Robust Blockchain-based Federated Learning

Aftab Akram[1][a], Clémentine Gritti[2][b], Mohd Hazali Mohamed Halip[3,4][c], Nur Diyana Kamarudin[3,4][d], Marini Mansor[3], Syarifah Bahiyah Rahayu[3,4][e], Melek Önen[1][f],

[1] *Department of Digital Security, EURECOM, 450 route des Chappes, 06410 Biot, France*

[2]*CITI Lab, INSA Lyon – Inria, 69100 Villeurbanne, France*

[3]*Faculty of Defence Science and Technology,* [4]*Cyber Security and Digital Industrial Revolution Centre, National Defence University of Malaysia, 57000 Kem Sungai Besi, Kuala Lumpur, Malaysia*

{*aftab.akram, melek.onen*}*@eurecom.fr, clementine.gritti@insa-lyon.fr,* {*hazali, nurdiyana, syarifahbahiyah*}*@upnm.edu.my, 2210416@alfateh.upnm.edu.my*

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Abstract: In Federated Learning (FL), clients collaboratively train a global model by updating it locally. Secure Aggregation (SA) techniques ensure that individual client updates remain protected, allowing only the global model to be revealed while keeping the individual updates private. These updates are usually protected through expensive cryptographic techniques such as homomorphic encryption or multi-party computation. We propose a new solution that leverages blockchain technology, specifically the Secret Network (SN), to provide privacy-preserving aggregation with aggregate integrity through Smart Contracts in Trusted Execution Environments (TEEs). Moreover, FL systems face the risk of Byzantine clients submitting poisoned updates, which can degrade the model performance. To counter this, we integrate three state-of-the-art robust aggregation techniques within the Smart Contract, namely Krum, Trim Mean and Median. Furthermore, we have evaluated the performance of our framework which remains efficient in terms of computation and communication costs. We have also exhibited similar accuracy results compared to state-of-the art scheme named SABLE.

1 INTRODUCTION

Collaborative Machine Learning (ML), including *Federated Learning* (FL), has attracted a lot of interest, recently. FL enables ML models to be trained while restricting the access to the local training datasets, thus preventing the disclosure of sensitive information. Informally, multiple clients jointly train a global model by training it locally and securely aggregating their updated parameters. Secure Aggregation (SA) (Kairouz et al., 2021; Mansouri et al., 2023) is conducted by a server such that the latter learns nothing from local inputs but the global model. Various techniques have been proposed to achieve SA, including Homomorphic Encryption (HE) (e.g., (Zhang et al., 2020)), masking (e.g., (Bonawitz et al., 2017)), Multi-Party Computation (MPC) (e.g., (Corrigan-Gibbs and Boneh, 2017)) and Trusted Execution Environments (TEEs) (e.g., (Kalapaaking et al., 2023)).

While FL has carefully considered the challenge of preserving the privacy of the clients' updates, it brings extra security concerns. As mentioned above, multiple clients, including possibly compromised ones, participate in the iterative training process. In particular, a Byzantine client can aim to manipulate the global model by poisoning local datasets or to submit manipulated model updates. Consequently, the accuracy of the FL training can be severely impacted, making model poisoning a serious threat to FL systems. Such Byzantine behavior introduces serious concerns regarding the integrity and robustness of FL systems, and thus has attracted more attention over the last few years (Miao et al., 2022).

Defenses against such attacks mostly rely either on anomaly detection (Fung et al., 2020; Shen et al., 2016) or Byzantine-robust estimators (Blanchard et al., 2017; Chen et al., 2018). Nevertheless, such solutions remain expensive when integrated with SA which usually rely on resource-expensive crypto-

[a] https://orcid.org/0009-0003-2402-4058
[b] https://orcid.org/0000-0002-0835-8678
[c] https://orcid.org/0000-0002-8233-0219
[d] https://orcid.org/0000-0002-9018-7694
[e] https://orcid.org/0000-0002-1996-5166
[f] https://orcid.org/0000-0003-0269-9495

graphic techniques such as MPC. Consequently, the design of new SA protocols for FL systems should incorporate practical defenses against model poisoning. One way is to enhance norm bounds on clients' local updates (Naseri et al., 2022), which can easily be adapted to secure FL systems. Norm bounds have already been deployed as a countermeasure against untargeted attacks (Shejwalkar et al., 2021) and targeted attacks (Lycklama et al., 2023; Rathee et al., 2023; Bell et al., 2023). However, existing solutions come with limitations. Most of them imply the participation of two (or more) non-colluding servers to achieve the desired security properties (Rathee et al., 2023). Other solutions have been designed in a single-server setting (Lycklama et al., 2023; Bell et al., 2023) but require the use of expensive mechanisms such as Zero-Knowledge Proofs (ZKPs).

Furthermore, the integrity of correct aggregation is another challenging task in existing FL solutions. In the case of single-server FL systems, the result from aggregation may be compromised by a potentially malicious server whose aim can be to obtain information from local updates. Hence, verifying the integrity of aggregation also becomes essential. Some FL solutions with aggregation verifiability (Guo et al., 2021; Buyukates et al., 2022) have been proposed but incur large overheads in terms of computation and communication.

1.1 Problem statement

In this paper, we are interested in ensuring and implementing three security guarantees and defenses:

• Protecting the *privacy* of clients' local updates. Each local update is kept private from the server while the latter recovers the aggregated model through SA mechanisms. Informally, each client hides its local update before sending it to the server using techniques such as HE and masking. The server aggregates hidden updates and recovers the global model but not individual updates.

