Federated Learning for Intrusion Detection in IoT Security: A Hybrid Ensemble Approach

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Abstract—Critical role of Internet of Things (IoT) in various domains like smart city, healthcare, supply chain and transportation has made them the target of malicious attacks. Past works in this area focused on centralized Intrusion Detection System (IDS), assuming the existence of a central entity to perform data analysis and identify threats. However, such IDS may not always be feasible, mainly due to spread of data across multiple sources and gathering at central node can be costly. Also, the earlier works primarily focused on improving True Positive Rate (TPR) and ignored the False Positive Rate (FPR), which is also essential to avoid unnecessary downtime of the systems. In this paper, we first present an architecture for IDS based on hybrid ensemble model, named PHEC, which gives improved performance compared to state-of-the-art architectures. We then adapt this model to a federated learning framework that performs local training and aggregates only the model parameters. Next, we propose Noise-Tolerant PHEC in centralized and federated settings to address the label-noise problem. The proposed idea uses classifiers using weighted convex surrogate loss functions. Natural robustness of KNN classifier towards noisy data is also used in the proposed architecture. Experimental results on four benchmark datasets drawn from various security attacks show that our model achieves high TPR while keeping FPR low on noisy and clean data. Further, they also demonstrate that the hybrid ensemble models achieve performance in federated settings close to that of the centralized settings.

Index Terms—IoT Security, Ensemble Learning, Federated Learning, Noise Robust Classification

I. INTRODUCTION

Internet of Things (IoT) are one of the most effective combinations of physical objects and networks. It involves the uses of embedded systems, wireless networks, machine learning, automation and many other fields. As IoT are becoming critical infrastructure, they can be targets of attackers and need to be proactively protected. Intrusion detection system (IDS) is one of the most common security mechanisms used to thwart malicious attacks. IDS may be anomaly-based or signature-based. Signature-based models generally work well for previously known attacks but not for new/unknown attacks. Machine learning models are increasingly applied in IDS, which work better in detecting previously unknown attacks.

Most of the attacks in IoT networks can be broadly categorized into four groups: Denial of Service (DoS), Probe, Remote to Local (R2L), User to Root (U2R). According to the literature [1], [2]. U2R and R2L mimic normal traffic characteristics to a huge extent and hence, difficult to detect. In modern days, a huge number of IoT devices can be connected to a vast network and not all part of the networks see these attacks in equal proportions. For example, some portion of the network may see DoS attack more while the other portion may see more U2R and R2L attacks. Hence data pertaining to these attacks are often collected at a centralized facility to train the models which can detect all type of attacks. However, transferring data to the central node may incur high transfer costs, significant communication overhead, operational constraints [3]. Moreover, due to privacy concerns, it may not be practically feasible to collect data from many devices and store them in a single entity.

In many IoT networks, the nodes are often equipped with enough computational capabilities such that they can process the data locally. Hence instead of collecting the data at a central node, each source node can train models locally and only share the parameters of the trained models with the central node that can combine the shared parameters appropriately to get the final aggregated model. This federated learning has emerged as a popular method where nodes cooperate, connect and form an aggregated model. This work proposes a Probabilistic Hybrid Ensemble Classification (PHEC) model for detecting threats in IoT networks (in centralized settings) and adapting it to federated settings. The term hybrid in PHEC signifies that multiple classifiers of different types are combined to predict labels. The term probabilistic indicates that the confidence value in the predicted label is taken into consideration rather than the actual labels of the individual classifiers. Also, Ensemble suggests that a group of classifiers work to give better results.

The main advantage of the PHEC model is its versatility and flexibility – we can achieve from low False Positive Rate (FPR) to high True Positive Rate (TPR) by tuning the threshold $\gamma$. As is well know in the literature, simultaneously achieving high TPR and low FPR may not be practically feasible – decreasing FPR reduces TPR and increasing TPR raises FPR [4], [5]. Depending on the type of application, high TPR may be more desirable while FPR up to a threshold is acceptable (fire alarm systems, health and medical diagnosis etc.); in other cases, low FPR is more critical while TPR above a threshold is desirable (justice systems). The proposed model can be adapted to application needs by simply tuning a single hyperparameter $\gamma$ to achieve the desired trade-off between TPR and FPR.

In the centralized setup of PHEC, we first process the data and perform dimensionality reduction. Two classifiers based on KNN and Random forest algorithms are trained separately.
using the extracted set of features. Then, the classifiers’ outputs are averaged and depending on whether the average is above pre-defined threshold, the final label is decided.

PHEC model is also adapted to federated settings with suitable modifications. In federated settings, model parameters (the weights and biases) need to be shared across devices. However, as there are no weights associated with KNN and Random Forest, we use Multi-layer Perceptron (MLP) for training at each node. The final output is the ensemble result of all the Multi-layer Perceptrons.

In the federated setup, model parameters obtained by averaging the node parameters may not be good in detecting rare attacks. This is because during training, nodes generally face more samples of common attacks like DoS and Probe, which contribute more in defining the aggregated model. So, relatively infrequent attacks become difficult to detect. Another problem that may arise is that different nodes often face different type of attacks (different attacks generally have different characteristics). As an example, let’s say node-1 faces more DoS attacks and node-2 faces mostly Probe attacks. Let \( W_1, W_2 \) denote model parameters for node-1 and node-2 respectively. Even though \( W_1 \) and \( W_2 \) may be very good individually for DoS and Probe attacks respectively, but the federated model obtained by averaging these parameters \( (W_1 + W_2)/2 \) may not be much effective on either of the attacks! The main reason is the non-iid nature of the training data across different nodes. In our proposed model, we aim to overcome these issues. The proposed federated PHEC is designed in a way so that each node gets specialized in detecting a particular kind of an attack and then instead of averaging out, we stack them. This kind of aggregation prevents high influence of majority samples on the aggregated model.

Often accuracy of the federated frameworks [3] is significantly lower compared to the centralized settings. However, the proposed federated PHEC architecture shows good accuracy and TPR while keeping FPR within tolerable limit.

We next consider the case where labels may be corrupted by noise. Performance of most of the supervised machine learning algorithms drop in the presence of noise. We need Noise Robust Models to perform well in the presence of label-noise in the training data. It is seen that classifiers that use weighted convex surrogate loss functions, like Biased SVM and Weighted Logistic Regression are provably noise-tolerant [6]. Using weighted version of the convex surrogate loss functions, we modify the PHEC framework and propose Noise-Tolerant PHEC in federated and centralized settings.

