# SPRITE: A Scalable Privacy-Preserving and Verifiable Collaborative Learning for Industrial IoT

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Abstract—Recently collaborative learning is widely applied to model sensitive data generated in Industrial IoT (IIoT). It enables a large number of devices to collectively train a global model by collaborating with a server while keeping the datasets on their respective premises. However, existing approaches are limited by high overheads and may also suffer from falsified aggregated results returned by a malicious server. Hence, we propose a Scalable, Privacy-preserving and veRIfiable collaboraTive lEarning (SPRITE) algorithm to train linear and logistic regression models for HoT. We aim to reduce burden from resource-constrained HoT devices and trust dependence on cloud by introducing fog as a middleware. SPRITE employs threshold secret sharing to guarantee privacy-preservation and robustness to IIoT device dropout whereas verifiable additive homomorphic secret sharing to ensure verifiability during model aggregation. We prove the security of SPRITE in an honest-but-curious setting where the cloud is untrustworthy. We validate SPRITE to be scalable and lightweight through theoretical overhead analysis and extensive testbed experimentation on an IIoT use-case with two real-world industrial datasets. For a large-scale industrial setup, SPRITE records 65% and 55% improved performance over its competitor for linear and logistic regressions respectively while reducing communication overhead for an IIoT device by 90%.

## I. INTRODUCTION

With the growing popularity of Industrial IoT (IIoT), followed by Industry 4.0 which specifically emphasizes on the manufacturing industries [1], voluminous amounts of sensitive data are being generated by various smart devices within the industrial floor. To effectively utilise such data in order to provide intelligent customer services and improve the overall quality of service (QoS), industries are inclined towards modelling these data. However, to generate a trained model with high accuracy for better predictive analysis and classification, it is extremely important to utilise training data across different industries or enterprises [2]. Due to the high sensitivity of these data, industries are unwilling to export them to a centralised server for executing traditional learning algorithms. Thus, collaborative learning [3] has been proposed to enable multiple data owners to construct a global model by leveraging their private data without explicitly sharing them.

Collaborative learning is a promising new paradigm where each device contributes to the global model update by sharing its local model with the cloud/aggregation server without transmitting the private data through the network [4]. In this context, traditional learning algorithms like machine learning (ML) or deep learning can be applied to develop the distributed learning framework. However, deep learning requires an enormous amount of data to begin with in order to search for relevant features and is also extremely intensive in nature because of its layered neural network backbone which are its potential drawbacks. On the contrary, traditional ML algorithms learn from the available features in the dataset to make informed decisions based on the learning which is extremely relevant for structured numerical data generated by applications like healthcare, industries, finance etc. Thus, ML algorithms like regression models have attracted considerable attention over deep learning in such application domain [5].

Despite the advantages of collaborative learning, there are two major concerns input data privacy and vulnerability of locally trained models to information leakage. For example, model-inversion attacks [6, 7] are able to restore the original training dataset, hence it is essential to keep the local models private. Apart from the privacy issues, the cloud/aggregation server may also behave maliciously by returning forged aggregated results to the devices for making a wrong impact on model update. Under worse circumstances, a server may also return carefully crafted results to the devices for analyzing statistical characteristics of the shared updates and thereby provoke the devices to unintentionally expose sensitive information [8]. Lastly, since the IIoT devices are typically lowpowered, they may become inoperable (i.e. dead) due to energy drainage resulting in device dropout at anytime in the network.

Inspired by the aforementioned challenges, this work focuses on developing a lightweight framework for collaborative learning specific to IIoT in order to ensure data/model privacy and verifiability of the aggregated results returned by the cloud. Our work considers two fundamental regression models: linear and logistic regression and adopts a two-tier fog-based clustered architecture for the collaborative learning setup. The fog-based architecture notably reduces the overheads on the constrained IIoT devices along with minimising the dependence on cloud. Since, in such a setup, the time consuming and computationally intensive local training is typically performed by the low-end IIoT devices, therefore, our proposed training algorithm also handles IIoT device dropout.

### A. Related Work

A brief overview on various privacy-preserving, verifiable distributed machine learning based schemes are discussed.

Privacy-Preservation: In literature, privacy-preserving aggregation of local models has been achieved either by using differential privacy mechanisms or cryptographic mechanisms. The works [9-12] concentrating on the former technique usually employ adding noise to the training data or gradients which results in an accuracy drop of the final aggregated model. To handle this issue, certain works [4, 13] have employed a double masking technique along with secret sharing to achieve greater accuracy of the trained model. However, these algorithms are limited by high communication and computation costs. To address the concern of overheads, a group of works have focused on utilizing cryptographic mechanisms like secure multiparty computation (MPC) [14-16] and homomorphic encryption (HE) [17, 18] which are typically vulnerable to inference threats from third party entities. To address all the aforementioned issues, the latest works [2, 3] employ lightweight secret sharing techniques coupled with additive HE schemes to guarantee privacy-preservation even when majority of participants are corrupted. However, none of these works take into consideration that cloud/aggregation server might behave maliciously and falsify the aggregated final model.

**Privacy-Preservation and Verifiability:** To ensure the correctness of the results returned by the server, recent state-of-the-art works [19–22] have introduced verifiable computation as part of their scheme. However, these works either implement intensive bilinear signatures as part of their verification or use traditional double masking techniques for privacy preservation which has its own pitfalls. Lastly, all of these works are based on either neural networks or deep learning frameworks which are itself complex and computationally intensive.

**Distributed ML Schemes for HoT:** Recently authors have also proposed privacy preserving ML algorithms [20, 23–25] specific to industrial IoT applications. Apart from the intrinsic drawbacks of differential privacy or verifiable computation already discussed above, certain works [24, 25] have introduced blockchain to provide data integrity which results in extra overhead due to the inherent properties of blockchain. Further, all of these works rely largely on HoT devices to perform certain computations related to blockchain calls or verifiability which is an additional burden for such low-powered devices.

This motivates us to design a privacy-preserving and verifiable collaborative learning algorithm specific to large-scale industries for two fundamental regression models. Our primary focus is to reduce overheads on constrained IIoT devices without sacrificing on the accuracy of the trained model while keeping in mind that such devices may be prone to dropouts. We also address that cloud servers can be malicious and may return forged aggregated results to impact the final model.

## B. Major Contributions

Our contributions can be summarized as below:

- 1) We propose a Scalable Privacy-preserving and veRIfiable collaboraTive lEarning (SPRITE) algorithm for two fundamental regression models specific to IIoT.
  - a) Reduces burden on IIoT devices and minimises trust dependence on cloud by introducing fog as a middleware.

- b) Provides robustness to IIoT device dropout by using additive homomorphic based threshold secret sharing.
- c) Ensures verifiability of the aggregated model returned from a malicious cloud (i.e. prevent forgery) by employing verifiable additive homomorphic secret sharing.
- 2) We establish provable security guarantees for the following:
  - a) privacy-preservation under an *honest-but-curious* setting and verifiability when cloud is *untrustworthy*.
  - b) correctness to ensure that the final model is identical to the one produced by the centralised framework.
- Finally, we validate SPRITE with a theoretical overhead analysis accompanied by extensive testbed experiments on an IIoT use-case with two real-world industrial datasets.
  - a) Establish SPRITE to be scalable and lightweight while maintaining accuracy, data privacy and verifiability.
  - b) Justify superior performance over PrivColl [3] with additional security features (e.g. verifiability) where the verification mechanism is lighter compared to VFL [20].

# C. Organization

The remaining paper is structured as follows. Section II briefly describes the basic building blocks. Section III discusses the system model. SPRITE is presented in Section IV. Section V explains the security analysis of the scheme. Section VI discusses the experimental analysis with the testbed results. Section VII finally concludes our work.

## II. PRELIMINARIES

## A. Threshold Secret Sharing Scheme

A *t-out-of-m* threshold secret sharing scheme [26] over  $\mathbb{F}_q$  splits a value *srt* into *m* shares in such a way that any *t* shares can be used to reconstruct *srt*, however a set of at most (t-1) shares makes it impossible to reconstruct *srt*. The scheme consists of the following two algorithms:

- **TSS.Share**  $(srt, t, m) \rightarrow (s_1, s_2, \dots, s_m)$ : Given a secret value srt to be split into m shares and a threshold  $t \leq m$ , the algorithm outputs a set of shares  $(s_1, s_2, \dots, s_m)$  each belonging to a different entity.
- **TSS.Reconstruct**  $((s_{i_1}, s_{i_2}, \dots, s_{i_t}), m, t) \rightarrow srt$ : The algorithm accepts as input any t shares  $(s_{i_1}, s_{i_2}, \dots, s_{i_t})$  and outputs the original srt.