• Ensuring the *robustness* of the global model against Byzantine behavior. The global model is expected to be robust against Byzantine faults occurring either in the training data (e.g. by a malicious client who manipulates the training data) or during the protocol execution (e.g. from the information exchanged during the protocol). A solution is to compare the local updates received from clients and remove the outliers before the server proceeds with aggregation.

• Developing a solution with aggregation *integrity*. We aim to enable the correctness of local inputs' aggregation: clients should be guaranteed that their genuine local input has been correctly received and used for the generation of the new global model. A solution is to rely on consensus mechanisms from blockchain technologies to ensure the correct execution of aggregation operations.

1.2 Our Contributions

With the aforementioned goals, we propose to take advantage of blockchain technologies to inherently ensure aggregation correctness. To ensure integrity and input privacy at the same time, we choose the particular Secret Network[1] (SN) framework. SN is a public blockchain that relies on TEEs to execute smart contract operations privately and correctly.

Therefore, in our solution, a network of nodes maintain the blockchain to replace the traditional FL server. This design choice prevents single point of failure while guaranteeing aggregation correctness and immutability through the use of consensus mechanisms. To ensure the privacy of clients' training updates, we enable SA inside TEEs. Client inputs are first encrypted and sent to SN. They are then decrypted inside a TEE where aggregation occurs. Furthermore, to validate the legitimacy of a client's training update, we deploy and evaluate a specific smart contract within SN which utilizes three state-of-the-art robust aggregation techniques, namely Krum, Trim Mean, and Median, to diminish the impact of potentially Byzantine nodes.

To summarize, combining SN with our robust aggregation smart contract simultaneously guarantees the integrity and immutability of the aggregation operations in a decentralized setting, client input privacy and Byzantine robustness of the global model, while preventing single point of failure.

We also test our solution in a real environment. We consider a medical dataset used to train over a Neural Network (NN) for arrhythmia prediction. Training updates are sent to the testnet of SN and taken as inputs in our smart contract to check their genuineness. We show that our proposed solution works in practice. We also evaluate the performance of our solution with the classical MNIST scenario in order to compare it with the closest related scheme named SABLE (Choffrut et al., 2023).

1.3 Paper Outline

In Section 2, we explore the existing robust SA works. In Section 3, we introduce the various concepts on which relies our blockchain-based FL solution. In Section 4, we present our privacy-preserving and robust SA solution through the use of TEEs within the

[1] https://scrt.network/

blockchain SN. In Section 5, we analyse and evaluate our solution to assess its robustness in practice, from experiments based on a real (fully anonymised) medical dataset and on the MNIST dataset. Finally, in Section 6, we conclude our paper.

2 Related Work

Multi-Party Computation (MPC): Several works have previously explored privacy-preserving FL systems robust against Byzantine nodes. Approaches such as (Corrigan-Gibbs and Boneh, 2017; Hao et al., 2021; Nguyen et al., 2021; Zhang et al., 2022) use MPC along with other cryptographic techniques, such as Zero-Knowledge Proofs and Oblivious Transfer. Nevertheless, those solutions assume the involvement of two honest-but-curious servers that do not collude, which can be seen as too restrictive.

Other robust FL MPC-based solutions (Hao et al., 2021; Roy Chowdhury et al., 2022) implement weaker robustness mechanisms, thereby compromising the convergence guarantees of the global models. For instance, the method proposed in (Hao et al., 2021) is based on FLTrust framework (Cao et al., 2020), which requires the server to have access to a trusted and clean dataset, which is a strong assumption compared to most of FL systems that leverage solely client gradients. Similarly, while the solution in (Roy Chowdhury et al., 2022) shows practical effectiveness, it lacks formal convergence guarantees, which are essential for Byzantine-resilient FL systems (Allouah et al., 2023a; Khazbak et al., 2020).

Works in (Liu et al., 2021; Lu et al., 2019; Arachchige et al., 2020) have employed MPC in combination with blockchain to provide privacy. However, these approaches primarily focus on protecting the privacy of the participating clients, without addressing the robustness needed to defend against malicious clients attempting to poison global models.

Differential Privacy (DP): Works such as (Allouah et al., 2023b; Guerraoui et al., 2021; Zhu and Ling, 2022) have explored the use of Differential Privacy (DP) in Byzantine-resilient FL algorithms to protect client privacy from malicious servers. These methods typically rely on noise injection into the gradients to ensure privacy, though this often leads to an acceptable but not an optimal trade-off between privacy and model accuracy. For example, in (Guerraoui et al., 2021), the authors, through theoretical analysis and numerical experiments using publicly available datasets, demonstrate that it is impractical to achieve both DP and Byzantine resilience simultaneously.

Homomorphic Encryption (HE): A few prior works (Wang et al., 2021; Rahulamathavan et al., 2023; Miao et al., 2022; Bell et al., 2023) have explored the use of HE to ensure privacy in FL systems. For instance, the work in (Wang et al., 2021) proposes a blockchain-based FL solution that employs Paillier HE cryptosystem to implement the Multi-Krum aggregator. However, this approach does not fully implement Multi-Krum within the encrypted domain due to operational limitations of the cryptosystem (i.e., additions only). As a result, this partial implementation leads to considerable leakage towards the aggregation nodes, significantly compromising the privacy of the clients. Moreover, the method proposed in (Rahulamathavan et al., 2023) grants the server access to the evolving model at each step of the learning process, threatening the privacy of the clients. The solution in (Miao et al., 2022) presents a blockchain-based FL system to ensure privacy and robustness. The authors apply the Cheon-Kim-Kim-Song (CKKS) scheme, which implements fully HE to encrypt local gradients, thus enhancing privacy protection. Additionally, they utilize the FLTrust framework (Cao et al., 2020) for robustness, which restrictively relies on a trusted server with access to a clean dataset, as discussed earlier. Lastly, robust mechanisms for SA are presented in (Bell et al., 2023) such that malicious inputs can be first detected through norm bounding techniques, and then discarded. Nevertheless, extra overheads have a substantial impact on the resulting FL system, making the latter not deployable in practice.

