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Review Paper: A Detailed Review of Federated Learning in Cybersecurity with a Focus on Sandbox Integration

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Abstract— ***The threat of cyber-attacks, especially malware, is rapidly evolving and requires complex solutions that protect individual information from unauthorized access while providing high protection against malicious software. Federated Learning (FL) is a novel form of machine learning that enables model updates to be transferred among various clients without considering original data to be sent to a central hub. Several studies have investigated FL in cybersecurity; however, previous models present challenges associated with poisoning attacks, data heterogeneity, and no integration of sandbox for malware analysis. Based on this review thus critically discussed the current limitations on FL research in cybersecurity and possible solutions. Finally, they discuss the idea of combining Docker-based sandboxes with FL to solve these challenges, and they advocate for a feature-robust, privacy-preserving malware detection framework.***

Index Terms— ***Federated Learning, Malware Detection, Security Sandbox, Model Poisoning, Data Privacy, Docker, Threat Detection, Cybersecurity.***

I. INTRODUCTION

This is a constantly growing area of challenge given the advancements of cyber-attacks especially the malware type. ES These traditional approaches of detection like signature-based detection system and centralized data processing fails to cope up with such threats at the same time maintaining privacy. Centralized feature calls for sharing of raw data which is likely to result in privacy violation especially within banking, health, and security sectors.

A. Federated Learning (FL)

FL has come up as one of the probable solutions that would enable decentralized model training. One form of the distributed models involves each client training a local model on its data then transferring the model gradients or weights to a central unit. The updates are collected by the central server to enhance a global model all while the actual data is never visible. This process ensures privacy but introduces new challenges, such as:

- **Model Poisoning**: However, the local updates performed by clients can be malicious in the sense they will provide compromised information that will affect the global model.
- **Data Heterogeneity**: Data cross over between clients might not be Independent and Identically Distributed (Non-IID), thus affecting performance.
- **Lack of Sandbox Integration**: Existing models for malaria detection includes those based in FL are not equipped with sandboxes, which are fundamentally required for dynamic analysis of instances of malware.

Hence, this review paper seeks to evaluate the current studies on FL in cybersecurity and offer a solution of incorporating Docker-based sandboxes within the FL framework with the enhancement of the security and efficiency of the system.

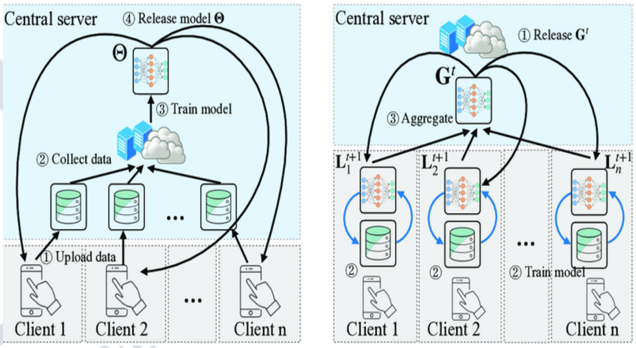

Figure 1. Centralized vs. Federated Learning – with reference to the flow chart of centralized learning as well as federated learning framework. In the federated learning system, (a) clients upload local dataset to a trust central server, (b) while, clients keep their private data locally.

II. REVIEW OF FEDERATED LEARNING IN CYBERSECURITY

In more detail, this paper aims to provide a review of the federated learning in cybersecurity proposed frameworks and approaches.

A. Federated Learning for Cybersecurity:

An Overview FL enables to jointly train models of machine learning for multiple devices (clients) while transmitting raw data to a concerned central server. This kind of decentralized approach is especially helpful where the privacy of an application is concerned, such as in cybersecurity applications. Nevertheless, cybersecurity threats as well as malware detection need dynamic analysis whereas the analyzed FL-based systems do not posse this type of analysis yet.

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Research Paper Summaries:

- **"Federated Learning for Globally Coordinated Threat Detection"** (arXiv:2205.11459v3): This paper develops FL as a model for threat detection that integrates global coordination. It concentrates on bulk simultaneous detection of threats activity without disclose identity of its clients. It does respond to some extent to model poisoning attacks; it is not efficient enough for handling heterogeneous data at the client side.
- **"Federated Learning: Challenges, Methods, and Future Directions"** (arXiv:1908.07873): This work "Fl Opportunities, Challenges, Methods, and Future Directions," (1908.07873): Specifies the difficulties that affect FL systems namely data privacy, efficiency in communication, and robustness of the model. The authors suggest different approaches to address these problems, nevertheless, the absence of integration with sandbox decreases applicability in malware identification.
- **"Advances and Open Problems in Federated Learning"** (arXiv:1912.04977): The following paper provides an overview of the state-of-the-art developments and the challenges in FL ((DOI: 10.1109/ TCLT52584.2020.0900497). Whereas it gives a good account of the application of FL in different sectors, its major highlighted issues of model poisoning and communication latency imply lacunas pertaining to the protection of FL-based CYBERSECURE systems.