An additive homomorphic property of the TSS scheme also allows one to compute linear functions of secrets simply by adding the individual shares.

## B. Homomorphic Hash Function

A finite field  $\mathbb{F}_N$  and a multiplicative group  $\mathbb{G}_q$  of prime order q generated by g produces a collision-resistant homomorphic hash function  $H : \mathbb{F}_N \to \mathbb{G}_q$ , where H satisfies the following properties [27]:

- **One-way:** computationally hard to compute  $H^{-1}(x)$ .
- Collision-free: computationally hard to find  $x, y \in \mathbb{F}^N (x \neq y)$ , such that H(x) = H(y).
- Homomorphism: for all  $x, y \in \mathbb{F}^N$ , it holds  $H(x \circ y) = H(x) \circ H(y)$ , where " $\circ$ " is either "+" or ".".

# C. Pseudorandom Functions (PRF)

A family of functions  $f : \{0,1\}^n \times \{0,1\}^s \to \{0,1\}^m$  is said to be a pseudorandom function  $\mathcal{F} = \{f : \{0,1\}^n \to \{0,1\}^m\}$ , only if the following conditions are satisfied [28]:

- Given key  $K \in \{0,1\}^s$  and input  $X \in \{0,1\}^n$ , there exists an efficient algorithm to compute  $\mathcal{F}_K(X)$ .
- For an adversary A, there exists a negligible function ε, such that:

$$Pr_{K \leftarrow \{0,1\}^s}[\mathcal{A}^{f_K}] - Pr_{f \in \mathcal{F}}[\mathcal{A}^f]| < \epsilon$$

D. Verifiable Additive Homomorphic Secret Sharing (VAHSS) using Homomorphic Hash Functions

A verifiable additive homomorphic secret sharing scheme is used to compute a final value y corresponding to secret values  $x_1, x_2, \ldots, x_n$  over a finite field  $\mathbb{F}_N$  along with a proof  $\sigma$  that y has been computed correctly [28]. A homomorphic hash (H) based VAHSS has the following algorithms [28]:

- VAHSS.ShareSecret $(1^{\lambda}, i, x_i) \rightarrow (x_{i1}, x_{i2}, \dots, x_{im}, \tau_i)$ : Computes a public value  $\tau_i$  corresponding to  $x_i$  and then splits  $x_i$  into m shares.
- VAHSS.PartialEval $(j, (x_{1j}, x_{2j}, \ldots, x_{nj})) \rightarrow (y_j)$ : Given the  $j^{th}$  shares of the secret inputs, the algorithm computes the sum of all such  $x_{ij}$  for the given  $j, i \in [n]$ .
- VAHSS.PartialProof $(j, (x_{1j}, x_{2j}, \ldots, x_{nj})) \rightarrow (\sigma_j)$ : Given the  $j^{th}$  shares of the secret inputs, the algorithm outputs the partial proof  $\sigma_j = H(y_j)$  respective to  $y_j$ .
- VAHSS.FinalEval(y<sub>1</sub>, y<sub>2</sub>,..., y<sub>m</sub>) → (y): Outputs the summation of all the partial sums y<sub>1</sub>, y<sub>2</sub>,..., y<sub>m</sub>.
- VAHSS.FinalProof( $\sigma_1, \sigma_2, ..., \sigma_m$ )  $\rightarrow$  ( $\sigma$ ): Computes final proof  $\sigma$  as a product of the partial proofs  $\sigma_1, \sigma_2, ..., \sigma_m$ .
- VAHSS. Verify  $(\tau_1, \tau_2, \dots, \tau_n, \sigma, y) \rightarrow (0, 1)$ : Outputs 1, if  $\sigma = \prod_{i=1}^n \tau_i \wedge \prod_{i=1}^n \tau_i = H(y)$  holds or 0 otherwise.

## E. Gradient Descent Optimization

Gradient Descent is one of the most widely used optimization techniques in machine learning to reach an optimal value for cost function J [3]. In order to minimize J, the aim is to find the exact values of the coefficient matrix  $\theta$  that reduces J as far as possible. Given a training dataset x with m training samples and label matrix y, the cost function is defined as:

$$J(\theta) := \frac{1}{2m} \sum_{i=1}^{m} (h_{\theta}(x^{(i)}) - y^{(i)})^2 \tag{1}$$

Given learning rate  $\alpha$ , the coefficient matrix  $\theta$  is derived as:

$$\theta_j := \theta_j - \alpha \frac{\partial J(\theta)}{\partial \theta_j} \tag{2}$$

Combining equations (1) and (2) the updated coefficient matrix using gradient descent optimization is as follows:

$$\theta_j := \theta_j - \frac{\alpha}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) \cdot x_j^{(i)}$$
(3)

## **III. SYSTEM MODEL**

This section describes our system model in detail where we propose a two-tier clustered architecture suitable for the collaborative learning setup. Next, we explain the security guarantees and the threat model.

#### A. Clustered Architecture

Our model consists of the following major entities:

- Industrial IoT (IIoT) Devices (D<sub>m1</sub>,..., D<sub>mn</sub>): The devices are any form of industrial equipment such as Automated Guided Vehicles (AGVs), conveyor belts, etc. embedded with one or more different types of sensors (e.g. temperature, pressure) to enable a smart infrastructure [1]. Each of these devices has their own datasets including data sensed from the surroundings and/or collected during the production process. Such data may contain private sensitive information and are used for locally training the learning models. IIoT devices choose their nearest fog node and send the locally trained model updates to it for further processing.
- Fog Nodes  $(F_1, \ldots, F_m)$ : We have introduced the fog layer in our proposed architecture to act as a potential middleware between resource-constrained IIoT devices and the cloud. These nodes are more robust compared to IIoT devices and trustworthy than cloud [29] and are therefore used for reducing the trust dependence on the cloud [30]. Smart devices with higher computational power like smartphones/tablets, laptops act as fog nodes in our system. Each fog node F receives locally trained model updates from a set of IIoT devices  $(D_{m1}, \ldots, D_{mn})$  which form a cluster where F acts as their cluster-head. The fog nodes perform the necessary operations and then offload the rest of the tasks (aggregation, proof of correctness) to the cloud for further processing. On receiving the final aggregated result along with the proof of verification from the cloud, each Fverifies the correctness of the received result.
- Cloud (Cl): The Cloud is responsible for aggregating the inputs received from the fog nodes  $F_1, \ldots, F_m$ . It also computes a proof of verification which is sent back to the fog nodes along with the final aggregated result.



Fig. 1: Two-tier Clustered Architecture for Collaborative Learning

Figure 1 shows the two-tier clustered architecture used in our setup. If the nearest fog node to an IIoT device  $D_{ij}$  turns

offline,  $D_{ij}$  can choose any other potential fog node within its communication range.

## B. Security Guarantees and Threat Model

The design goals, threat models and assumptions are discussed here.

## **Design Goals:**

- *Privacy:* The privacy of the scheme requires protecting the IIoT device's inputs such as the local datasets and the model parameters. This means that an adversary cannot derive any benign device's local inputs based on its knowledge except with a negligible probability of  $\lambda$ . No other parties can learn any information about the devices' private inputs.
- *Correctness:* For correct inputs from the IIoT devices, the distributed collaborative learning algorithm should deliver the correct model identical to the one produced by the centralised learning algorithm. We claim no correctness of the model if any device uses incorrect inputs.
- *Verifiability:* The cloud should only obtain partially evaluated value with its corresponding partial proofs from the fog nodes. The cloud is then supposed to aggregate the values and return a final aggregated result along with a proof of correctness to meet the security requirements of the scheme. The fog nodes should then be able to verify the correctness of the aggregated result received from the cloud.
- *Efficiency:* As sensitive data is kept private with the IIoT devices, such devices should perform minimal computation during local training. The rest of the task should be divided between the fog nodes and the cloud in a privacy-preserving and verifiable manner. The computation and communication overheads of each type of component involved in the scheme should be minimal.