A more recent work (Choffrut et al., 2023) utilizes HE to implement privately robust aggregation technique, more specifically, Trim Mean and Median. Since the solution sorts gradient values while being homomorphically encrypted at the server side for Trim Mean and Median, it incurs a high computational cost, particularly at the server end. Our blockchain-based approach shares strong similarities with (Choffrut et al., 2023) as it uses Trim Mean to deal with robustness issues. We choose to compare this work with ours to better assess the deployability of the latter in a real FL environment.

3 Background

3.1 Federated Learning

FL consists of a distributed ML framework where multiple clients collaboratively train a global model under the supervision of a FL server. In a Synchronous FL (SyncFL) setting (McMahan et al., 2017), at each FL round, clients train a global model on their private local data (e.g., through Stochastic Gradient Descent) and forward their updates to the server. When updates from all clients are received by the server, the latter proceeds to the aggregation phase by averaging those updates, resulting into a new global model. This global model is sent back to the clients for a new round of training. Rounds repeat until the global model shows some desired level of accuracy.

Buffered Asynchronous FL (BAsyncFL) (Nguyen et al., 2022) enables clients to send their local updates to the server without the need for synchronized communication across all parties. Unlike SyncFL, where all participating clients must complete their local training before aggregation at each given round, BAsyncFL allows clients to send updates when ready, improving the scalability and efficiency of the system. To handle this, updates are integrated into a buffer such that their aggregation happens once the buffer is full.

Secure Aggregation (SA): To obtain a global model from multiple privacy-preserved locally-trained models, SA has been widely used through various techniques such as HE (e.g., (Zhang et al., 2020)), masking (e.g., (Bonawitz et al., 2017)), MPC (e.g., (Corrigan-Gibbs and Boneh, 2017)) and TEEs (e.g., (Kalapaaking et al., 2023)).

Robustness:

Among all participating clients, some may behave maliciously and provide corrupted or manipulated data to the server, to compromise the integrity of the global model. We call such malicious clients *Byzantine nodes*. As demonstrated in (Blanchard et al., 2017), even a single Byzantine node can significantly disrupt the aggregation process, especially when simple averaging is used, leading to inaccurate outcomes. To mitigate this risk, robust techniques can be used, such as Krum (Blanchard et al., 2017), Trim Mean (Yin et al., 2018) and Median (Yin et al., 2018).

Integrity:

Privacy-preserving FL with verifiable aggregation (Guo et al., 2021; Buyukates et al., 2022) guarantees that the server cannot obtain information from clients' local updates by manipulating aggregation operations. Specifically, clients can be ensured that the server has generated a new global model by aggregating their inputs as expected.

3.2 Secret Network

Secret Network[2] (SN) is an interoperable blockchain protocol offering privacy guarantees through the execution of smart contract within TEEs. Informally, SN encrypts the data before storing them in smart contracts, preserving the privacy of the information collected within dApps (decentralized applications). A network of SN nodes is responsible of securely processing smart contract computations through consensus mechanisms. The native cryptocurrency SCRT serves as a medium for participating in on-chain governance, facilitating network transactions, and rewarding users for securing the network through staking. A major use case is in DeFi (decentralized finance), where privacy-preserving smart contracts enable confidential transactions while facilitating various activities such as lending, borrowing and trading. SN design relies on two main components, namely the Cosmos SDK[3] and the Tendermint[4] consensus engine. This combination provides a robust foundation for scalable, private and permissionless smart contracts that seamlessly integrate with the broader interchain ecosystem.

Actors: The SN network consists of a set of nodes, called *delegates*, who are elected by token holders, called *delegators*, to represent and validate transactions on their behalf. Delegators participate by staking or delegating their tokens to specific delegates of their choice. The number of staked tokens determines the weight of a delegator's vote. Delegates campaign for votes from delegators, showcasing their technical competence, reliability and contributions to the network to gain support. The delegates with the most votes become active block producers, called *validators*, taking turns to produce blocks and validate transactions. The SN protocol allows a limited number of 100 delegates.

Consensus: A consensus mechanism defines how nodes in the network agree on the state of a blockchain. SN utilizes the Delegated Proof of Stake (DPoS) mechanism for consensus (Saad et al., 2021). Here, users participate in the validation and maintenance of the network by voting for a limited number of delegates. These few selected delegates, also known as the validators, are entrusted with the responsibility of validating blocks and ensuring the smooth operation of the network. This approach enhances the speed of the network compared to other

[2] https://scrt.network/
[3] https://docs.cosmos.network/
[4] https://tendermint.com/

Proof of Stake (PoS) systems, resulting in lower fees and increased throughput.

Transactions and Blocks: Transactions are verified and grouped into blocks by the active delegates. The latter then propose those blocks to the network for validation. Other nodes in the network, including standby delegates, verify them. Once consensus is reached, through the majority of the network (here, at least 2/3 of the validators) agreeing on the validity of the proposed blocks, the latter are added to the blockchain. Delegates who successfully produce blocks and participate in the consensus process receive rewards. In particular, rewards are distributed among both the validators and the delegators who staked their tokens with the former.