In summary, our contributions are as follows:

- We develop PHEC architecture for centralized IDS that aims to achieve good TPR while keeping FPR below a user-given permissible limit. The hyper-parameter \( \gamma \) allows the system to balance between TPR and FPR.
- To address the privacy concerns related to the data, we adapt PHEC in federated settings. We propose a different kind of model aggregation ‘FedStacking’ here. It is seen from the experiments that federated system works faster than the centralized system.
- We evaluate the performance of PHEC on four standard datasets, namely ‘NSL-KDD’, ‘DS2OS Traffic Traces’, ‘Gas Pipeline Dataset’, ‘Water Tank Dataset’. On the ‘NSL-KDD’ dataset, improvement is up to 10% TPR in centralized settings and up to 6% accuracy in Federated settings. We achieved 1% improvement in TPR on the ‘DS2OS Traffic Traces’ dataset (centralized and federated Settings). We also observed more than 97% TPR for a minimal amount of FPR on both the ‘Gas Pipeline’ and ‘Water Tank’ datasets in centralized and federated Settings.
- To account for the label-noise problem, we propose Noise-Tolerant PHEC in both centralized and federated settings. We are the first to propose Label-Noise Robust Intrusion Detection System in IoT Security to the best of our knowledge.

A. Related Work

Intrusion detection System in Network Security has been well studied in last few years. Existing IDS involves statistical models, machine learning approaches and signal processing models. Classical statistical models like Hidden Markov Model, Bayes Theory [7] have been implemented in this regard. **Centralized IDS setup:** In the domain of Anomaly-based intrusion detection, supervised learning classification models like Random Forest, Naive-Bayes Classifier, SVM, Logistic Regression are often used [8], [9]. Unsupervised approaches [10] come handy especially when there is a shortage of labeled data. A hybrid model based on SVM and hierarchical clustering BIRCH is proposed in [11], which performed well on DoS and Probe attacks but poorly on U2R and R2L attacks. [1] proposed a hybrid model in centralized settings to detect threats in IoT networks. To make the models computationally efficient, [12] applied mutual information to select the optimal number of features for Intrusion Detection System. Most of the earlier works [13]–[15] did not include FPR into account and primarily focused on TPR and accuracy. PHEC is different from the earlier works as we focus on optimizing both FPR and TPR simultaneously to the best possible extent. Its performance is good not only in detecting common attacks like DoS but also in detecting rare category of threats like U2R and R2L.

**Federated IDS setup:** With the advent of fog computing, edge & cloud computing, distributed frameworks have renewed interest. Many researchers have explored federated Learning and its applications in recent past [16] and broader problems and open challenges are discussed in [17]. [3] proposed IDS in federated settings in IoT networks. They compared on-device training and federated learning framework in their work and carried experimentation on the NSL-KDD dataset [18]. Similar work was also done in [19], where Logistic Regression was used to detect threats in IoT networks. Most of the previous works related to federated learning [3], [19] use a simple weighted average (FedAvg) to update the central server model.
Here, we propose a different model aggregation to adapt PHEC in federated settings.

Noise-Tolerant IDS: Label-Noise problem is often studied in the standard classification task. The use of weighted convex surrogate loss functions to reduce the effect of label noise is proposed in [6], [20], [21] provided a sufficient criteria for a loss function to be noise-robust. In this regard, they showed that sigmoid loss, ramp loss, etc. are noise tolerant. [22] showed that risk minimization under 0–1 loss function has impressive noise-tolerance properties. Class-Conditional Noise is also studied by some researchers [23]. Here, we are considering the Symmetric Label Noise (SLN) problem only and have proposed Noise Tolerant IDS in centralized and federated settings.

Organizational of the paper: Section II describes the architecture of the Probabilistic Hybrid Ensemble Classifier. Section III introduces the proposed algorithm in centralized settings and gives its analysis. Section IV discusses the proposed IDS in federated settings and Section V explains how the PHEC can be adapted to address the Symmetric Label Noise (SLN) problem. Section VI gives a brief description of the benchmark datasets used for the experiments. Details of the experiments and results are discussed in Section VIII. Section IX discussions the experiments on noisy labeled data. Conclusions with future work is indicated in Section X.

II. PROBABILISTIC HYBRID ENSEMBLE ARCHITECTURE

In this section we discuss Probabilistic Hybrid Ensemble Classifier (PHEC) for IDS. PHEC involves an ensemble of classifiers whose predictions are combined to label a given sample as threat or normal. Each classifier is separately trained and are applied on each input parallely. A similar setup was proposed by Pajouh [1], where multiple classifiers were used serially and in a sequential manner. The parallel architecture gives the advantage of controlling the False Positive Rate (FPR). We use the standard definitions of TPR and FPR. Let TP, TN denote the number of True Positives & True Negatives respectively and FP, FN denote the number of False Positives & False Negatives respectively. Then,

$$TPR = \frac{TP}{TP+FN} \quad \text{and} \quad FPR = \frac{FP}{FP+TN}.$$ 

PHEC architecture is shown in Figure 1. Let n denote the number of classifiers in PHEC. Each classifier gives a probability or confidence on classifying an input as a threat. For a given sample, let $p_i$ for all $i = 1, 2, \ldots, n$ denote the confidence of the i-th classifier in classifying it as a threat. On $\{p_i\}$s, we apply aggregator function $f : [0, 1]^n \rightarrow [0, 1]$ to get the final score, which is then compared against a threshold $\gamma$. If $f(p_1, p_2, \ldots, p_n) \geq \gamma$, then the sample is labeled as threat, else it is labeled as normal. The parameter $\gamma$ is based on the specified tolerance on FPR.

In security systems, often permissible value of FPR is specified. Let $u$ denote maximum tolerable limit of FPR. Under these circumstances, the objective is to maximize the True Positive Rate (TPR) while keeping the FPR below $u$. For a given $u$, let $g(\gamma)$ denote the TPR and $h(\gamma)$ denote the FPR of PHEC. We set $\gamma \in [0, 1]$ such that it maximizes the TPR subjected to the FPR constraint as follows:

$$\max_{0 \leq \gamma \leq 1} g(\gamma) \quad \text{subjected to} \quad h(\gamma) \leq u. \quad \text{(1)}$$

III. PHEC MODEL IN CENTRALIZED SETUP

This section considers the case where the entire training data can be made available in a single system. We first discuss how each classifier is trained in PHEC and how their outputs are combined to obtain the final label. Figure 2 shows the four stages of the training phase in PHEC.