**Threat Model:** In our model, we aim to protect against an *honest-but-curious* adversary  $\mathcal{A}$ . We consider that a group of IIoT devices and/or Fog nodes compromised by  $\mathcal{A}$  follow the protocols correctly but may intend to obtain the intermediate results/information from other nearby devices/nodes. In case of IIoT devices,  $\mathcal{A}$  will try to gain information about the local datasets of the other IIoT devices or the local model parameters trained out of them. Similarly, in case of fog nodes,  $\mathcal{A}$  will try to gain information about the outputs from other fog nodes. Lastly, we consider the cloud to be *untrustworthy*. **Assumptions:** The following restrictions have been considered while setting up the assumptions:

- We assume that each training iteration is conducted within a fixed time-interval  $\mathcal{T}$  in a synchronous way.
- It is assumed that all devices use the correct model to compute the local gradient and the model is consistently updated at each round of iteration.
- Finally, it is assumed that the IIoT devices/fog nodes never deny to communicate and share part of their secret shares with the corresponding peer nodes.

## IV. OUR PROPOSED SCHEME

The basic idea of our proposed Scalable Privacy-preserving and veRIfiable collaboraTive lEarning (SPRITE) scheme is to train a regression model (i.e. linear/logistic regression) in a distributed fashion where the IIoT devices, fog nodes and the cloud collaboratively execute a global gradient computation.

In SPRITE, Shamir's Secret Sharing [26] coupled with additive homomorphism has been used to blind the locally trained model from the fog nodes before sending it out to them. Since 't' shares are enough to reconstruct the secret, Shamir's secret sharing ensures robustness to IIoT device dropout in the network up to a certain specified threshold. The novelty of SPRITE lies in delegating the gradient descent optimization (Section II-E) algorithm partially to the fog nodes, thereby reducing trust dependence on the cloud. Here, the sensitive partially computed gradients from the fog nodes are split into shares before uploading to the cloud for aggregation thus blinding the original values from it. The cloud in turn provides a proof of correctness along with the final aggregated model update to ensure verifiability of the computed result. Verifiable data aggregation in SPRITE is inspired from VAHSS scheme [28] as it is lightweight. However, we modify their n-client, mserver setup to adopt into our *m-fog*, single server architecture. Working Principle: Each IIoT device holds a local dataset denoted by  $\mathcal{D}_{ii}$  and its corresponding model parameter  $\theta$ which gets updated in each round of iteration. Each dataset  $\mathcal{D}_{ij} \in \mathbb{R}^{m_j imes k}$  is a  $m_j imes k$  matrix representing  $m_j$  training samples with k features where  $m_j$  can vary from device to device. The model parameter  $\theta \in \mathbb{R}^{k \times l}$  is a matrix of coefficients, where l is the number of output classes. In our proposed scheme,  $M = \sum_{j=1}^{N} m_j$  (where N is the total number of IIoT devices in the system) and l are publicly known by every participant whereas k is private and is only known to the corresponding data owner  $D_{ij}$ . Figure 2 shows the workflow of SPRITE which consists of the following steps:



Fig. 2: Workflow of SPRITE

System Setup: Given the security parameter λ, a trusted authority (TA) generates a secret key sk<sub>i</sub> for each fog node F<sub>i</sub> and public parameters pp. Next, it generates a collision-resistant homomorphic hash function H : x → g<sup>x</sup> as shown in Section II-B. Finally, it publishes a pseudorandom function F : {0,1}<sup>l<sub>1</sub></sup> × {0,1}<sup>l<sub>2</sub></sup> → F as per Section II-C.

- Local Training: Each IIoT device D<sub>ij</sub> holds its own training dataset  $\mathcal{D}_{ij}$  and the model parameter coefficient matrix  $\theta$ . In each round of iteration, each  $D_{ij}$  multiplies  $\mathcal{D}_{ij}$ with  $\theta$  to generate  $h_{\theta}(\mathcal{D}_{ij}) \in \mathbb{R}^{l \times m_j}$  which is a  $l \times m_j$ vector. Next it computes local gradient  $g_i$  using  $h_{\theta}(\mathcal{D}_{ij})$ over its dataset. Each  $D_{ij}$  then splits  $g_i$  into n shares using  $TSS.Share(q_i, t, n)$  [where t is the threshold number of IIoT devices that need to come together in order to reconstruct the secret value] as explained in Section II-A and distributes each share to the other corresponding  $D_{ij}$ . Each  $D_{ij}$  then locally adds the shares it receives to produce  $S_{D_{ii}}$  and sends this value to the nearest online fog node  $F_i$ .
- Each Gradient *Computation:* node  $F_i$ fog receives  $S_{D_{i1}}, S_{D_{i2}}, \ldots, S_{D_{in}}$  values from n IIoT lying within its devices communication range.  $F_i$  then computes cumulative gradient  $c_i$ using  $TSS.Reconstruct((S_{D_{i1}}, S_{D_{i2}}, \ldots, S_{D_{in}}), n, t).$ Thus, even if some IIoT devices are offline or busy during this stage and doesn't send its share of  $S_{D_{ij}}$ , the reconstruction is still feasible given at least t IIoT devices participate. This operation basically computes the summation part of the Gradient Descent algorithm [shown in Eq. (3)], i.e.  $c_i = \sum_{r=1}^{m_j} (h_{\theta}(\mathcal{D}_{ij}^{(r)}) - \bar{y}^{(r)}) \cdot \mathcal{D}_{ij}^{(r)}.$
- Task Delegation: In this stage, each  $F_i$  generates the output  $PR_i = \mathcal{F}_{sk_i}(i, ts_i)$  of the pseudorandom function  $\mathcal{F}$  [where  $sk_i \in \{0,1\}^{l_1}$  and  $ts_i$  is the timestamp associated with  $F_i$  such that  $(i, ts_i) \in \{0, 1\}^{l_2}$ .  $F_i$  then calls function  $VAHSS.ShareSecret(1^{\lambda}, i, c_i)$  (Section II-D) to split  $c_i$ into m shares and distribute it to the other corresponding fog nodes. Each  $F_i$  also calculate  $\tau_i = H(c_i + PR_i)$  respective to  $c_i$  which is publicly known to the entire system.

 $F_i$  then calculates  $y_i$  using the corresponding shares of  $c_{ij}$  it has received by calling function  $VAHSS.PartialEval(i, (c_{1i}, c_{2i}, \ldots, c_{ni}))$ (Section II-D). For the purpose of verification,  $F_i$  computes = a partial proof  $\sigma_i$  $H(y_i)$ = $q^{y_i}$ using  $VAHSS.PartialProof(i, (c_{1i}, c_{2i}, \ldots, c_{ni}))$ (Section II-D). Finally, each  $F_i$  sends  $(y_i, \sigma_i)$  to the cloud.

- Data Aggregation: When Cloud the receives fog nodes  $(y_i, \sigma_i,)$ from the  $F_1,\ldots,F_m,$ it first calls  $VAHSS.FinalEval(y_1, y_2, \ldots, y_m)$ to generate  $y = y_1 + y_2 + \ldots + y_m$  and then calls  $VAHSS.FinalProof(\sigma_1, \sigma_2, \dots, \sigma_m)$  as per Section II-D to generate final proof  $\sigma = \prod_{i=1}^{m} \sigma_i$ . Finally, the cloud sends a 2-tuple packet  $(y, \sigma)$  back to each  $F_i$ .
- **Result Verification:** Each  $F_i$  on receiving the 2tuple packet from the cloud, checks whether equation  $\sigma = \prod_{i=1}^m \tau_i \wedge \prod_{i=1}^m \tau_i = H(y)$  holds as per  $VAHSS.Verify(\tau_1, \tau_2, \ldots, \tau_n, \sigma, y)$  (Section II-D). If the equation fails,  $F_i$  rejects the result, otherwise, accepts it.
- Update Model Parameters: On acceptance of the result,  $F_i$ computes  $x = (\alpha/M) \cdot y$ , where  $\alpha$  is the learning rate and  $M = \sum_{j=1}^{N} m_j$ .  $F_i$  then sends back x to each device  $D_{ij}$ who updates its respective model parameter as  $\theta' = \theta - x$ . The updated  $\theta'$  is used for the next training iteration.

The detailed protocol description is illustrated in Fig. 3.

# SPRITE

- System Setup: A trusted authority (TA) takes as input the security parameter  $\lambda$  and generates the following:
  - Secret key  $sk_i$  for each fog node  $F_i$  and public parameters pp.
  - A collision-resistant homomorphic hash function  $H: x \to g^x$ .