Cryptocurrency: SCRT is the native cryptocurrency of SN, enabling the following functions:

• *Governance:* SCRT holders participate in the governance of SN by voting on proposals. Each staked SCRT equals one vote, and validators vote with the combined total of all their delegators' staked SCRT. Governance proposals require a simple majority of staked SCRT to pass, and the voting period lasts for 7 days.

• *Gas Fees:* Gas fees are paid in SCRT for processing transactions. These fees compensate validators and stakers on the network for their efforts in securing and maintaining the network's operation.

Trusted Execution Environments (TEEs): A TEE creates a secure area within a processor where data is isolated from other system components. This secure area, called *enclave*, acts as a black box for computations, ensuring that the internal state remains hidden. SN has chosen the Intel's Software Guard Extensions (SGX) implementation for its TEE framework (Will and Maziero, 2023). In a smart contract, private metadata is encrypted before being sent to validators for processing. Validators only decrypt this data within their TEE, ensuring that it remains inaccessible to them. Computations are then performed on the decrypted data, and the output is encrypted before being sent off the TEE and stored on the blockchain. Enclaves in SN generate and store their attestation keys, which are used only once during registration. The enclaves create subsequent keys for communication with the network, in particular to decrypt private inputs of smart contracts and encrypt resulting outputs.

4 Robust SN-based FL Solution

4.1 Overview

Multiple clients train locally their own dataset, resulting into local models. Those local models are then sent encrypted to SN. The latter is in charge of aggregating those local models to obtain a new global model, in such a way that it learns nothing about the individual models but only the resulting aggregate. Moreover, SN is responsible of checking each submitted individual model before aggregation. In particular, the blockchain verifies that every model proposed by a client is correct and will not poison the future global model.

Let N clients $C_1, \cdots, C_n$ be users of the blockchain ecosystem. Each of these clients holds a pairwise key shared with SN. One client, say C_1, trains the model locally using its own dataset and submits to SN the resulting input, encrypted using its pairwise key k_1 shared with SN (1).

As soon as an encrypted input arrives, SN launches the robust aggregation process (2). To do so, inside the TEE, inputs are decrypted and possibly ordered, and the robust techniques (e.g. Krum, Trim Mean, Median) are calculated on those inputs. For instance, the input from C_1 is decrypted using k_1 inside the TEE. SN first includes it into an initially empty list that represents the buffer. *SN* collects other inputs until the list is full. Steps (1) and (2) launch the transaction $Tr1$, which is financially covered by C_1. Once the list is full, SN aggregates all inputs in this list such that outliers are discarded (based on the selected robust technique), resulting in a new global model (3). This model can be queried by each client. Then, the list becomes empty. This step triggers a transaction since the global model has been updated and the list has been emptied. This transaction is paid by the owner of the smart contract.

We aim for deploying our solution in buffered FL settings (Nguyen et al., 2022).Clients execute their training as their pace as long as the used global model is fresh enough (it does not need to be the latest model accessible by query). When submitting their inputs to SN, clients must include the hash of the transaction from which the global model was computed. Hence, SN can check the freshness of the inputs before proceeding to the robust aggregation step, using the transaction hash (giving the time and the block). Moreover, the list plays the role of the buffer in our solution. SN is responsible of collecting enough correct inputs from clients before moving towards aggregation. Figure 1 depicts the flow of our blockchain-based scenario.

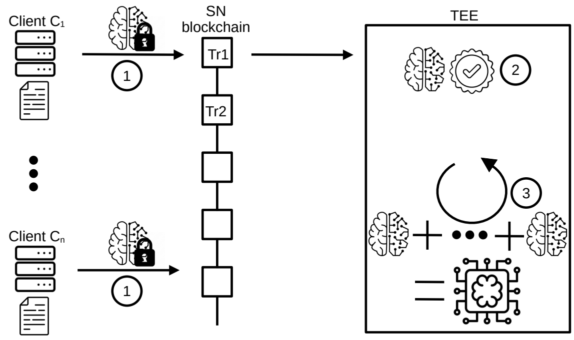


Figure 1: Overview of our FL scenario.

4.2 SN-based System

4.2.1 System Phases

Setup: During the setup phase, the clients register to the SN ecosystem. They become basic users of the network, with some stake but without the intention of participating in the maintenance of the blockchain (i.e. through the roles of delegates and delegators). Clients aim to launch transactions to submit their local inputs to SN for robust aggregation. They also receive the appropriate key material to communicate with SN, allowing them to encrypt their inputs and decrypt the outputs respectively.

Training: Clients locally train the model on their own dataset. Once training is over, they submit their updates to SN by encrypting them using a symmetric key shared between each client and the network. This kind of submission triggers a transaction, meaning that clients must pay fees to SN where some are used for gas and other for paying delegates.

Robust Aggregation: Clients' inputs are stored in a buffer of a FL-oriented smart contract until the buffer is full. SN, through this smart contract, first aggregates the stored inputs and obtains the aggregate. The latter serves as the new global model and can be queried by clients for another training round.

To enhance robust aggregation, the smart contract embeds robust techniques, namely Krum, Trim Mean and Median. More specifically, the smart contract receives local inputs from clients through transaction in their encrypted form. Within the TEE, these inputs are decrypted, ordered and aggregated following one of the three techniques.

4.2.2 Smart Contract

Workflow: The smart contract proceeds as follows to achieve robust aggregation. The smart contract first receives local updates from clients and adds them to its buffer. Note that only one input (i.e., vector) is accepted per client per buffer round to prevent DoS attacks. Once the buffer is full, it checks their validity by ordering them according to the chosen robust technique. For instance, a bound on the number of corrupted clients is defined that excludes the most left and right inputs in the ordered list. Once input exclusion has happened, the smart contract aggregates all the remaining updates, resulting into a new global model. The latter can be queried by clients.