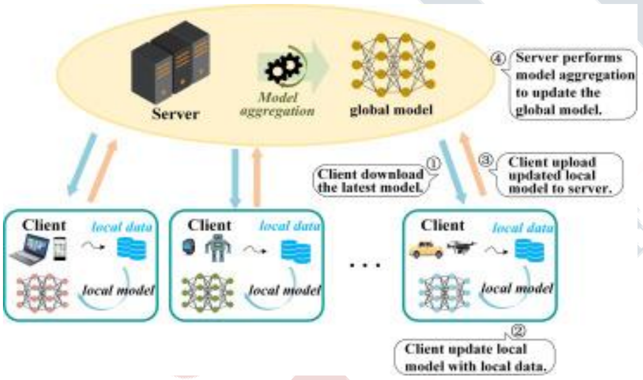


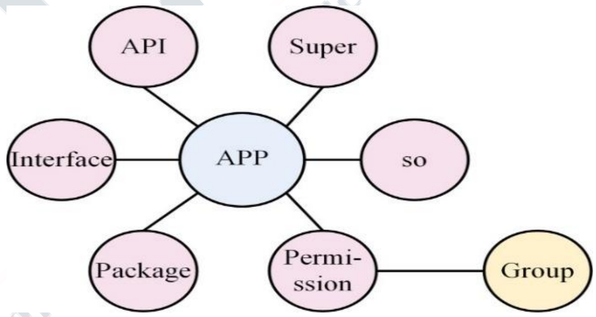
Figure 2. Overview of the general FL framework. During the nth round of communication, each user downloads the new global model from the server to start with ① and uses its own local dataset for iterative training ② to create new global models, the server ③ which performs model collection ④ and then performs training.

B. Privacy-Preserving Malware Detection Using FL

A good anti-malware system has to maintain user anonymity while providing great effectiveness. Some authors have used FL to detect malware particularly in contexts such as mobile devices and the IoT … FL contains private data on the client side and processes raw values but lacks a sandbox for dynamic analysis to detect complex malware programs.

Research Paper Summaries:

- **"Less is More: A Privacy-Respecting Android Malware Classifier Using Federated Learning"** (arXiv:2007.08319): This is another paper that develops an FL-based malware classifier that no raw data is shared between devices. While analysing the benefits of decentralized training, the paper reports the absence of an overall integrated sandbox environment for studying malware activity. Moreover, for data model updates at each client, it fails to give good model performance owing to variations in data distribution across clients.
- **"Distributed Detection of Malicious Android Apps While Preserving Privacy Using Federated Learning"** (https://doi.org/10.3390/s23042198): This paper provides example of educational data mining where an FL-based system for detection of malicious Android apps is depicted. They reveal the advantages of FL in maintaining privacy while classifying malware, more issues raised concerns the challenges of accurate model forecast due to different data owned by different clients.



Graph 1: Heterogeneity of Data Across Clients

C. Challenges in Federated Learning-Based Malware Detection

There are several challenges in applying FL to malware detection, which include:

1. **Model Poisoning Attacks**: Evil clients can input incorrect updates to the model which will affect the global model negatively. That is why securing the aggregation process is crucial to guaranteeing resilience.
2. **Data Heterogeneity**: The data at the clients themselves is non-IID and therefore when training a global model, it may not perform well when applied to individual clients.
3. **Lack of Real-Time Malware Analysis**: However, traditional FL systems fail to include dynamic sandbox environment that is necessary to orchestrate the examination of behaviour of the suspicious files in a real-time manner.

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4. **Research Paper Summaries:**

- **"Threats, Attacks, and Defences to Federated Learning: Issues, Taxonomy, and Perspectives"** (https://doi.org/10.1186/s42400-021-00105-6): This paper elaborates on the security threats to FL with an emphasis on Model Poisoning and Inference Attacks. It also enunciates types of attacks and structural defences. However, it does not incorporate solutions for dynamic risk assessment in real time using sandboxing editions.
- **"A Federated Learning Multi-Task Scheduling Mechanism Based on Trusted Computing Sandbox"** (https://doi.org/10.3390/s23042093): This work also introduces a multi-task scheduling strategy for the FL, which relies on trusted computing sandboxes. But though it includes sandbox environments, it is still theoretical architecture and doesn't provide a practical solution for handling dynamically appeared malware at clients.