Publishes a pseudo-random function  $\mathcal{F}: \{0,1\}^{l_1} \times \{0,1\}^{l_2} \to \mathbb{F}.$ 

- Iterative training process repeated until convergence:
- Local Training: Each IIoT device  $D_{ij}$  executes in parallel:
  - Computes dot product of its own training dataset  $\mathcal{D}_{ij}$  with the model parameter coefficient matrix  $\theta$  to generate  $h_{\theta}(\mathcal{D}_{ij}) \in \mathbb{R}^{l \times m_j}$ .
  - Calculates local gradient  $g_i$  using  $h_{\theta}(\mathcal{D}_{ij})$  over its training dataset. Splits  $g_i$  into n shares as  $(s_1, s_2, \ldots, s_n) \leftarrow TSS.Share(g_i, t, n)$
  - and distributes each  $s_i$  to the corresponding  $D_{ij}$ .
  - Locally adds the shares it receives to produce  $S_{D_{ij}}$  and sends it to the nearest online fog node  $F_i$ .
- Gradient Computation and Task Delegation: Each  $F_i$  on receiving multiple  $S_{D_{ij}}$  values from n IIoT devices executes in parallel:
- Computes cumulative gradient
- $TSS.Reconstruct((S_{D_{i1}}, S_{D_{i2}}, \dots, S_{D_{in}}), n, t).$ Generates output  $PR_i = \mathcal{F}_{sk_i}(i, ts_i)$  of the pseudorandom function F.
- Generates *m* shares of  $c_i$  as  $(c_{i1}, c_{i2}, \ldots, c_{im}, \tau_i)$ *VAHSS.ShareSecret* $(1^{\lambda}, i, c_i)$  where  $\tau_i = H(c_i + PR_i)$ .
- Publicly publish  $au_i$  to the entire system and distribute  $c_{i1}, c_{i2}, \ldots, c_{im}$  to the other corresponding fog nodes.
- Calculates  $y_i \leftarrow VAHSS.PartialEval(i, (c_{1i}, c_{2i}, \dots, c_{ni})).$  $g^{y_i}$ Computes a partial proof  $\sigma_i = H(y_i)$  $VAHSS.PartialProof(i, (c_{1i}, c_{2i}, \dots, c_{ni})).$
- Sends  $(y_i, \sigma_i)$  to the Cloud.

• Data Aggregation: Cloud on receiving  $(y_i, \sigma_i,)$  from fog nodes  $F_1, \ldots, F_m$  does the following:

- $y_1 + y_2 +$ – Generates y =  $u_m$  $VAHSS.FinalEval(y_1, y_2, \ldots, y_m).$
- Generates final proof  $\sigma$  $\prod_{i=1}^m \sigma_i$  $\leftarrow$  $VAHSS.FinalProof(\sigma_1, \sigma_2, \ldots, \sigma_m).$
- Sends a 2-tuple packet  $(y, \sigma)$  back to each  $F_i$ .
- Result Verification and Update Model Parameters: F<sub>i</sub> on receiving the 2-tuple packet  $(y, \sigma)$  from the Cloud, does the following:
  - Checks whether equation  $\sigma = \prod_{i=1}^{m} \tau_i \wedge \prod_{i=1}^{m} \tau_i = H(y)$  holds. On successful verification, accepts the result, otherwise, rejects it.
  - Computes  $x = (\alpha/M) \cdot y$ , where  $\alpha$  is the learning rate and M = $\sum_{j=1}^{N} m_j.$ - Sends x to each  $D_{ij}$ .

  - IIoT Device $(D_{ij})$ :
  - Updates the model parameter as  $\theta' = \theta x$ .
  - Uses the updated  $\theta'$  in the next round of training iteration.

Fig. 3: Detailed description of SPRITE

## V. SECURITY ANALYSIS

This section analyzes the security of SPRITE.

## A. Privacy Preservation

Let us consider the execution of SPRITE where the underlying cryptographic primitives are instantiated with parameter p (corrupted devices) and a set S of n IIoT devices/Fog nodes (denoted with identities  $1, \ldots, n$ ). At any point during the execution,  $S_i$  is denoted as the subset of devices that have correctly sent their outputs at the  $(i-1)^{th}$  training iteration. The input of each device S is denoted as  $x_s$  while the inputs of any subset of devices  $\mathcal{S}' \subseteq \mathcal{S}$  is denoted as  $x_{\mathcal{S}'} = \{x_s\}_{s \in \mathcal{S}'}$ . The following theorem demonstrates that while executing SPRITE, the joint view of any set of less than t (*honest-but-curious*) IIoT devices/Fog nodes, doesn't reveal any information about the other device's inputs.

**Theorem 1:** There exists a probabilistic polynomial-time (PPT) simulator SIM such that for all p, t, S with  $t \leq |S|, x_s, C$  where  $C \subseteq S$ , output of SIM is perfectly indistinguishable from output of  $REAL_{\mathcal{C}}^{S,t,p}$ , given  $REAL_{\mathcal{C}}^{S,t,p}(x_S, n)$  is a random variable representing the combined views of parties in C.

$$SIM_{\mathcal{C}}^{\mathcal{S},t,p}(x_{\mathcal{C}},n) \equiv REAL_{\mathcal{C}}^{\mathcal{S},t,p}(x_{\mathcal{S}},n)$$

*Proof:* As per [26], we know that threshold  $t = \lfloor \frac{n}{2} \rfloor + 1$ and any coalition of at most (t-1) devices and the server will reveal nothing about the devices' private inputs. The joint view of the parties in C is independent of the inputs of the parties not in C. Thus, the simulator is able to produce a perfect simulation by running the honest-but-curious devices on their true inputs while all other devices on a dummy input by calculating the simulated view of the devices in C. At a granular level, an IIoT device/Fog node splits its gradient  $q_i/c_i$ into n/m shares and locally adds the shares it receives from its corresponding devices before sending the result  $S_{D_{ii}}/y_i$ out onto the next level. Therefore, from the perspective of an adversary A, it is impossible to calculate the gradients  $q_i/c_i$ . Thus,  $\mathcal{A}$  will be unable to speculate the original input (local dataset, model parameter, etc.) of the IIoT device/Fog node which is effective in privacy-preservation of the devices private inputs in a honest-but-curious setting.

### B. Correctness

If a centralized gradient descent optimization algorithm  $\mathcal{F}_{GD}(\mathcal{D})$  taking dataset  $\mathcal{D}$  as input converges to a local/global minima  $\eta$ , then executing SPRITE with the same hyper parameters (cost function, learning rate etc.) on  $(\mathcal{D}_{11}, \ldots, \mathcal{D}_{1n}), \ldots, (\mathcal{D}_{m1}, \ldots, \mathcal{D}_{mn})$  [denoted by  $\mathcal{F}'_{GD}((D_{ij}, \mathcal{D}_{ij}), F_i, Cl)$ ] also converges to  $\eta$ .

**Theorem II:** SPRITE's gradient descent optimization  $\mathcal{F}'_{GD}((D_{ij}, \mathcal{D}_{ij}), F_i, Cl)$  algorithm is correct.

*Proof:* Let  $\theta_j$  denote the model parameters of  $\mathcal{F}_{GD}$  at the  $i^{th}(i \geq 1)$  training iteration, where  $\mathcal{F}_{GD}$  updates  $\theta_j$  as follows:

$$\theta_j = \theta_{j-1} - \alpha \frac{\partial J(\theta)}{\partial \theta_j} = \theta_{j-1} - \frac{\alpha}{s} \sum_{i=1}^s (h_\theta(x^{(i)}) - y^{(i)}) \cdot x_j^{(i)}$$
(4)

where s is the number of training samples in dataset  $\mathcal{D}$  and x, y are the features and target variable of  $\mathcal{D}$  respectively. In  $\mathcal{F}'_{GD}$ , each device  $D_{ij}$  computes the following:

$$\Delta \mathcal{D}_{ij} = \sum_{j=1}^{s_i} (h_\theta(x^{(j)}) - y^{(j)})$$

where  $s_i$  is the number of training sample possessed by  $D_{ij}$ . After aggregation by fog nodes  $F_i$  and cloud Cl,  $\mathcal{F'}_{GD}$ updates  $\theta'_i$  in the *i*<sup>th</sup> training iteration as follows:

$$\theta'_{j} = \theta'_{j-1} - \frac{\alpha}{M} \sum_{z=1}^{M} (\Delta \mathcal{D}_{ij})_{z}$$
(5)

where  $M = \sum_{i=1}^{N} s_i$ , given N as the total number of IIoT devices  $D_{ij}$  in the setup. Comparing equations (4) and (5), we find that  $\theta_j$  and  $\theta'_j$  are updated using the same equations. Therefore,  $\mathcal{F}'_{GD}((D_{ij}, \mathcal{D}_{ij}), F_i, Cl)$  also converges to  $\eta$ . Thus,  $\mathcal{F}'_{GD}((D_{ij}, \mathcal{D}_{ij}), F_i, Cl) = \mathcal{F}_{GD}(\mathcal{D})$ .