Client Management: The smart contract is owned by a party belonging to SN. The owner can add and revoke clients. Clients are defined as authorised when the smart contract is instantiated. This means that only authorised clients can submit local inputs through transactions. On the other side, any party in SN, not only the authorised clients, can query the smart contract. For instance, anyone can query the list of authorised clients and the latest global model. The size of the buffer is defined as being at least half of the number of authorised clients.

Smart Contract Management: The owner is in charge of activating the smart contract. Additionally, she can deactivate it at any time. The smart contract has been developed such that the owner can make it not queriable (except to check whether the smart contract is active) and not modifiable.

Input Management: Clients' inputs are vectors whose size can be consequent, of the order of thousands. To fit within the SN framework, vectors can be sent in smaller segments. Clients are asked to append the round information of the current buffer. They find such information when accessing the new global model to train. Clients are restricted to submit one input per buffer round, even if this input is rejected (not validated). Once the buffer is full (i.e., its maximum size is reached), the aggregation of all inputs within the buffer is launched.

4.3 Robust Techniques

To manage Byzantine nodes, we employ and evaluate three robust aggregation techniques, namely *Krum* (Blanchard et al., 2017), *Trim Mean* (Yin et al., 2018), and *Median* (Yin et al., 2018).

Krum selects the input that is the closest to the majority by calculating the Euclidean distance between each pair of inputs. It then sums the distances of the closest inputs and selects the one with the lowest total distance, effectively filtering out outliers.

Trim Mean calculates the average of local inputs, after discarding a predefined threshold of the highest and lowest values among sorted inputs. This threshold represents the hypothetical number of Byzantine nodes in the system. Doing so, the influence of extreme outliers is reduced. Median determines the middle value of the sorted local inputs, providing robustness against extreme outliers w.r.t. predefined hypothetical number of Byzantine nodes.

In practice, those robust techniques first consider inputs as they arrive to SN. Then, inputs are ordered to exclude a predetermined amount of outliers. This amount represents the presumable number of corrupted clients in the system. Finally, aggregation is executed on the remaining inputs.

5 Experimental Evaluation

5.1 Experimental Settings

Datasets and Distribution among clients: To implement and evaluate our solution, we consider two scenarios with two datasets: (i) a local medical dataset that consists of 2126 patients' (fully anonymized) medical information such as age, blood pressure, pulse, waist, uric acid, etc., and helps predict heart arrhythmia; (ii) the MNIST dataset for image classification (Deng, 2012). We consider a cross-silo distributed system composed of SN (which can be seen as a single server) and n clients. More concretely, these two medical and MNIST datasets are distributed among 10 and 15 FL clients, respectively. In a realistic cross-silo environment, clients often have different data distributions; hence, in our setting, similar to the one in SABLE (Choffrut et al., 2023), the dataset is partitioned among all clients following a Dirichlet distribution parameterized with α (Hsu et al., 2019). To capture the desired level of data heterogeneity and examine its impact, we set α in $\{0.5, 1, 5\}$ for the medical dataset (the higher α the more homogeneous the distribution among clients). We choose $\alpha = 1$ as in SABLE for the MNIST dataset, reflecting a heterogeneous distribution.

Byzantine Nodes and Attacks: Training a FL model on the medical and MNIST datasets while keeping it privacy-protected becomes even more complex when defending against a subset of Byzantine nodes who try to deter the model's performance. We have implemented the four classes of Byzantine nodes that are enumerated in SABLE:

- In a *Fall Of Empires* (FOE) attack (Xie et al., 2020), Byzantine nodes send $(1-\tau)\mathbf{v}_t$, where $\mathbf{v}_t$ is the average of vectors sent by honest nodes at round t and τ is the attack factor.
- In an *A Little Is Enough* (ALIE) attack (Baruch et al., 2019), Byzantine nodes send $\mathbf{v}_t + \tau\sigma_t$, where σ_t is the coordinate-wise standard deviation of honest vectors.
- In a *Label Flipping* (LF) attack (Allen-Zhu et al., 2020), Byzantine nodes flip each label l to $9-l$, where labels range from $\{0,\dots,9\}$, and compute gradients on these modified labels.
- In a *mimic* attack (Karimireddy et al., 2020), Byzantine nodes imitate the honest node that incurs the largest variance with respect to the gradients and transmit the same values to SN. To evaluate the impact of such attacks, we introduce f Byzantine nodes in our two scenarios, with f varying from 0 to 3 and 0 to 5, respectively.

Models and Hyperparameters: For the medical scenario, each client trains a Feed Forward Neural Network (NN) composed of three fully connected layers (FCLayers) with two activation functions, with model batch size $b = 32$ and learning rate $\gamma = 0.01$.

Because SN only works with integers, we quantize the model parameters and set the precision value $\delta = 10^4$. On the other hand, for the MNIST scenario, we adopt the same setting of the one used in SABLE in order to be able to compare easily. For both scenarios, the model is trained in 100 rounds (we observe that this number is sufficient for the model to converge).

5.2 Experimental Results

We first evaluate the performance of our SN-based FL solution within the medical scenario. In particular, we assess the learning performance of the model, in comparison to its non-attacked counterpart, while gradually increasing the number f of malicious clients. We then evaluate our solution using the MNIST dataset to accurately compare our results with those obtained in SABLE. In both scenarios, we also evaluate the communication and computation costs.

