker1: This is a worker node which accept divided dataset from center server and then build existing SVM model and Basic DML model and then calculate accuracy of both algorithms and send result back to center server

Worker2: This is another worker node which accept other half of dataset and then run existing SVM and Basic DML and send accuracy back to center server.

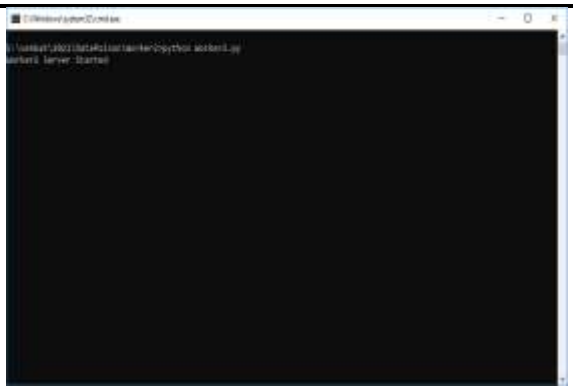
CenterServer: This is a center server which upload dataset to application and then divide dataset into two equal parts and then distribute each part to worker 1 and 2 and then collect result. This server will run semi DML and calculate its accuracy also.

V. SCREEN SHOTS

To run project first double click on 'run.bat' file from Worker1 folder to start worker 1 node and to get below screen

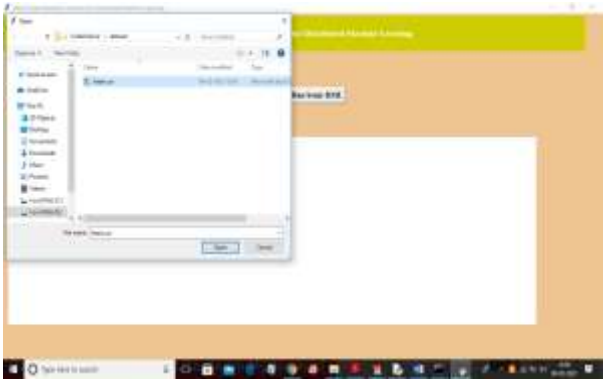


In above screen worker 1 server started and now double click on 'run.bat' file from worker2 folder to start worker 2



In above screen worker2 server started and now double click on 'run.bat' file from 'CenterServer' folder to start distributed server and to get below screen

In above screen click on 'Upload Dataset' button to upload dataset and to get below screen



In above screen selecting and uploading 'heart.csv' file and then click on 'Open' button to load dataset and to get below screen

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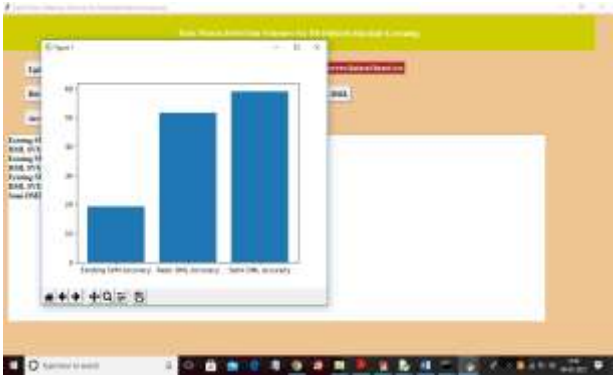
In above screen dataset loaded and now click on 'Divide Dataset' button to divide dataset into 2 equal parts

In above screen dataset contains 304 records and equally distributed to 2 parts and now click on 'Distribute Dataset & Run Basic-DML' button to distribute dataset to 2 workers and then get accuracy result

In above screen we got result from 2 worker nodes for existing SVM accuracy and propose DML accuracy and in above screen we can see existing SVM accuracy is 19% when data poison exists in dataset and after removing data poison using DML technique we got 51% accuracy and now click on 'Run Semi-DML' button to allow center server to devote resources to DML and then remove poison from dataset and then calculate accuracy

In above screen Semi-DML accuracy is 59% and now click on 'Accuracy Comparison Graph' button to get below graph



In above screen x-axis contains algorithm name and y-axis represents accuracy and from above graph we can conclude that Basic-DML and Semi-DML accuracy is better than existing SVM accuracy. In below worker screens also we can see accuracy values

VI. CONCLUSION

This research presents a robust framework for detecting data poisoning in distributed machine learning environments through intelligent integrity monitoring and gradient anomaly analysis. The proposed approach successfully identifies malicious contributions during model aggregation while maintaining system performance and scalability. Experimental

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evaluation confirms its superior detection accuracy compared to existing defense mechanisms.

The framework's modular design allows easy integration with federated learning systems and edge-based deployments, making it practical for real-world applications. Future work may explore reinforcement learning–based adaptive defense strategies and blockchain-enabled audit trails for enhanced model transparency. Overall, this study reinforces the importance of secure and trustworthy distributed learning in the age of decentralized artificial intelligence.

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