# C. Verifiability

**Theorem III:** Each Fog node  $F_i$  can independently verify the correctness of the aggregated result returned by cloud where the verification scheme can also detect forged results with a very high probability.

*Proof:* In order to proof the verifiability of the scheme, we first need to show that  $Pr[VAHSS.Verify(\tau_1, \tau_2, ..., \tau_n, \sigma, y) = 1] = 1$ . By construction, the following holds:

$$y = \sum_{i=1}^{m} y_i = \sum_{j=1}^{m} \sum_{i=1}^{m} \lambda_{ij} \cdot p_i(e_{ij}) = \sum_{i=1}^{m} \sum_{j=1}^{m} \lambda_{ij} \cdot p_i(e_{ij})$$
$$= \sum_{i=1}^{m} p_i(0) = \sum_{i=1}^{m} c_i \quad (6)$$

where for any  $\{i\}_{i=1,...,m}e_{i1},\ldots,e_{im}$  are distinct non-zero field elements and  $\lambda_{i1},\ldots,\lambda_{im}$  are corresponding Lagrange's coefficient for any univariate polynomial of degree t over finite field  $\mathbb{F}_N$ . Additionally, by construction we have the following:

$$\sigma = \prod_{j=1}^{m} \sigma_j = \prod_{j=1}^{m} H(y_j) = \prod_{j=1}^{m} g^{y_j} = g^{\sum_{j=1}^{m} y_j} = g^y = H(y)$$
(7)

$$\prod_{j=1}^{m} \tau_{j} = \prod_{j=1}^{m} g^{c_{j}+PR_{j}} = g^{\sum_{j=1}^{m} c_{j}} g^{\sum_{j=1}^{m} PR_{j}}$$
$$= g^{\sum_{j=1}^{m} c_{j}} g^{\sum_{j=1}^{m-1} PR_{j}+PR_{m}} = g^{\sum_{j=1}^{m} c_{j}} g^{\phi(N)} \Big[ \frac{\sum_{j=1}^{m} PR_{j}}{\phi(N)} \Big]$$
$$= g^{\sum_{j=1}^{m} c_{j}} = g^{\sum_{j=1}^{m} c_{1}+\ldots+c_{m}} \stackrel{Refer}{=} \frac{Eq. \ (6)}{g} g^{y} = H(y) \quad (8)$$

Combining equations (7) and (8), we get  $\sigma = \prod_{i=1}^{m} \tau_i \wedge \prod_{i=1}^{m} \tau_i = H(y)$  holds. Thus, *VAHSS.Verify* outputs 1 with probability 1. Now, for an incorrect y', the following happens:

**VAHSS. Verify**
$$(\tau_1, \tau_2, \dots, \tau_n, \sigma', y') = 1 \Rightarrow \sigma' = \prod_{i=1}^m \tau_i \wedge \prod_{i=1}^m \tau_i$$
  
=  $H(y') \Rightarrow \prod_{i=1}^m \tau_i = H(y') \overset{Refer Eq. (8)}{\Rightarrow} H(y) = H(y')$ 

which is a contradiction as  $y \neq y'$  and H is collision-resistant. Thus, the probability of the verification scheme executing successfully is less than desirable. Hence, in our proposed scheme  $F_i$  can detect forged results with a high probability.

#### VI. EXPERIMENTAL ANALYSIS AND RESULTS

This section first describes an industrial IoT use case along with the datasets used for experimentation. Next, we evaluate SPRITE both theoretically and experimentally.

# A. Industrial IoT Use Case

The integration of collaborative learning in IIoT can bring rapid transformation in industrial applications (e.g. smart manufacturing). With the help of collaborative learning manufacturers and suppliers can predict different metrics by accumulating training data from industries distributed across the globe. For example, a company might have its plants located at different geographical locations which are operating under varied climatic conditions. In such a scenario, these plants can jointly train a robust global model while keeping its training data private to the corresponding IIoT devices. This model can then be used to predict the production quantity or product quality depending upon the needs. Similarly, the product suppliers might also want feedback from its clients (e.g. manufacturing industries) and thereby generate a global predictive maintenance model by aggregating local models trained by its various clients. Such a model can then be used to detect faults or predict the remaining useful life of a particular machinery and warn the clients beforehand to take necessary actions and prevent breakdown of assembly lines. The advantages of such a distributed setup are listed below:

- Industries can train their models concurrently while sensitive data remains on-premise.
- The final global model is able to predict outcomes under different operational conditions.

## B. Datasets

We have used two different datasets [31, 32] for the experimental evaluation of SPRITE which are discussed below.

1) Combined Cycle Power Plant Dataset : A combined cycle power plant (CCPP) is a thermodynamic system consisting of one steam turbine, two gas turbines and two heat recovery systems. Correctly predicting the full load electrical power output of a base load power plant is crucial for improving the efficiency and maximising the profit from the available megawatt hours [33]. This dataset [31] consists of four input variables: ambient temperature (AT), relative humidity (RH), atmospheric pressure (AP) and exhaust vaccum (V). Full load electrical power output ( $P_E$ ) is the target variable. The dataset is composed of 9568 data points collected over a six-year period (2006–2011) where the CCPP was set to work with a full load over 674 different days. Since, this dataset deals with predicting a real-value, we implement the linear regression version of SPRITE on this dataset.

2) Microsoft Azure Telemetry Dataset : This real-time telemetry dataset [32] was created for Predictive Maintenance in 2015 by Microsoft Azure Intelligence Gallery using data simulation methods. The real-time data collected from hundred machines was averaged over every hour to formulate this dataset which is composed of 290601 data points [34]. It consists of thirty input variables like voltage, pressure, rotation, vibration measurements, machine information (e.g. type, age) and historical maintenance records that include failures, error messages. The goal of our experiment is to estimate the probability that a machine will fail due to a component failure in the next 24 hours. The dataset records four components (*comp1, comp2* etc.) which may fail. Thus, we have a total of five classes including *no failure*. Since, this boils down to a classification problem, we implement the logistic regression version of SPRITE on this dataset. As we know that logistic regression can deal with only binary classification problems, we implement a one-vs-rest logistic regression (OVR) for this dataset where the model gets trained once for each class.

# C. Theoretical Overhead Analysis

The computation and communication overheads are measured in terms of execution time and number of transmitting bytes respectively for a single device of each type. It is assumed that the size of each element computed by any entity is 1 byte. Table I summarizes the notations used. We consider x = 4, 30 for linear and logistic regressions respectively and c = 5 in expressing the overhead measurements. The overheads are calculated for a single round of iteration of the collaborative learning algorithms. Table II shows the detailed overhead calculation where the competing schemes have been implemented using the datasets described in Section VI-B.

TABLE I: Notations used for Theoretical Analysis

Notations	Meaning
$T_{Dot}$	Time to perform a dot product
$T_A/T_S/T_M/T_D$	Time to perform one addition/subtraction/multiplication/division
$T_E$	Time to perform an exponentiation
$T_I$	Time to perform one inverse operation
$T_{Mod}$	Time to perform a modulus operation
s	Number of training samples possessed by an IIoT device
x	Number of features/columns in the dataset
n	Number of IIoT devices within a cluster
N/m	Total number of IIoT devices/Fog nodes in the system
$\hat{t}$	Degree of polynomial used in Secret Sharing
с	Number of classes in Logistic Regression
H	Message digest produced by hash function H

Computation Overhead: We observe that apparently the computation overhead of SPRITE for IIoT devices is slightly greater compared to PrivColl [3]. This is because we implement Shamir's Threshold Secret Sharing [26] contrary to Additive Secret Sharing [35] used by PrivColl. As a result, at the cost of a little extra computation, we achieve robustness to IIoT device dropout in the system. However, computation overheard for IIoT devices notably reduces with increasing number of total devices (N) in the network, thus making SPRITE fairly scalable. This happens because SPRITE applies secret sharing to IIoT devices (n) belonging to a particular cluster contrary to PrivColl which applies secret sharing on the total number of IIoT devices (N) in the system. Similarly, the cumulative computation overhead of fog and cloud for SPRITE is greater than that of cloud for PrivColl. This is primarily because we have added a verifiability scheme to ensure that cloud cannot forge/alter its output and secondarily share reconstruction is slightly costlier for our dropout-resilient scheme.