Medical scenario: Firstly, in our experiments, we notice that, when we move towards more homogeneous data distributions, all robust aggregation techniques converge faster, independently of the underlying attack. This is depicted in Figure 2 for FOE attacks (we observe the same behavior for the other attacks but because of lack of space, we do not show them here.). Therefore, we decide to set $\alpha = 1$ for all remaining experiments, as depicted in Figure 3.

Figure 3 then resents the accuracy results of the trained model using the three robust aggregation techniques (results with Krum, Trim Mean, and Median are depicted in the first, second and last column, respectively). Each row corresponds to the study of one specific attack and each graph shows results with four case-studies: one honest and three malicious cases, i.e., $f \in \{0,1,2,3\}$.

Regarding the quality of the aggregation technique, we observe that Krum shows the greatest resilience in more heterogeneous environments in the case of FOE attacks. We believe the reason for this performance is that changing the sign does not affect the Euclidean distance between the values. On the other hand, when ALIE or LF attacks are implemented, all aggregation techniques seem to show similar accuracy results, and compared to FOE attacks, these two attacks do not create harm to the model. Under the mimic attack, Figure 3(d) shows that the Trim Mean aggregation technique is less robust than Krum and Median techniques. Nevertheless, we realize that the training still converges to an acceptable accuracy level ($\approx 90\%$).

Technique	t_{tran} (s)	t_{agg} (ms)	BW (KB)
Krum	4.2	120	13.67
Trim Mean	4.0	110	13.67
Median	4.1	100	13.67

Table 1: Communication and computational costs of Krum, Trim Mean and Median for the medical scenario. "BW" denotes bandwidth.

The communication and computational costs for the medical scenario are presented in Table 1, where $n = 10$, $f = 3$ and $\delta = 10^4$. Here, t_{tran} is defined as the time required for each client to submit their local update to SN, specifically the time needed to upload their parameters to the blockchain via a transaction. On the other hand, t_{agg} denotes the time taken by SN to execute the smart contract by applying the selected robust technique to the clients' updates, aggregating them, and sending the updated values to all FL clients.

As seen in Table 1, the Trim Mean technique achieves the best trade-off between communication and computational costs, with a slightly lower t_{tran} compared to the other methods. The Median technique requires marginally less aggregation time t_{agg}. Hence, the variations in computational are mainly due to the processing complexities unique to each technique. Moreover, all three techniques exhibit the same bandwidth usage (i.e., 13.67 KB) since each client utilizes the same CNN model for training, resulting in identical gradient sizes. Each gradient value is represented by an integer quantized with a factor of 10^4 and can be stored in 16 bits.

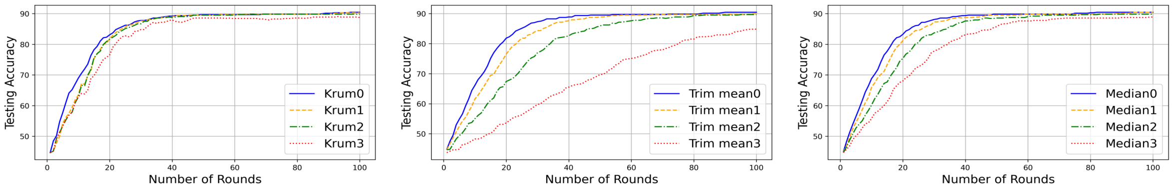
MNIST scenario: Figure 4 illustrates the learning performance of our solution on the MNIST scenario, using the same model and hyperparameter settings outlined in SABLE. In particular, $n = 15$, $f \in \{0,1,3,5\}$ and $\alpha = 1$. We launch the four aforementioned attacks, as in SABLE, to properly compare our solution with the latter. Table 2 offers a detailed comparison between our work and SABLE in terms of communication and computational costs, based on the MNIST dataset, with $n = 15$ and $f = 5$. This configuration simulates a realistic scenario in which up to a third of the nodes may be compromised SABLE. Within this context, t_{tran} denotes the time each client needs to submit its local update to the SN, while t_{agg} indicates the time taken by the SN to execute the smaer contract.

System	Technique	t_{tran} (s)	t_{agg} (s)	BW (KB)
SABLE	Trim Mean	not available	1040.4	5*
Our Work	Trim Mean	4.1	2.96	19.42
	Median	4.1	2.61	19.42
	Krum	4.2	3.48	19.42

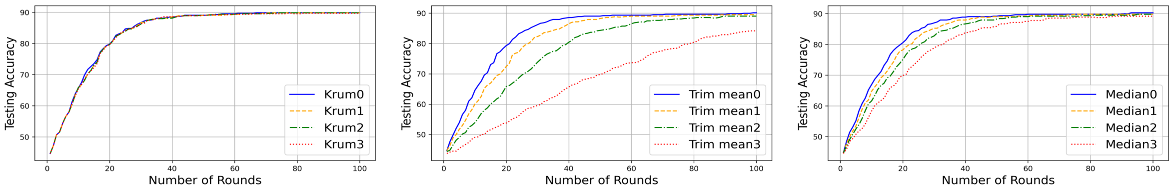
Table 2: Performance comparison on the MNIST dataset with 79,510 model parameters. (* Such a value is suggested in (Choffrut et al., 2023) but is not explained.)

SABLE aims to support robust aggregation techniques over homomorphically encrypted data. It has only been implemented with Trim Mean in practice. Specifically, the Median method has been suggested as an extension of Trim Mean, with similar results, while Krum has not been deployed due to its potential incompatibility with the HE scheme used in SABLE. Moreover, in SABLE, the entire homomorphic aggregation process is not completed at the server side as expected. Instead, the final averaging step (i.e., division by the total number of local inputs), is executed by each client, introducing additional computational overhead on the client side. Additionally, the bandwidth usage is estimated to 5 KB in SABLE but not explicitly confirmed neither theoretically nor experimentally.