![Fig. 1. PHEC Architecture](image)

![Fig. 2. Block Diagram of Training Phase](image)
B. Dimensionality Reduction

This part uses Principal Component Analysis (PCA) for dimension reduction. This allows the classification framework to use fewer features and helps to make the detection system faster. However, instead of PCA, some other dimension reduction framework like LDA, Autoencoder can be tried out. However, PCA gave better performance on the NSL-KDD dataset as is evident from Table-IX. We denote the number of extracted features after dimensionality reduction as $M$. This value of $M$ is a hyperparameter that can be suitably chosen. An useful approach may be to use cross-validation to find the best possible value of $M$. However, this cross-validation itself is quite time-consuming and often, close to the optimal number of extracted dimensions workout well practically.

C. Classifier Selection and Training

In the centralized settings, we restrict to fewer classifiers as each classifier is trained on the entire dataset. We set $n = 2$ and use $K$-Nearest Neighbour (KNN) and Random Forest (RF) as the two classifiers. Both the classifiers are trained independently using their probabilistic outputs. One could use other classifiers like SVM, Logistic Regression. However, KNN and Random Forest are preferred due to its simplicity and ensemble nature respectively. Further, the usage of these two classifiers gave better performance than other combinations of classifiers. The aggregator function $f$ is simply the arithmetic mean, i.e., if the prediction probabilities of KNN and Random Forest classifier are $p_1$ and $p_2$ respectively, then

$$f(p_1, p_2) = \frac{(p_1 + p_2)}{2}.$$  

**Tuning $\gamma$:** Finding optimal $\gamma$ over the range $[0, 1]$ is challenging. Instead, we discretize $[0, 1]$ into a finite set of values and search for the best value of $\gamma$. We compute $g(\gamma)$ and $h(\gamma)$ over the validation dataset and obtain optimal value of $\gamma$ by solving optimization problem $\Pi$ (see Eq. (1)) over discrete values of $\gamma$. We denote the optimal value of $\gamma$ as $\gamma^*$.  

D. Testing Phase

For a test sample, let the trained KNN and RF predict the chances that it belongs to ‘Threat’ class with confidence $p_1$ and $p_2$, respectively. Then, the test sample is labeled as ‘Threat’ if $f(p_1, p_2) \geq \gamma^*$, it is labeled ‘Normal’ otherwise.

IV. PHEC IN FEDERATED SETTINGS

In this section we discuss the adaptation of PHEC in federated settings. The federated setup in [19] allows each node to train on local data that includes samples from different type of attacks and non-malicious samples. Then the node parameters are averaged to form the final aggregated model. The drawback of this model is that the training data are often dominated by samples of common attacks and the parameters of the aggregated central model obtained by averaging the parameters of the nodes do not generalize well to detect rare types of attacks. We overcome this issue by specializing each node for detecting a particular kind of attack and then combining them in a slightly different manner. Our federated setup is based on the idea that each node is trained to detect a particular type of attack and the parameters of each node are used separately at the central node to retain the characteristics of each node. We group different attacks in training data into $n$ major category based on their characteristics. One such example of grouping of various attacks is shown in Table-I. The value of $n$ depends on the network size, different devices connected to the network etc. However, most of the attacks that IoT networks face generally fall into any one of the 4 broader groups, namely User to Root (U2R), Remote to Local (R2L), Denial of Service (DoS), and Probe [1]. Hence for practical purposes, $n$ may be chosen as 4.

![Fig. 3. PHEC in federated framework](image)

**Federated Architecture:** The PHEC architecture in the federated setup is shown in Fig. 3. It consists of $n$ nodes and one central node. Each of the $n$ nodes use a local training dataset to train a Multi-Layer Perceptron (MLP) and share their MLP parameters with the central server where they are aggregated. For each sample data, the aggregated model outputs probability vector $(p_1, p_2, \ldots, p_n)$, where $p_i$ corresponds to the probability obtained using the parameters of the $i$ th MLP from $i$ th node. The sample is classified as ‘Threat’ / ‘Normal’ by thresholding $f(p_1, p_2, \ldots, p_n) \geq \gamma^*$. We next discuss how individual models are trained and model parameters are aggregated.

**Dataset Preparation:** For a completely new system, a test-bed may be setup to collect the data. All the samples belonging to $i$ th type of attack are collected and put in group $D(i)$. Now, the remaining non-malicious samples are added to each
group such that the malicious and non-malicious samples are in the ratio $1:1$. Usually, the number of non-malicious samples be much more than the malicious samples and hence multiple datasets with equal proportions of malicious and non-malicious samples can be created.

**Classifier Selection:** In the centralized setup of PHEC, Random Forest and KNN were used. However, they cannot be used in the federated setup as they are non-parametric. For better aggregation, the parametric model MLP is a natural choice. Here, each of the $n$ nodes involved trains one MLP each.

**Label Assignment:** Let $\hat{w}_i$ denote the set of MLP parameters of node $i$. Each sample passes through each of the $n$ MLPs. Let $p_i$ denote the probability that the sample belongs to malicious class as predicted by the MLP parameters of the $i$-th node. The aggregated model combines the probabilities from $n$ MLPs resulting in a probability vector $(p_1, p_2, \ldots, p_n)$. Then apply an aggregate function $f$ as follows:

$$f(p_1, p_2, \ldots, p_n) = \max(p_1, p_2, \ldots, p_n)$$

If $f(p_1, p_2, \ldots, p_n)$ exceeds $\gamma^*$, then the sample is labeled as ‘Threat’, else labeled as ‘Normal’, where $\gamma^*$ is a hyperparameter tuned using a validation set.

Now that the procedure to generate the labels from $\hat{w}_i$ and $\gamma^*$ is clear, we will discuss how to find the matrix $\hat{w}_i$ and the optimal threshold $\gamma^*$.

**Decentralized Training:** Each of the $n$ MLP classifiers is trained using the local dataset available to that particular node ($i$-th node has access to the local dataset $D(i)$). Backpropagation algorithm can be used to tune the parameters (set of weights & biases) of each of the $n$ MLPs.

For node $i = 1, 2, \ldots, n$, node parameters are updated in round $t$ as follows:

1) The gradient is calculated on $D(i)$ as $g_i = \nabla F_i(w_i^t)$, where $F_i(w_i^t)$ is the cross-entropy loss for the $i$-th node with the model parameters $w_i^t$.

2) The parameters of $i$-th node at $(t+1)$ iteration are updated as $w_i^{t+1} \leftarrow w_i^t - \eta g_i$, where $\eta$ is learning rate.

**Model Aggregation:** The model aggregation takes place in the central node. Individual nodes can download and use the aggregated model. The most common technique of model aggregation is FedAvg [3], [19]. Instead of FedAvg, we propose and use a stacked aggregation model (FedStacking).