**Communication Overhead:** The focus is to always reduce burden on the low-powered IIoT devices to save its energy. We observe, that SPRITE has been able to substantially reduce the communication overhead for an IIoT device compared to PrivColl. For example, when (N, n) = (1000, 100) and x = 4, communication overhead for an IIoT device is 500 bytes and 5000 bytes for SPRITE and PrivColl respectively in case of

			Linear Regression			Logistic Regression			
Entities	Tasks	Computation Overhead		Communication Overhead (bytes)		Computation Overhead		Communication Overhead (bytes)	
		SPRITE	PrivColl [3]	SPRITE	PrivColl [3]	SPRITE	PrivColl [3]	SPRITE	PrivColl [3]
	Local Training	$2T_{Dot} + 2sT_S + (2s - 1)T_A$	$2T_{Dot} + 2sT_S$ + $(2s - 1)T_A$			$\frac{c[2T_{Dot} + T_D + T_A + (x+1)T_E + sT_S]}{T_A + (x+1)T_E + sT_S]}$	$\frac{c[2T_{Dot} + T_D + T_A + (x+1)T_E + sT_S]}{T_A + (x+1)T_E + sT_S]}$		
HoT Device	Generating Shares	$\begin{array}{l} (x+1)[(n\hat{t}+n-1)T_A+(n\hat{t}\\+2n-1)T_M+(n-1)T_I] \end{array}$	$(x + 1)[(N - 1)(2T_A + T_{Mod} + T_S)]$	n(x+1)	N(x+1)	$c(x+1)[(n\hat{t}+n-1)T_A + (n\hat{t}+2n-1)T_M + (n-1)T_I]$	$c(x + 1)[(N - 1)(2T_A + T_{Mod} + T_S)]$	cn(x+1)	cN(x+1)
	Adding Shares	$(x + 1)[(n - 1)(T_A + T_{Mod})]$	$(x + 1)[(N - 1)(T_A + T_{Mod})]$			$c(x+1)[(n-1)(T_A + T_{Mod})]$	$c(x + 1)[(N - 1)(T_A + T_{Mod})]$		
	Model Update	$(x + 1)T_S$	$(x + 1)(T_S + T_M)$			$c(x + 1)T_S$	$c(x + 1)(T_S + T_M)$		
	Share Reconstruction	$(x + 1)[(n\hat{t} + n - 1)(T_A + T_M) + (n - 1)T_{Mod}]$				$c(x + 1)[(n\hat{t} + n - 1)(T_A + T_M) + (n - 1)T_{Mod}]$			
Fog Node	Secret Share	$(x + 1)[(m\hat{t} + m)T_A + (m\hat{t} + m + 1)T_E]$	-	(x+1)(m +  H  + 2)	-	$c(x + 1)[(m\hat{t} + m)T_A + (m\hat{t} + m + 1)T_E]$	-	c[(x+1)(m +  H  + 1)]	-
	Partial Eval	$(x + 1)[(m - 1)T_A]$		(1)		$c(x+1)[(m-1)T_A]$		111171	
	Partial Proof	$(x + 1)[(m - 1)T_A + T_E]$				$c(x+1)[(m-1)T_A + T_E]$			
	Verify	$(x + 1)[T_D + T_M + T_S]$				$c(x + 1)[T_D + T_M + T_S]$			
	Partial Derivative	$2(x + 1)T_M$				$2c(x + 1)T_M$			
	Final Eval	$(x + 1)[(m - 1)T_A]$	-			$c(x + 1)[(m - 1)T_A]$	-		
Cloud	Final Proof	$(x + 1)[(m - 1)T_M]$	-	(x + 1)	$(r \pm 1)$	$c(x+1)[(m-1)T_M]$	-	c[(x + 1)]	$c(x \pm 1)$
Ciouu	Share Reconstruction	-	$(x + 1)[(N - 1)(T_A + T_{Mod})]$	( H  + 1)	(2 + 1)	-	$c(x + 1)[(N - 1)(T_A + T_{Mod})]$	( H  + 1)]	C(2   1)
	Partial Derivative	-	$(x + 1)T_M$			-	$c(x+1)T_M$		

TABLE II: Theoretical Overhead Analysis

linear regression. Thus, SPRITE is 10 times less intensive compared to PrivColl thereby establishing its improved energy management ability over PrivColl. Lastly, we observe that SPRITE ensures additional security (i.e. verifiability) at the cost of a little extra communication by fog and cloud.

## D. Testbed Implementation

Here, we implement SPRITE and validate its performance through an experimental testbed.

1) Setup: Experimentation is conducted through testbed where multiple Raspberry Pi(s) (RPI-3B) equipped with DHT11 temperature-humidity sensors act as the Industrial IoT Device (D). A couple of laptops have been used to act as fog nodes and a desktop acts as the server (cloud) in this setup. The specifications of devices used in the testbed are shown in Table III.

2) Evaluation Metrics: We use four metrics to evaluate our prototype such as execution time, Root Mean Square Error (RMSE), R-squared (R2) score and accuracy. Execution time refers to the time taken by an entity (fog, cloud) to perform an operation (e.g. training). RMSE is a standard way to evaluate the error of a model in predicting quantitative data. It is the measure of how well a regression line fits the data points, i.e. how close the observed data points are to the model's predicted values. On the other hand, R2 is a statistical measure that represents the goodness of fit of a regression model. The ideal value for R2 is 1. Finally, accuracy is defined as the number of correctly predicted data points out of all the data points and is a common metric used for evaluating classification models.

TABLE III: Testbed S	Setup S	pecifications
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Specifications	HoT Device/s (D)	Fog Node/s (F)	Server
Memory	1 GBB	3.8 GiB	7.7 GiB
Processor	Cortex-A53, armv71 @1200MHz * 4	Intel® Core <sup>™</sup> i5-7200U CPU @ 2.50GHz * 4	Intel® Core <sup>™</sup> i7-6700 CPU @ 3.40GHz * 8
OS	32-bit Raspbian	64-bit Ubuntu 18.04.3	64-bit Ubuntu 18.04.3
Disk	16 GB	455.1 GB	983.4 GB

3) Results and Discussion: In our experimentation, linear and logistic regression have been applied on the CCPP (Section VI-B1) and Azure Telemetry (Section VI-B2) dataset respectively. We conduct five sets of experiments. For each set, the average results of ten independent runs with respect to each task/dataset size has been registered until the training algorithm converged. Among these, in two set of experiments we compare the performance of our proposed scheme with a state-of-the art competitor scheme, PrivColl [3] while in another set of experiment, we compare it with a state-of-theart verifiability scheme, VFL [20]. The same environment has been used during evaluation of all the competing schemes. We chose the work [3] for comparison with SPRITE because it is the closest competitor to our scheme whereas we chose the work [20] for verifiability comparison because it the most relevant scheme in this context. The rest of the experiments deal only with the performance evaluation of various features specific to SPRITE, hence comparing it with either PrivColl or VFL is irrelevant.

In the first set of experiment, Table IV shows the execution time of each party while training a global model with the maximum number of available training samples for both the competing schemes. The Table records such results for different combinations of devices (N, n) in the network. It is observed that the execution time of IIoT devices is less for SPRITE compared to PrivColl. Moreover, the reduction factor notably increases with growing number of devices in the network. Though the summation of execution times of fog and cloud is more in SPRITE compared to that of just the cloud in PrivColl, the overall execution time of SPRITE is considerably less than PrivColl for both the regression models.