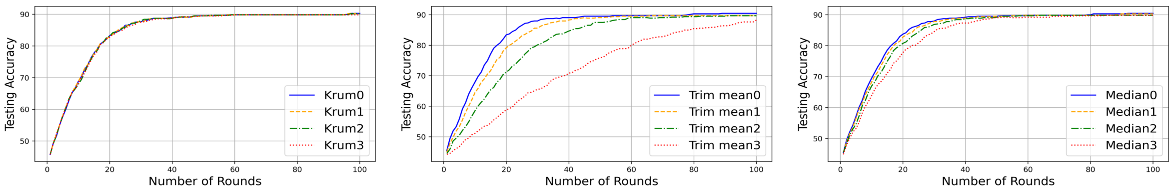
In contrast, our work offers a fully integrated and practical implementation of three robust aggregation techniques, namely Trim Mean, Median, and Krum. Moreover, the full aggregation process (including dividing the aggregate by the number of updates) occurs within the SN, and not at the client side. Our solution also improves the overall system efficiency, as evidenced by the reduced aggregation times t_{agg} by a factor of approximately 300 compared to SABLE. The bandwidth usage of our solution requires 19.42 KB (with 2-bit representation of parameters), while authors of SABLE claim to consume approximately



(a) $\alpha = 0.5$

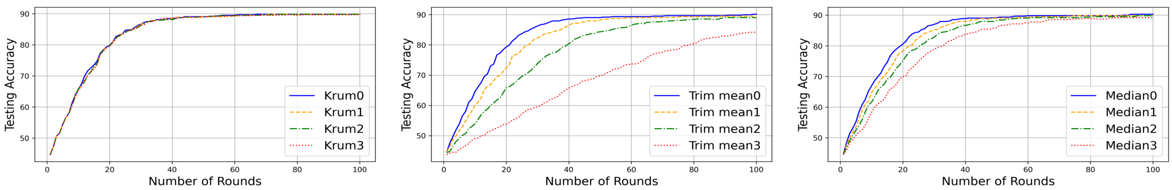


(b) $\alpha = 1$

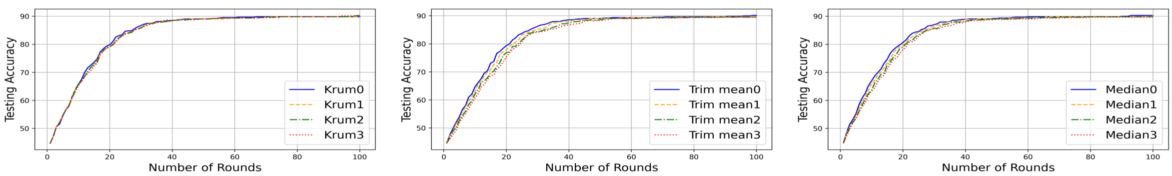


(c) $\alpha = 5$

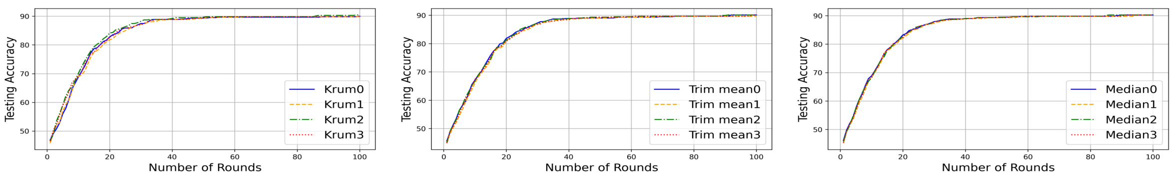
Figure 2: Accuracy results for KRUM, Trim Mean, and Median under FOE attacks over the medical dataset.