In IoT networks, different devices may face different attacks, resulting in non-iid data. Federated architecture with FedAvg Aggregation may not perform well on non-iid data. Secondly, the central model in FedAvg gets more influenced by attacks that frequently occur in training data, resulting in poor detection of rare type of attacks (e.g. U2R, R2L).

**FedAvg:** It is the weighted average of all the trained parameters. In the $t$-th iteration, an update of the central server model can be made as,

$$\tilde{w}_t = \sum_{i=1}^{n} \frac{a_i}{\sum_{i=1}^{n} a_i} w_i^t.$$ 

Here, $a_i$ denotes the size of the training data for the $i$ th node ($a_i = |D(i)|$) and $a = \sum_{i=1}^{n} a_i$.

**FedStacking:** We concatenate the parameters of the trained models (of $n$ nodes) in order to store them efficiently. Consider the matrix $\tilde{w}_t$ with the number of columns as $n$ such that $i$ th column corresponds to the model parameters $w_i^t$.

$$\tilde{w}_t = [w_1^t, w_2^t, \ldots, w_n^t]$$

Now the central node just needs to store the matrix $\tilde{w}_t$. The matrix $\tilde{w}_t$ corresponds to the resultant model set of parameters at the end of $t$-th iteration.

**Model Evaluation:** The model is evaluated on a validation dataset. As in the centralized setup, we discretized the values of $\gamma$ over $[0,1]$ into $S$ uniformly spaced values. Given a predefined value of $u$, the training is performed as follows.

For each iteration $t = 1, 2, \ldots$

1) Using $\tilde{w}_t$, generate the probability vector $(p_1, p_2, \ldots, p_n)$ for each sample in the validation data.

2) For each $\gamma \in S$, assign the label to all the samples in the validation data and evaluate associated TPR and FPR.

3) Find optimal $\gamma$ that maximizes TPR while keeping FPR below $u$ (see Eq. [1]). Say the optimal value of $\gamma$ in round $t$ is $\gamma^t$. A

4) Repeat until the stopping criteria is met.

**Stopping Criteria:** With the increase in iteration $t$, if it is seen that TPR has saturated/ TPR starts dropping, the training is stopped and the final parameters are stored. As soon as the central node detects the saturation of TPR, the same is communicated to the nodes and local training at all the nodes also stop. If the training is stopped at $t = T$, then $\gamma^T$ is taken as $\gamma^*$ and $\tilde{w}_T$ gives the final set of parameters. It is important to carefully choose the stopping point: stopping early may underfit the data whereas stopping late may lead to overfitting of data.

The choice of $n$ plays a major role in the federated settings. There may be trade-off between quicker detection and performance metrics. For large value of $n$, as more number of MLP classifiers get involved, Detection time increases (slower detection). On the other hand, with large $n$, we can make more specific grouping of different attacks, it may lead to better performance metrics.

Some of the benchmark datasets will involve a mix of multiple threats. The usual practice is to divide the benchmark datasets into $n$ groups, followed by pre-processing and supplying it locally to each of the individual node [3], [19]. To evaluate the proposed model, it is customary to split the dataset into multiple datasets and use it as local training data.

**V. Symmetric Label Noise-Tolerant PHEC**

Label-Noise is a common problem in the domain of supervised Machine-Learning. Symmetric Label Noise (SLN) is defined as the label noise problem where each label is flipped independently with some probability $\rho \in [0, 0.5]$ and the degree of flipping a label is independent of the actual label of the class. Class-Conditional random noise is the label noise problem where the degree of noise depends on the class in which the instance belongs. Consider a binary classification task with actual label $y \in \{-1, 1\}$ and the flipped label $\tilde{y}$, let’s define
\( \rho_{+1} = P(\tilde{y} = -1 | y = +1) \), \( \rho_{-1} = P(\tilde{y} = +1 | y = -1) \). For SLN Noise, \( \rho_{+1} = \rho_{-1} = \rho \). For the IDS using supervised methods, it is important to address the issue of the label-noise problem. We modify the proposed PHEC models in centralized and federated setup such that the modified PHEC performs well even in the presence of SLN noise.

Under the binary classification task, (20) proposed weighted loss function (convex surrogate functions) in the presence of SLN noise. An unweighted loss function in binary classification (where true label \( y \in \{-1, 1\} \)) takes the form,

\[
l(z, y) = l_1(z) + l_{-1}(z)
\]

where \( z \) represents the margin, \( z = yg(x), g(x) \) corresponds to the function of the specific classifier. \( l_1(z) \) and \( l_{-1}(z) \) indicate the loss function for the true label \( y = 1 \) and \( y = -1 \) respectively.

Proposed \( \alpha \)-Weighted loss function takes the form,

\[
l_\alpha(z, y) = (1 - \alpha)l_1(z) + \alpha l_{-1}(z)
\]

If the loss function given by \( l \) is convex, then this \( \alpha \)-weighted loss function \( l_\alpha(z, y) \) (with suitably chosen \( \alpha \)) turns out to be noise tolerant [6], [20]. As a consequence of this, suitably weighted Biased SVM and weighted Logistic Regression are provably Noise-Tolerant [6], [20].

Noise-Tolerant PHEC (NT-PHEC) in Centralized Setup:

In the proposed PHEC model in centralized setup, PCA is used for dimension reduction. PCA does not use the label information and hence, label noise-tolerant. For the noise tolerant PHEC, we propose the following modifications to the model proposed in section III.

1) Random Forest can be replaced by weighted Logistic Regression classifier. Finding optimal \( \alpha \) over the range \([0, 1]\) is challenging. Instead, we discretize \([0, 1]\) into a finite set of values and search for the best \( \alpha \).

2) The other classifier used in the proposed PHEC is KNN. KNN involving large number of nearest neighbors i.e. KNN with a higher value of \( K \) performs well in the presence of SLN Noise [24]. Intuitively, this is due to the fact that larger the value of \( K \), the lesser the effect of label noises on the majority decision that is taken by the KNN classifier. So, we propose to apply the constraint \( K \geq 5 \) for KNN.

Noise-Tolerant PHEC (NT-PHEC) in Federated Setup:

For MLP, the resulting cross-entropy loss function may turn out to be non-convex. However, to restore the convexity of the loss function, we propose to limit the number of layers to one input layer and one output layer that consists of a single neuron with a sigmoid activation function. This binary classification unit (with cross-entropy loss) performs similarly to a binary logistic regression classifier and it leads to optimizing over a convex surrogate loss function. Now, \( \alpha \)-weighted cross-entropy loss can be used as a noise-tolerant convex surrogate loss function. Rest of the architecture remains exactly same as that is proposed in section IV. To find the suitable value of \( \alpha \), we discretize \([0, 1]\) into a finite set of values and search for the best value of \( \alpha \).