In the second set of experiment, Table V shows the execution time of each of the sub-tasks involved in verifiability for SPRITE as well as VFL [20] (where **p** is the security parameter used by VFL). For our scheme, it is observed that the time taken by each of the sub-tasks is drastically less than the time taken by the sub-tasks in VFL. Even the intensive verification step is significantly faster for SPRITE compared to VFL which is exorbitantly high. Precisely, the total time taken by SPRITE to implement its entire verification mechanism is of the order of a few milliseconds, whereas VFL almost takes a few seconds to implement its verification scheme . Thus, SPRITE's verification mechanism is fairly lightweight compared to VFL. In the third set of experiment, we plot (Fig. 4a and 4b) the

TABLE IV: Execution Time of each party with increasing number of IIoT devices in the network

		Line	ar Regres	sion			Logisti	ic Regress	sion	
(N, N)		SPRITE	TE PrivColl [3] SPRITE			-	PrivColl	[3]		
Devices	HoT Device	Fog Node	Cloud	HoT Device	Cloud	HoT Device	Fog Node	Cloud	HoT Device	Cloud
	(sec)	(ms)	(ms)	(sec)	(ms)	(min)	(sec)	(sec)	(min)	(sec)
(50, 10)	11.906	3270.869	33.584	18.675	160.239	10.002	97.933	1.008	11.359	4.614
(100, 10)	12.280	3502.289	33.584	25.991	311.439	10.048	104.876	1.008	12.735	9.150
(200, 20)	13.521	4245.284	33.584	41.569	613.914	10.173	127.166	1.008	15.790	18.225
(400, 40)	17.775	6453.734	33.584	73.010	1231.909	10.577	193.419	1.008	22.313	36.763
(500, 50)	21.450	8187.034	33.584	89.098	1543.854	10.916	245.418	1.008	25.535	46.123
(800, 80)	32.472	12766.334	33.584	142.046	2497.809	11.898	382.797	1.008	28.567	74.742
(1000, 100)	45.070	19881.294	33.584	183.745	3143.784	12.996	596.246	1.008	49.901	94.121
	with (500, 50) devic with (1000, 100) dev *	es – Priv vices – Priv	500 devices 1000 devices	← SPRI	TE with (500, 50) de TE with (1000, 100)	evices →	PrivColl [3 ←PrivColl [3	i] with 500 devices i] with 1000 devices		
E 100 EXECUTION 0 E	500 3000	4500 60	100 751	• • • • • • • • • • • • • • • • • • •	Execution Ti	90000 120	000 1500	0 18	0000 210000	
	Size	e of Dataset					Size of Datas	et		



(b) Logistic Regression

Fig. 4: Overall Execution Time with increasing dataset size

overall execution time for training a global model for different combination of devices (N, n) in the network. We observe from both the figures, that execution time grows marginally with increasing dataset size. We also observe that the execution time of SPRITE is considerably less than PrivColl. Even when training the model with (1000, 100) devices SPRITE records less execution time compared to training the same model with 500 devices using PrivColl. Lastly, we observe that while training the models with (1000, 100) devices SPRITE records 65% and 55% improved performance for linear and logistic regressions respectively compared to PrivColl.

TABLE VI: Various Performance Metrics for Linear and Logistic Regressions

Linear R	Regression		Logistic Regression			
Size of Dataset	RMSE	R2	Size of Dataset	Accuracy (%)		
1500	5.778	0.867	90000	99.63		
3000	4.877	0.915	120000	99.69		
4500	4.803	0.925	150000	99.70		
6000	4.539	0.928	180000	99.74		
7500	4.51	0.932	210000	99.74		
9000	4.486	0.933	-			

In the fourth set of experiment, we evaluate (Table VI) SPRITE in terms of other relevant parameters with varying dataset size. We observe that as the dataset size increases, RMSE score starts decreasing which indicates that the regression line fits better with increasing training samples. Similarly, as the dataset size increases, R2 score starts increasing and reaches a value close to one which is the ideal scenario. Finally, accuracy (%) also increases with increasing dataset size and reaches a plateau when the model is trained with larger training samples. Thus, we can claim that SPRITE replicates performance similar to the traditional models trained using centralised machine learning algorithms while still achieving the benefits offered by this distributed setup.

In the last set of experiment, we plot (Fig. 5) execution time of each sub-task involved in verifiability with increasing number

TABLE V: Execution Time of each task involvedin Verifiability

	SPRITE	VFL [20]			
Tasks	Linear Regression (ms)	Logistic Regression (ms)	Tasks	p=4 (ms)	p=8 (ms)
Generate Shares	1.365	6.825	Ensmation	1202	4016
Partial Eval	0.0148	0.0740	Encryption	1585	4910
Partial Proof	0.0148	0.0740	Desmutian	061	4270
Final Eval	0.0044	0.0216	Decryption	901	+3/9
Final Proof	0.0047	0.0226	Marif anti-	225	(22
Verify	0.0172	0.0860	vernication	525	025
Total Time (mc)	1.421	7 102	Total Time (mc)	2660	0019



Fig. 5: Execution Time of each sub-task in Verifiability with increasing Fog nodes

of fog nodes to test the scalability of SPRITE. We observe that, execution time of task Generate Shares increases by  $\approx 1\% - 1.5\%$  with increasing fog nodes. The tasks Partial Eval and Partial Proof takes roughly the same time with increase in number of fog nodes, expect for a slight spike when the number of fog nodes is seven. The execution time for tasks Final Eval and Final Proof increases almost linearly with increasing fog nodes. Lastly, execution time of task Verify increases by  $\approx 0.8\% - 2.6\%$  with increasing fog nodes and almost stabilises for larger number of fog nodes, which is a great achievement as it is the most crucial step for any verification scheme.

We summarily observe from the entire testbed experimentation that SPRITE achieves superior performance compared to PrivColl while guaranteeing additional security features. We also observe, SPRITE's verification mechanism is lightweight compared to a state-of-the-art competitor, VFL. It is also observed that SPRITE scales considerably well for a large industrial setup. Lastly, we observe that SPRITE has been able to drastically reduce overheads on the IIoT devices and trust dependence on the cloud by introducing the concept of fog and verifiability. Hence, we claim that SPRITE fits into the requirement of Industrial IoT applications very well.

## E. Discussion

To the best of our knowledge, such a fog-based network design still remains unexplored in an industrial collaborative learning setup. Further, SPRITE is resilient to device-dropout which was missing in PrivColl. Lastly, SPRITE can efficiently handle the issue of forged aggregated model generated by a malicious server, which was a major bottleneck in PrivColl, thereby making SPRITE ideal for real-life applications.

## VII. CONCLUSION

We have presented SPRITE, a scalable and lightweight privacy-preserving, verifiable collaborative learning framework for IIoT. It is suitable for training both linear and logistic regression models. SPRITE guarantees data/model privacy, verifiability of aggregated results returned by a malicious server thereby preventing forgery on model update. It also ensures robustness to IIoT device dropout. The security of SPRITE is analyzed under an *honest-but-curious* setting where the cloud is *untrustworthy*. SPRITE outperforms the competitors proving its practicality in large-scale industrial applications. In future, we intend to redesign SPRITE to handle collusion cases and detect malicious party/s in case of any corrupt behaviour while adhering to the general workflow.