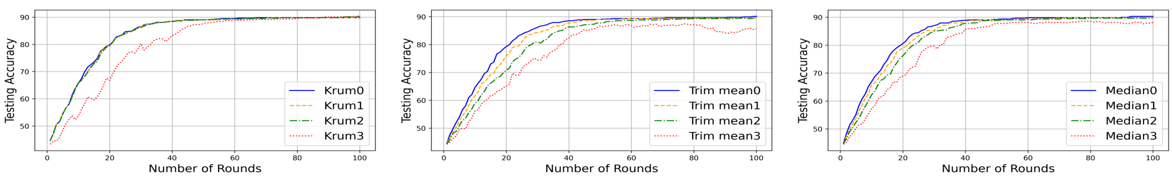
(a) FOE attack



(b) ALIE attack

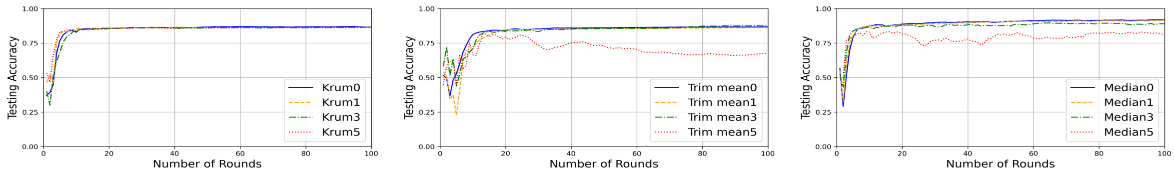


(c) LF attack

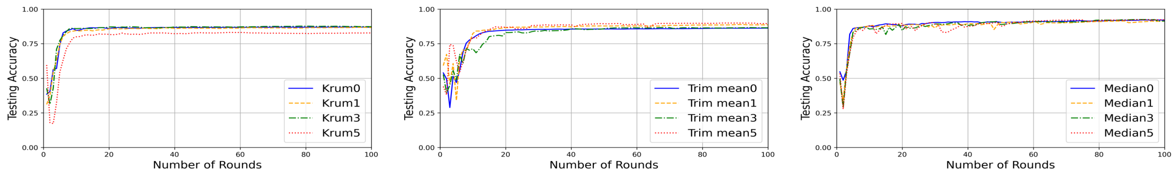


(d) Mimic attack

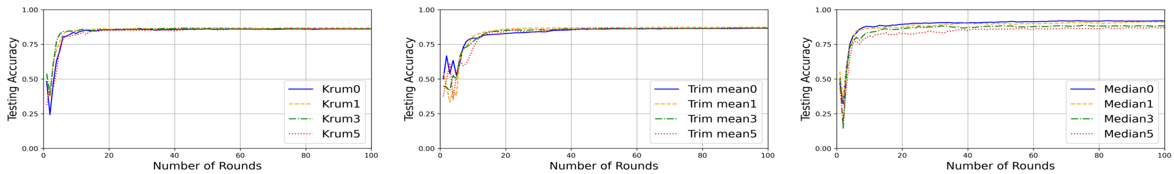
Figure 3: Accuracy results for KRUM, Trim Mean, and Median under the four attacks over the medical dataset.



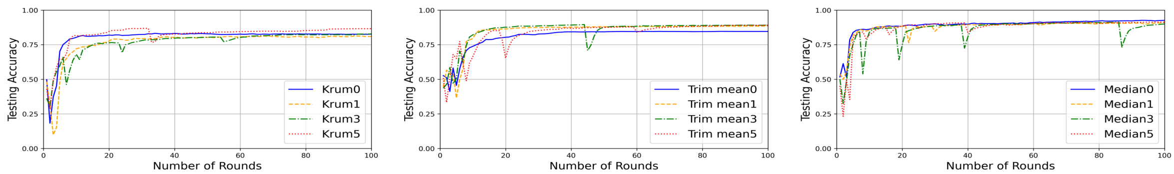
(a) FOE attack



(b) ALIE attack



(c) LF attack



(d) Mimic attack

Figure 4: Accuracy results for KRUM, Trim Mean, and Median under the four attacks over the MNIST dataset.

5 KB (we had difficulties to compute this number although adopting the same setting and quantization strategy). The bandwidth cost, in our case, still remains very low. On the other hand, we observe substantial gains in computational speed. Finally, we have evaluated the performance of the three aggregation techniques (i.e., Trim Mean along with both Median and Krum), which does not vary much in terms of computational and communication costs.

Regarding Figure 4, we show that we obtain a similar behavior compared with SABLE, which only implements Trim Mean. Moreover, as also observed in the medical scenario, we realize that Krum is the most suitable technique to overcome FOE attacks, whereas all three methods perform similarly under ALIE and LF attacks. Finally, the mimic attack seems to be the most difficult attack to prevent, and for this one, the worst aggregation method seems to be Trim Mean.

To summarize, based on this experimental study, we can claim that Krum seems the most suitable technique to overcome the four types of attacks with a negligible overhead in terms of computation and communication.

5.3 Discussion and Future Work

Through designing our robust and privacy-preserving solution over SN, we have met several challenges from the latter. The first one is related to blockchain-based storage fees. Clients submit their local input to the smart contract through transactions. This implies a financial cost, which is evaluated as gas fees as in Ethereum[5]. Aggregation happens only once the buffer is full, meaning that the smart contract keeps received inputs until aggregation. Gas fees increase with the number of inputs stored in the smart contract. In particular, if the initial transaction launched from the first vector has a cost worth x, then the subsequent Nth transaction from the Nth vector has a cost worth Nx. However, such a cost process has a limit in SN. The SN simply rejects the transactions and thus client vectors because the fees are seen as too high for the network. Consequently, we aim to explore how to overcome such a restrictive limitation to permit to operate our solution over real but huge datasets such as CIFAR.

[5] https://ethereum.org/

Another problem that we have encountered is related to the selection of techniques to enable robust aggregation. Other metrics exist, based on norm bounding (e.g., L_2, L_∞, Cosine distance, Hamming distance). Nevertheless, those metrics incur costly operations, which reach the financial limits of SN (i.e., costly operations require more gas fees). Consequently, some local inputs could be rejected before the buffer being full and thus, aggregation might never happen. A second option for future work is to consider more carefully how to deploy those norm bounding metrics in our solution.

6 Conclusion

In this paper, we addressed key challenges in FL by developing a solution that ensures the privacy of client updates along with the robustness and integrity of the global model. While SA within TEEs protects individual updates, FL systems remain vulnerable to malicious clients submitting poisoned updates that compromise model performance. To mitigate this, we proposed three methods that filter out outlier updates prior to aggregation, safeguarding the global model's robustness. Our framework also supports FL model integrity through consensus mechanisms, guaranteeing genuine clients to have their updates used for aggregation. By integrating blockchain technology through SN and using smart contracts within TEEs, our approach ensures privacy-preserving and robust aggregation of updates. Experimental results using a medical dataset and the MNIST dataset demonstrate the effectiveness of our solution in protecting client input privacy and preventing model poisoning, while keeping a favorable performance in terms of computation and communication.

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