The advantages of this proposed model are as follows:

1) This proposed architecture is Noise Tolerant.

2) For \( \alpha = 1/2 \), weighted cross-entropy loss turns out to be the same as unweighted cross-entropy loss function. With the \( \alpha \)-weighted loss, \( \alpha \) can be tuned in order to find the best possible value of \( \alpha \) in the range \([0, 1]\). As this range includes \( 1/2 \), range of \( \alpha \) in unweighted case is a strict subset of range of \( \alpha \) in weighted loss function. So, for the exactly same setup, an MLP classifier, trained with weighted cross-entropy loss (with optimally chosen \( \alpha \)) is expected to perform at least as good as the MLP classifier (with exactly the same architecture) trained on an unweighted loss function. However, due to discretization of \( \alpha \) over the range \([0, 1]\), it may be difficult to find out the optimal \( \alpha \) practically. Hence, the superiority of \( \alpha \)-weighted loss functions over unweighted loss functions may not be evident sometimes (if optimal \( \alpha \) is not chosen).

3) Any class imbalance nature present in the dataset (if exists), can be adjusted by suitable weighting of \( \alpha \).

VI. DESCRIPTION OF THE DATASETS

In this section, we describe four benchmark datasets that are used to evaluate the performance of the proposed models.

NSL-KDD Dataset [18], [23]: This NSL-KDD dataset is improved version of the KDD99 dataset. There were some problems pointed out on KDD99, which are later rectified in this NSL-KDD dataset. The modifications in NSL-KDD dataset are as follows:

1) Redundant records & features are removed from the training dataset. Duplicate Records are deleted from the test dataset.

2) Number of selected records from each difficulty level group is inversely proportional to the percentage of records in KDD99 dataset.

3) The number of samples are quite affordable in both training and test dataset, that makes it relatively easier and cheaper to experiment with.

This dataset is having 3 sections, one is the large ‘train+’ dataset, second one is the ‘Train+\_20Percent’ and last one is the ‘test+’ data. The first two are used for training purposes where ‘Train+\_20Percent’ is a 20% subset of the ‘train+’ dataset. There are 41 features and one label column in all three datasets. It is important to note that 17 such new type of attacks exist in ‘test+’ dataset that are not present in the training data. This makes NSL-KDD very relevant in IoT security, as it is very important to detect previously unknown attacks. Here, this grouping of smaller category attacks into a larger category is essential due to the following reasons:

1) For many attacks, very few training samples are available. It is difficult to train a machine learning algorithm on these very few number of samples.

2) There exist many sub-classes of attacks in the test dataset, which do not exist in training data. So, it is impossible to detect unknown attacks without such grouping.
The grouping of sub-classes of attacks into broader categories is given in Table II. Similar grouping was used in [14]. Even though all these attacks are present in the data, still both training as well as test data are very skewed and the distribution is non-uniform in training and test datasets. There exists class imbalance in NSL-KDD data. More than half of the samples (data points) in the training data belongs to normal traffic and U2R & R2L are extremely rare in terms of frequency. Even with this low frequency of U2R, R2L attacks, this data is a very realistic and quite accurate representation of distribution of modern-day attacks in IoT networks. This is because the most frequent attack in IoT network is DoS, also U2R and R2L are extremely rare in reality. Even though R2L & U2R are rare, these occasional attacks may make the entire network vulnerable to malware.

**DS2OS Traffic Traces [26]:** This is an open source benchmark dataset in IoT security, contributed by [26]. The creators captured the data using four simulated IoT sites with different type of services: light controller, thermometer, movement sensors, washing machines, batteries, thermostats, smart doors and smartphones. Each of the sites had a different organization and a different number of services. They created a virtual IoT environment using Distributed Smart Space Orchestration System (DS2OS) for producing synthetic data.

**Table I**

| Feature Number | Features          | Type of Data |
|----------------|-------------------|--------------|
| 1              | Source ID         | Nominal      |
| 2              | Source Address    | Nominal      |
| 3              | Source Type       | Nominal      |
| 4              | Source Location   | Nominal      |
| 5              | Destination Service Address | Nominal |
| 6              | Destination Service Type | Nominal |
| 7              | Destination Location | Nominal    |
| 8              | Accessed Node Address | Nominal |
| 9              | Accessed Node Type | Nominal      |
| 10             | Operation         | Nominal      |
| 11             | Value             | Continuous   |
| 12             | Timestamp         | Discrete     |
| 13             | Normality         | Nominal      |

Table-II describes the different types of attacks and their distributions. Clearly, majority of the attack samples belong to the ‘Denial of Service’ type. Table-III describes different features and their corresponding datatypes. Here the target variable is ‘Normality’.

**Table II**

| Attack                  | Frequency | % of Data | % of Anomaly |
|-------------------------|-----------|-----------|--------------|
| Denial of Service       | 5780      | 0.61%     | 57.79%       |
| Data Type Probing       | 334       | 0.09%     | 03.41%       |
| Malicious Control       | 889       | 0.24%     | 08.87%       |
| Malicious Operation     | 805       | 0.22%     | 08.03%       |
| Scan                    | 1547      | 0.43%     | 15.44%       |
| Spying                  | 532       | 0.14%     | 05.31%       |
| Wrong Setup             | 122       | 0.03%     | 01.21%       |

**Gas Pipeline Data (SCADA Traffic and Payload Datasets) [27]:** This is a freely available dataset collected in Gas Pipeline. It was generated from network flow records that was captured with a serial port data logger. Here two categories of features are present, namely network traffic features and payload content features. Network traffic features include the device address, function code, length of packet, packet error checking information and time intervals between packets. While “network traffic features” account for the communication patterns in networks, “Payload content features” takes care of the system’s current state.

First two datasets [18], [26] include features only related to network traffic. However, this Gas Pipeline Data includes features involving payload patterns as well as Network Traffic.

**Table III**

| Feature Number | Features          | Type of Data |
|----------------|-------------------|--------------|
| 1              | Source ID         | Nominal      |
| 2              | Source Address    | Nominal      |
| 3              | Source Type       | Nominal      |
| 4              | Source Location   | Nominal      |
| 5              | Destination Service Address | Nominal |
| 6              | Destination Service Type | Nominal |
| 7              | Destination Location | Nominal    |
| 8              | Accessed Node Address | Nominal |
| 9              | Accessed Node Type | Nominal      |
| 10             | Operation         | Nominal      |
| 11             | Value             | Continuous   |
| 12             | Timestamp         | Discrete     |
| 13             | Normality         | Nominal      |

Table-IV describes the different types of attacks and its distribution in the dataset. Clearly, majority of the attack samples belong to the ‘Denial of Service’ type. Table-III describes different features and their corresponding datatypes. Here the target variable is ‘Normality’.