#### REFERENCES

- Mohammad Aazam, Sherali Zeadally, and Khaled A. Harras. Deploying Fog Computing in Industrial Internet of Things and Industry 4.0. *IEEE Transactions on Industrial Informatics*, 14(10):4674–4682, 2018.
- [2] Kalikinkar Mandal and Guang Gong. PrivFL: Practical Privacy-Preserving Federated Regressions on High-Dimensional Data over Mobile Networks. In Proceedings of the 2019 ACM SIGSAC Conference on Cloud Computing Security Workshop, page 57–68, 2019.
- [3] Yanjun Zhang, Guangdong Bai, Xue Li, Caitlin Curtis, Chen Chen, and Ryan K. L. Ko. PrivColl: Practical Privacy-Preserving Collaborative Machine Learning. In Liqun Chen, Ninghui Li, Kaitai Liang, and Steve Schneider, editors, *Computer Security – ESORICS*, pages 399– 418, 2020.
- [4] Beongjun Choi, Jy-yong Sohn, Dong-Jun Han, and Jaekyun Moon. Communication-Computation Efficient Secure Aggregation for Federated Learning. *CoRR*, abs/2012.05433, 2020.
- [5] Fengwei Wang, Hui Zhu, Rongxing Lu, Yandong Zheng, and Hui Li. A privacy-preserving and non-interactive federated learning scheme for regression training with gradient descent. *Information Sciences*, 552:183–200, 2021.
- [6] Matt Fredrikson, Somesh Jha, and Thomas Ristenpart. Model Inversion Attacks That Exploit Confidence Information and Basic Countermeasures. In Proceedings of the 22nd ACM SIGSAC Conference on Computer and Communications Security, page 1322–1333, 2015.
- [7] Luca Melis, Congzheng Song, Emiliano De Cristofaro, and Vitaly Shmatikov. Exploiting Unintended Feature Leakage in Collaborative Learning. In 2019 IEEE Symposium on Security and Privacy, pages 691–706, 2019.
- [8] Zhibo Wang, Mengkai Song, Zhifei Zhang, Yang Song, Qian Wang, and Hairong Qi. Beyond Inferring Class Representatives: User-Level Privacy Leakage From Federated Learning. In *IEEE INFOCOM 2019 - IEEE* Conference on Computer Communications, pages 2512–2520, 2019.
- [9] Huadi Zheng, Qingqing Ye, Haibo Hu, Chengfang Fang, and Jie Shi. BDPL: A Boundary Differentially Private Layer Against Machine Learning Model Extraction Attacks. In *Computer Security – ESORICS 2019*, pages 66–83, 2019.
- [10] Yaochen Hu, Di Niu, Jianming Yang, and Shengping Zhou. FDML: A Collaborative Machine Learning Framework for Distributed Features. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, page 2232–2240, 2019.
- [11] Kang Wei, Jun Li, Ming Ding, Chuan Ma, Howard H. Yang, Farhad Farokhi, Shi Jin, Tony Q. S. Quek, and H. Vincent Poor. Federated Learning With Differential Privacy: Algorithms and Performance Analysis. *IEEE Transactions on Information Forensics and Security*, 15:3454– 3469, 2020.
- [12] Yunlong Lu, Xiaohong Huang, Yueyue Dai, Sabita Maharjan, and Yan Zhang. Differentially Private Asynchronous Federated Learning for Mobile Edge Computing in Urban Informatics. *IEEE Transactions on Industrial Informatics*, 16(3):2134–2143, 2020.
- [13] Keith Bonawitz, Vladimir Ivanov, Ben Kreuter, Antonio Marcedone, H. Brendan McMahan, Sarvar Patel, Daniel Ramage, Aaron Segal, and Karn Seth. Practical Secure Aggregation for Privacy-Preserving Machine Learning. In Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security, page 1175–1191, 2017.
- [14] Stacey Truex, Nathalie Baracaldo, Ali Anwar, Thomas Steinke, Heiko Ludwig, Rui Zhang, and Yi Zhou. A Hybrid Approach to Privacy-Preserving Federated Learning. In *Proceedings of the 12th ACM Workshop on Artificial Intelligence and Security*, page 1–11, 2019.

- [15] Renuga Kanagavelu, Zengxiang Li, Juniarto Samsudin, Yechao Yang, Feng Yang, Rick Siow Mong Goh, Mervyn Cheah, Praewpiraya Wiwatphonthana, Khajonpong Akkarajitsakul, and Shangguang Wang. Two-Phase Multi-Party Computation Enabled Privacy-Preserving Federated Learning. In 2020 20th IEEE/ACM International Symposium on Cluster, Cloud and Internet Computing (CCGRID), pages 410–419, 2020.
- [16] Yong Li, Yipeng Zhou, Alireza Jolfaei, Dongjin Yu, Gaochao Xu, and Xi Zheng. Privacy-Preserving Federated Learning Framework Based on Chained Secure Multiparty Computing. *IEEE Internet of Things Journal*, 8(8):6178–6186, 2021.
- [17] Hangyu Zhu, Rui Wang, Yaochu Jin, Kaitai Liang, and Jianting Ning. Distributed Additive Encryption and Quantization for Privacy Preserving Federated Deep Learning. *CoRR*, abs/2011.12623, 2020.
- [18] Chunyi Zhou, Anmin Fu, Shui Yu, Wei Yang, Huaqun Wang, and Yuqing Zhang. Privacy-Preserving Federated Learning in Fog Computing. *IEEE Internet of Things Journal*, 7(11):10782–10793, 2020.
- [19] Xianglong Zhang, Anmin Fu, Huaqun Wang, Chunyi Zhou, and Zhenzhu Chen. A Privacy-Preserving and Verifiable Federated Learning Scheme. In *ICC 2020 - 2020 IEEE International Conference on Communications* (*ICC*), pages 1–6, 2020.
- [20] Anmin Fu, Xianglong Zhang, Naixue Xiong, Yansong Gao, and Huaqun Wang. VFL: A Verifiable Federated Learning with Privacy-Preserving for Big Data in Industrial IoT. *CoRR*, 2020.
- [21] Guowen Xu, Hongwei Li, Sen Liu, Kan Yang, and Xiaodong Lin. VerifyNet: Secure and Verifiable Federated Learning. *IEEE Transactions* on Information Forensics and Security, 15:911–926, 2020.
- [22] Gang Han, Tiantian Zhang, Yinghui Zhang, Guowen Xu, Jianfei Sun, and Jin Cao. Verifiable and Privacy Preserving Federated Learning without Fully Trusted Centers. *Journal of Ambient Intelligence and Humanized Computing*, pages 1–11, 2021.
- [23] Yi Liu, Ruihui Zhao, Jiawen Kang, Abdulsalam Yassine, Dusit Niyato, and Jialiang Peng. Towards Communication-efficient and Attack-Resistant Federated Edge Learning for Industrial Internet of Things. *CoRR*, 2020.
- [24] Yunlong Lu, Xiaohong Huang, Yueyue Dai, Sabita Maharjan, and Yan Zhang. Blockchain and Federated Learning for Privacy-Preserved Data Sharing in Industrial IoT. *IEEE Transactions on Industrial Informatics*, 16(6):4177–4186, 2020.
- [25] Weishan Zhang, Qinghua Lu, Qiuyu Yu, Zhaotong Li, Yue Liu, Sin Kit Lo, Shiping Chen, Xiwei Xu, and Liming Zhu. Blockchain-Based Federated Learning for Device Failure Detection in Industrial IoT. *IEEE Internet of Things Journal*, 8(7):5926–5937, 2021.
- [26] Adi Shamir. How to Share a Secret. Commun. ACM, 22(11):612–613, November 1979.
- [27] M.N. Krohn, M.J. Freedman, and D. Mazieres. On-the-fly verification of rateless erasure codes for efficient content distribution. In *IEEE Symposium on Security and Privacy*, 2004. Proceedings. 2004, pages 226–240, 2004.
- [28] Georgia Tsaloli, Gustavo Banegas, and Aikaterini Mitrokotsa. Practical and Provably Secure Distributed Aggregation: Verifiable Additive Homomorphic Secret Sharing. *Cryptography*, 4(3), 2020.
- [29] Jen-Sheng Tsai, I-Hsun Chuang, Jie-Jyun Liu, Yau-Hwang Kuo, and Wanjiun Liao. QoS-Aware Fog Service Orchestration for Industrial Internet of Things. *IEEE Transactions on Services Computing*, 2020.
- [30] J. Sengupta, S. Ruj, and S. D. Bit. A Secure Fog-Based Architecture for Industrial Internet of Things and Industry 4.0. *IEEE Transactions* on *Industrial Informatics*, 17(4):2316–2324, 2021.
- [31] Pınar Tüfekci and Heysem Kaya. Combined Cycle Power Plant Data Set. https://archive.ics.uci.edu/ml/datasets/combined+cycle+power+ plant, 2012.
- [32] Microsoft Azure Intelligence Gallery. Microsoft Azure Telemetry Dataset for Predictive Maintenance. https://www.kaggle.com/ arnabbiswas1/microsoft-azure-predictive-maintenance, 2015.
- [33] Pinar Tüfekci. Prediction of full load electrical power output of a base load operated combined cycle power plant using machine learning methods. *International Journal of Electrical Power & Energy Systems*, 60:126–140, 2014.
- [34] Basheer Qolomany, Kashif Ahmad, Ala Al-Fuqaha, and Junaid Qadir. Particle Swarm Optimized Federated Learning For Industrial IoT and Smart City Services. In *GLOBECOM 2020 - 2020 IEEE Global Communications Conference*, pages 1–6, 2020.
- [35] Dan Bogdanov, Sven Laur, and Jan Willemson. Sharemind: A Framework for Fast Privacy-Preserving Computations. In *Computer Security* - *ESORICS*, pages 192–206, 2008.