III. PROPOSED CONCEPT

In registering for decentralized learning, participants enable the creation of restricted, private safety domains. Therefore, drawing from the limitations recognized in the prior studies, we contribute a new paradigm which is the blend of Docker-based security sandboxes together with Federated Learning to improve the identification of malware with privacy preservation.

A. Concept Overview

The authors in propose the usage of Docker based sandboxes for creating the isolated environment for malware analysis and the application of Federated Learning for secure and private model training. The Docker sandbox enables files to run in an isolated manner; FL ensures that private data are run only on every client's system. Clients establish their local models based on the data computed on the sandbox and send to the central server only the deltas of those models.

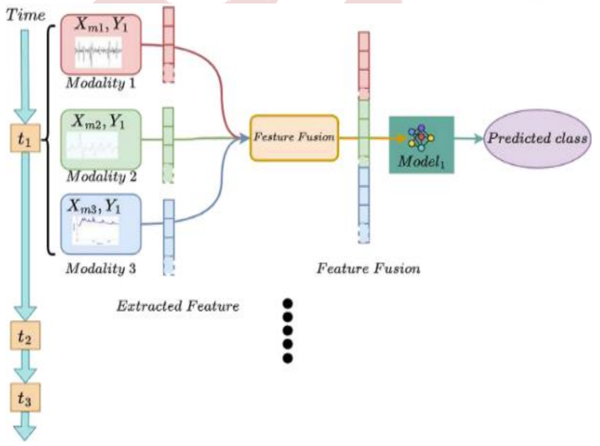

Figure 3. Proposed Framework – Federated Learning with Docker Sandbox Integration.

B. Federated Learning Sandbox Architecture

a. Docker-Based Sandbox

Files which are thought to be malware are placed in Docker containers. Every client has a containerized environment for malware testing within which the samples are run with no threat to system integrity. Such containers may report file system changes, network activity, and system calls which accompany a file, offering beneficial attributes for malware categorization.

- **Isolation and Security**: The isolation skills of Docker make it impossible for malicious files to affect the host system.
- **Portability**: Containers can be adopted to various client settings making it easy to scale up easily.

b. Federated Learning Model

FL model is trained from data obtain in the sandboxed environment on each of the clients. The process includes the following steps:

- **Local Training**: With this kind of architecture, each clients data stored locally is fed into an ML model that tries to detect and learn the behaviour of Malware.
- **Model Updates**: Instead of sending raw data, clients send model weights and gradients computing at the other's end to be averaged.
- **Global Model Aggregation**: It again sends updates from many clients to update the global malware detection model in the server side. It is then returned to clients for enhancing local performance according to proposals made by the author of this writing.

C. Addressing Key Challenges

a. Model Poisoning

In this work, the proposed system also has protective measures against model poisoning attacks. Several secure aggregation methods are used to ensure the authenticity of the model updates to merge into the global models.

b. Data Heterogeneity

Therefore, to overcome the issue of non-IID data across clients, the system uses multi-task learning than clients train models for their environments, for instance, IoT malware and Android malware environments. This approach guarantees that the global model captures different conducting behavior of malware.

c. Real-Time Malware Detection through Sandbox

With Docker based sandboxes, real time malware analysis can be conducted. Files are loaded at run-time into an enclave and executed to generate behavior to train the local models. This method offers a direct operate threat detection approach, which is missing in traditional FL models.

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D. Implementation of the Security Sandbox

a. Docker Setup

The approach involves each client running Docker and setting up a sandbox container containing basic tools for detection of malware. Because Docker is light, it can be effectively deployed on mobiles and IoT devices that are likely to be resource limited.

b. Federated Learning Workflow

Clients perform the following steps:

- **File Testing**: Files are conducted and uploaded inside the Docker sandbox.
- **Local Model Training**: Machine learning model is trained at local environment using the collected logs of the sandbox.
- **Model Sharing**: Users only submit new model parameters to the central server instead of raw client data being used.
- **Global Model Aggregation**: The updates collected by the central server can enhance the Global malware detection model for all the individual servers.

c. Malware Detection and Testing

After the global model gets updated, the clients carry out the classification of files, as either possessing malicious or benign content. The system makes it possible to test during operation, and therefore increases the effectiveness of detecting malware.

IV. CONCLUSION

This review identifies key limitations in existing FL-based malware detection systems and proposes an innovative solution: a union of native presumed-safety Docker-based security sandboxes with federated neuromorphic learning. This approach contradicts the issues of model poisoning, consistency in the analyzed data, besides, dynamic analysis of malware. More work in the future will be target at enhancing the communication protocols, the accuracy of the model and extending the framework to embed other categories of computer cyber threats.

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