**Table IV**

| Model               | γ∗  | TPR  | FPR  | Accuracy | u   |
|---------------------|-----|------|------|----------|-----|
| PHEC                | 0.015 | 94.6 | 12.34 | 91.6     | 13  |
| PHEC                | 0.030 | 92.28 | 9.94 | 91.34    | 10  |
| PHEC                | 0.060 | 88.04 | 6.22 | 90.77    | 6.5 |
| PHEC                | 0.065 | 86.98 | 5.39 | 90.27    | 6   |
| PHEC                | 0.075 | 85.38 | 5.25 | 89.98    | 5.25|
| TDTC [1]            | N/A | 84.82 | 5.56 | N/A      | N/A |
| Two-Tier [2]        | N/A | 83.24 | 4.83 | N/A      | N/A |
| Naive Bayes [3]     | N/A | 76.56 | N/A  | N/A      | N/A |
| Random Forest [5]   | N/A | 80.67 | N/A  | N/A      | N/A |
| SVM [8]             | N/A | 69.52 | N/A  | N/A      | N/A |
| Decision Trees [48] | N/A | 81.05 | N/A  | N/A      | N/A |

If TDTC [1] and PHEC (at γ∗ = 0.075) are compared in Table IV, it can be seen that for PHEC, results have significantly improved in terms of both FPR and TPR. It indicates direct superiority of PHEC over TDTC [1]. Compared to Two-Tier model [2], TPR in PHEC (at γ∗ = 0.075) improved by 3.14% at the cost of only additional 0.42% FPR. Also, it is seen that as γ∗ drops, desired metric TPR gets improved but that happens at the cost of larger value of FPR.
The results in Table VII are obtained when models are trained on larger training dataset. Number of extracted dimensions considered are 16. If results of PHEC are compared with that of Two-Tier [2] and TDTC [1] models, it is seen that the TPR has improved by a large margin at the expense of very small increase to the metric FPR. Compared to the Two Tier model [2], TPR has improved by 8.09% at the expense of 1% extra FPR in PHEC ($\gamma^* = 0.050$). Also, compared to the TDTC [1], TPR has improved by by 5.20% at the expense of only 1.58% extra FPR in PHEC ($\gamma^* = 0.050$).

**Classification Results (For Each Category of Attack):** We evaluate the effectiveness of the proposed PHEC algorithm on common as well as on uncommon category of attacks. The results show that PHEC is the best performing model for common (Probe) as well as uncommon attacks (U2R, R2L).

For Table-VI, FPR is 5.39%, $\gamma^* = 0.065$ and $\alpha = 6\%$.

**TABLE VI**

RESULTS ON 'TEST+' DATA FOR EACH CATEGORY OF ATTACK (MODEL TRAINED ON 'TRAIN+ 20PERCENT' DATASET)

| Attack | Total | Detected as Threat | Not Detected | TPR |
|--------|-------|--------------------|--------------|-----|
| R2L    | 2885  | 1571              | 1314         | 54.45  |
| U2R    | 67    | 53                | 14           | 79.10  |
| DoS    | 7460  | 7124              | 336          | 95.50  |
| Probe  | 2421  | 2415              | 6            | 99.75  |

For Table-VII, FPR is 6.44%, $\gamma^* = 0.05$ and $\alpha = 6.5\%$.

**TABLE VII**

RESULTS ON 'TEST+' DATA FOR EACH CATEGORY OF ATTACK (MODEL TRAINED ON LARGER TRAINING DATASET)

| Attack | Total | Correctly Classified | Misclassified | TPR |
|--------|-------|----------------------|---------------|-----|
| R2L    | 2885  | 1957                 | 928           | 67.83  |
| U2R    | 67    | 40                   | 27            | 59.70  |
| DoS    | 7460  | 7154                 | 306           | 95.90  |
| Probe  | 2421  | 2397                 | 24            | 99.75  |

2) **PHEC in Federated Setup**: Table-X shows the performance of proposed PHEC Model in federated settings. Even though performance in Federated Settings dropped compared to PHEC in centralized settings, still very high TPR along-with decent accuracy can be obtained here. In a recent work on IoT security [3], test accuracy reported on NSL-KDD dataset in Federated settings was around 82% but significantly improved performance is obtained here.

**TABLE V**

RESULTS ON 'TEST+' DATASET (MODEL TRAINED ON LARGER TRAINING DATASET)

| Model     | $\gamma^*$ | TPR | FPR | Accuracy | $u$ |
|-----------|-------------|-----|-----|----------|----|
| PHEC      | 0.010       | 95.85 | 12.70 | 92.17 | 13 |
| PHEC      | 0.020       | 93.07 | 10.91 | 91.41 | 11 |
| PHEC      | 0.045       | 90.87 | 6.80 | 91.89 | 7  |
| PHEC      | 0.050       | 90.06 | 6.44 | 91.52 | 6.5|
| SVM-IDS   | N/A         | 82.82 | 15   | N/A  | N/A |
| Two-Tier  | N/A         | 81.97 | 5.44 | N/A  | N/A |
| TDTC      | N/A         | 84.86 | 4.86 | N/A  | N/A |
| SOM-IDS   | 28%         | 75.49 | N/A | N/A  | N/A |

**TABLE VIII**

COMPARATIVE ANALYSIS OF PHEC ON 'TEST+' DATASET

| Algorithm       | Trained on | Probe | DoS | U2R | R2L |
|-----------------|------------|------|-----|-----|-----|
| PHEC            | Train+     | 99   | 95.90 | 59.70 | 67.83 |
| PHEC            | Train+20%  | 99.75 | 95.50 | 79.10 | 54.45 |
| SVM with BIRCH  | N/A        | 99.5 | 97.5   | 28.8 | 19.7 |
| TDTC [1]        | N/A        | 87.32 | 88.20 | 70.15 | 42 |
| Two-tier [2]    | N/A        | 79.76 | 84.68 | 67.16 | 34.81 |
| Association IDS [8] | N/A    | 96.8 | 74.9   | 0.79 | 0.38 |
| HFR-MLR [29]    | N/A        | 80.2 | 89.70 | 29.50 | 34.20 |
| ESC-IDS [30]    | N/A        | 99.5 | 84.1   | 31.5 | 14.1 |

**TABLE IX**

EFFECT OF DIMENSION REDUCTION ON RESULTS

| Dimension Reduction | $\gamma^*$ | FPR | TPR |
|---------------------|-----------|-----|-----|
| Autoencoder         | 0.010     | 13.625 | 89.74 |
| Autoencoder         | 0.020     | 11.46  | 84.92 |
| Autoencoder         | 0.045     | 9.88   | 78.10 |
| Autoencoder         | 0.050     | 7.90   | 97.51 |
| LDA                 | 0.010     | 13.29  | 72.25 |
| LDA                 | 0.020     | 13.23  | 72.13 |
| LDA                 | 0.045     | 13.23  | 72.13 |
| LDA                 | 0.050     | 13.23  | 72.13 |
| PCA                 | 0.010     | 12.7   | 93.07 |
| PCA                 | 0.020     | 10.91  | 93.07 |
| PCA                 | 0.045     | 6.80   | 90.875 |
| PCA                 | 0.050     | 6.44   | 90.06 |
| PCA+LDA             | 0.010     | 13.15  | 72.67 |
| PCA+LDA             | 0.020     | 13.09  | 72.48 |
| PCA+LDA             | 0.045     | 13.09  | 72.48 |
| PCA+LDA             | 0.050     | 13.09  | 72.48 |

**TABLE X**

EXPERIMENTAL RESULTS OF PHEC ON NSL-KDD DATASET ('TEST+' DATASET) IN FEDERATED SETTINGS

| $\gamma^*$ | Accuracy | TPR | Precision | FPR | Training Data       |
|------------|----------|-----|-----------|-----|---------------------|
| 4          | 10       | 0.75 | 88.42     | 96.67 | 'Train+'            |
| 4          | 9        | 0.875 | 87.27     | 93.16 | 'Train+'            |
| 4          | 10       | 0.015 | 83.78     | 88.46 | 'Train+_20Percent' |

B. **DS2OS Traffic Traces Dataset**

1) **PHEC in Centralized Setup**: Table-XI & XII presents comparative results on training and test dataset of ‘DS2OS Traffic Traces’ respectively. Here, the maximum tolerable limit of FPR $u$ is fixed at 1%.
TABLE XI
EXPERIMENTAL RESULTS ON ‘DS2OS TRAFFIC TRACES’ DATASET (TRAINING DATA) IN CENTRALIZED SETTINGS

| Model          | Accuracy | TPR  | FPR  | F1-Score |
|----------------|----------|------|------|----------|
| PHEC [31]      | 99.97    | 100  | 0.026| 99       |
| Logistic Regression [31] | 98.3  | 98   | N/A  | 98       |
| SVM [31]       | 98.2     | 98   | N/A  | 98       |
| Decision Tree [31] | 99.4  | 99   | N/A  | 99       |
| Random Forest [31] | 99.4  | 99   | N/A  | 99       |
| Neural Net [31] | 99.4     | 99   | N/A  | 99       |

TABLE XII
EXPERIMENTAL RESULTS ON ‘DS2OS TRAFFIC TRACES’ DATASET (TEST DATA) IN CENTRALIZED SETTINGS

| Model          | Accuracy | TPR  | FPR  | F1-Score |
|----------------|----------|------|------|----------|
| PHEC [31]      | 99.98    | 100  | 0.016| 99.3     |
| Logistic Regression [31] | 98.3  | 98   | N/A  | 98       |
| SVM [31]       | 98.2     | 98   | N/A  | 98       |
| Decision Tree [31] | 99.4  | 99   | N/A  | 99       |
| Random Forest [31] | 99.4  | 99   | N/A  | 99       |
| Neural Net [31] | 99.4     | 99   | N/A  | 99       |

2) **PHEC in Federated Setup:** PHEC achieves more than 98% accuracy on ‘DS2OS Traffic Traces’ data in federated settings.

TABLE XIII
EXPERIMENTAL RESULTS ON ‘DS2OS TRAFFIC TRACES’ DATASET (TEST DATA) IN FEDERATED SETTINGS

| $u$ | $n$ | $\gamma^*$ | Accuracy | TPR | FPR  | Precision | F1-score |
|-----|-----|-------------|----------|-----|------|-----------|----------|
| 2   | 7   | 0.925       | 98.27    | 97.69 | 1.674 | 61.5      | 75.49    |

C. Gas pipeline Data (SCADA Traffic and Payload Datasets)

1) **PHEC in Centralized Setup:** Table-XIV presents the experimental results on ‘Gas Pipeline’ dataset. Results indicate the excellence of performance of PHEC in centralized settings.

TABLE XIV
EXPERIMENTAL RESULTS ON ‘GAS PIPELINE’ DATA IN CENTRALIZED SETTINGS (TEST DATA)

| $u$ | $\gamma^*$ | Accuracy | TPR | FPR  | Precision | F1-score |
|-----|-------------|----------|-----|------|-----------|----------|
| 2   | 0.3         | 98.38    | 97.56 | 1.15 | 97.98     | 97.77    |

2) **PHEC in Federated Setup:** Table-XV shows that the performance observed in Federated settings (in PHEC) is marginally better than centralized settings! Generally, centralized settings gives better performance metrics, here we observe slight exception in results.

D. Water Tank (SCADA Traffic and Payload Data)

1) **PHEC in Centralized Setup:** Here PHEC is implemented on ‘Water Tank’ dataset in centralized settings and results are presented in Table-XVI. Results show that for a very less FPR (< 1%), obtained TPR and Accuracy are very high! (Both are > 99%).

2) **PHEC in Federated Setup:** Table-XVII shows that even though performance of PHEC dropped in federated settings, still the performance is quite good.

E. Comparison of Time in Centralized and Federated Settings

Here we compare the time required to detect a test sample in centralized and federated settings. It can be seen that time required is (10-100) times less in federated setup. This is very useful in IoT security as often, intrusions have substantial effect on system and detecting at earlier stage makes sure that immediate actions can be taken.

TABLE XVIII
COMPARISON OF TIME IN CENTRALIZED AND FEDERATED SETTINGS

| Dataset               | Settings | Time/Instance |
|-----------------------|----------|---------------|
| NSL-KDD               | Centralized | 9.02 * 10^{-8}s |
| NSL-KDD               | Federated | 1.14 * 10^{-8}s |
| DS2OS                 | Centralized | 37.1 * 10^{-8}s |
| DS2OS                 | Federated | 0.736 * 10^{-8}s |
| Gas Pipeline Data     | Centralized | 6.96 * 10^{-8}s |
| Gas Pipeline Data     | Federated | 0.882 * 10^{-8}s |
| Water Tank Data       | Centralized | 10.6 * 10^{-8}s |
| Water Tank Data       | Federated | 8.89 * 10^{-8}s |

VIII. IMPLEMENTATION AND RESULTS ON NOISY DATA

A. Centralized Settings

Degree of noise (in Percentage) is represented by $\rho$ and we consider, $\rho \in \{10, 20\}$.

The following steps are taken to generate noisy training labels.

1) For each instance of the training data, generate one uniform random number $v$ that lies in-between $[0, 1]$.
2) If $100v \leq \rho$, then change the label of that instance. Otherwise, keep it as it is.

Now, the training data is having $\rho\%$ of the training samples with noisy labels.
The performance of Noise Tolerant PHEC (NT-PHEC) on noisy and clean data are tabulated in Table-XIX and Table-XX respectively.

### TABLE XXI
**Experimental Results on Clean Data Using Noise Tolerant PHEC in Centralized Settings**

| Dataset    | $\rho$ | Accuracy | FPR | TPR   |
|------------|--------|----------|-----|-------|
| NSL-KDD    | 10     | 83.77    | 3.2 | 73.92 |
| DS2OS      | 10     | 98.97    | 0.01| 98.56 |
| Gas Pipeline | 10   | 94.26    | 0.1 | 98.53 |
| Water Tank | 20     | 94.64    | 0.66| 96.72 |

### B. Federated Settings

The results obtained using Noise Tolerant PHEC (NT-PHEC) on noisy as well as on clean data are presented in this section.

### TABLE XXII
**Experimental Results on Noisy Data Using Noise Tolerant PHEC in Federated Settings**

| Dataset    | $\rho$ | Accuracy | FPR | TPR   |
|------------|--------|----------|-----|-------|
| NSL-KDD    | 10     | 76.48    | 19.12| 92.30 |
| NSL-KDD    | 20     | 74.22    | 21.44| 92.39 |
| DS2OS      | 10     | 91.66    | 7.34 | 63.54 |
| DS2OS      | 20     | 90.48    | 8.50 | 62.87 |
| Gas Pipeline | 10   | 94.26    | 1.28 | 87.79 |
| Gas Pipeline | 20   | 93.98    | 1.28 | 87.04 |
| Water Tank | 10     | 90.47    | 0.0017| 64.21 |
| Water Tank | 20     | 90.22    | 0.28 | 64.35 |

### C. Comparison of Results on Noisy and Clean Data

Here, we compare the accuracy obtained using NT-PHEC and PHEC in both centralized and federated settings.

The following observations can be made on noisy data:

1) It can be observed in Table-XXIII that for different degrees of noise, the accuracy obtained by Noise Tolerant PHEC is better than that obtained from PHEC for each of the four datasets. On noisy data, mean difference of the accuracy obtained by NT-PHEC and PHEC in centralized settings is 8.53% (approx).

2) As evident from Table-XXIV, performance metrics obtained by NT-PHEC is better than that obtained by PHEC in federated settings. On noisy data, the mean difference of accuracy (across four datasets, for various degrees of noise) between NT-PHEC and PHEC in federated settings is 2.6735% (approx).

On clean data, PHEC performs better than NT-PHEC, in federated and centralized settings. The mean difference of accuracy between PHEC and NT-PHEC in centralized and federated settings are 2.1% & 4% respectively (approx.).

### TABLE XXIII
**Comparison of Experimental Results on Noisy Data Using Noise Tolerant PHEC and PHEC in Centralized Settings**

| Dataset    | $\rho$ | Accuracy of PHEC | Accuracy of NT-PHEC |
|------------|--------|------------------|------------------|
| NSL-KDD    | 10    | 83.22            | 83.77            |
| NSL-KDD    | 20    | 81.02            | 81.02            |
| DS2OS      | 10    | 98.96            | 99.96            |
| DS2OS      | 20    | 95.13            | 95.13            |
| Gas Pipeline | 10   | 97.48            | 97.48            |
| Gas Pipeline | 20   | 94.74            | 94.74            |
| Water Tank | 10    | 97.83            | 97.83            |
| Water Tank | 20    | 86.95            | 93.74            |

### TABLE XXIV
**Comparison of Experimental Results on Noisy Data Using Noise Tolerant PHEC and PHEC in Federated Settings**

| Dataset    | $\rho$ | Accuracy of PHEC | Accuracy of NT-PHEC |
|------------|--------|------------------|------------------|
| NSL-KDD    | 10    | 72.87            | 76.48            |
| NSL-KDD    | 20    | 68.28            | 74.22            |
| DS2OS      | 10    | 89.9             | 91.66            |
| DS2OS      | 20    | 88.46            | 90.48            |
| Gas Pipeline | 10   | 91.36            | 94.26            |
| Gas Pipeline | 20   | 89.98            | 93.988           |
| Water Tank | 10    | 89.82            | 90.47            |
| Water Tank | 20    | 89.72            | 90.42            |

1) In centralized settings, PHEC uses Random Forest instead of weighted Logistic Regression. Random Forest
performs better on clean data due to ensembling of results. For NT-PHEC, by imposing the constraint $K \geq 5$ on the KNN classifier, the feasible region for $K$ becomes a subset of the feasible region for $K$ of KNN in PHEC. So, the optimal $K$ of KNN in PHEC is at least as good as that of KNN in NT-PHEC. Due to these reasons, PHEC performs better than NT-PHEC on clean data.

2) For the NT-PHEC in federated settings, the MLP is having one input layer and one output layer with single neuron. There exists no hidden layer in this case. The MLP in PHEC has the luxury of using multiple hidden layers with any number of neurons along-with any non-linear activation functions. Due to the large extent of flexibility of MLP, it captures the pattern of the data better than a simplified MLP (of NT-PHEC) and hence PHEC outperforms NT-PHEC on clean data.

IX. CONCLUSION

We propose a probabilistic hybrid ensemble classifier (PHEC) in IoT security in centralized settings and then adapt it to federated settings. PHEC maximizes TPR while keeping the FPR within permissible limit. Experimental results demonstrate that it performs better than state-of-the-art Intrusion Detection Systems. Even though the results obtained in centralized setup are better than that of federated settings, performance metrics obtained in federated settings is quite close to centralized settings. It is advisable to use PHEC in the centralized settings if there exists no privacy issue and entire data processing in a single system is feasible. Otherwise, it is advisable to adapt the proposed model PHEC in federated settings. The classifiers used in PHEC use the training data labels to learn the pattern from the data. If labels of the training data get noisy, performance of PHEC drops. To overcome this, we use weighted convex surrogate loss functions to propose Noise-Tolerant PHEC in federated & centralized settings. Experimental results on noisy data demonstrate that Noise-Tolerant PHEC works well in the presence of SLN Noise.

An interesting direction of future work may be to come up with Intrusion Detection Systems such that it can be trained even in the absence of anomaly samples in the training data, the one class models may be useful there.

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