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XGBoost for Imbalanced Multiclass Classification-Based Industrial Internet of Things Intrusion Detection Systems

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Abstract: The Industrial Internet of Things (IIoT) has advanced digital technology and the fastest interconnection, which creates opportunities to substantially grow industrial businesses today. Although IIoT provides promising opportunities for growth, the massive sensor IoT data collected are easily attacked by cyber criminals. Hence, IIoT requires different high security levels to protect the network. An Intrusion Detection System (IDS) is one of the crucial security solutions, which aims to detect the network's abnormal behavior and monitor safe network traffic to avoid attacks. In particular, the effectiveness of the Machine Learning (ML)-based IDS approach to building a secure IDS application is attracting the security research community in both the general cyber network and the specific IIoT network. However, most available IIoT datasets contain multiclass output data with imbalanced distributions. This is the main reason for the reduction in the detection accuracy of attacks of the ML-based IDS model. This research proposes an IDS for IIoT imbalanced datasets by applying the eXtremely Gradient Boosting (XGBoost) model to overcome this issue. Two modern IIoT imbalanced datasets were used to assess our proposed method's effectiveness and robustness, X-IIoTDS and TON_IoT. The XGBoost model achieved excellent attack detection with F1 scores of 99.9% and 99.87% on the two datasets. This result demonstrated that the proposed approach improved the detection attack performance in imbalanced multiclass IIoT datasets and was superior to existing IDS frameworks.

Keywords: Industrial Internet of Things (IIoT); Intrusion Detection System (IDS); imbalanced data; multiclass classification; XGBoost

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1. Introduction

The Industrial Internet of Things (IIoT) contains physical service systems and digital equipment such as sensors, actuators, vehicular networks, interfaces of integration and communication, etc. The IIoT has been used to generate extensive data from multiple sensors and IoT devices. Therefore, the IIoT is utilized for intelligent operations in various management domains, such as smart cities, smart homes, smart factories, smart grids, smart agriculture, etc., [1–3]. Nevertheless, massive data are created from sensors within the IIoT network, making it increasingly attractive for cyber attacks worldwide. For example, the opening up of the connected devices to expand the IIoT network [4] has increased the threats of cyber attacks. Hence, the IIoT faces attacks that endanger the risk of operating seamlessly in supply organizations.

Cyber attackers steal or obliterate information from computers and network structures, promoting cyberwar. Several types of attacks are Man-in-the-Middle (MitM), data theft, botnet, port-sweep, address-sweep, network scanning, and port-scan attacks. Due to the enormous variety of IoT devices, there can be an unsecured connection from Machine-to-People (M2P) and Machine-to-Machine (M2M); so, hackers can easily steal and hold vital information. This not only violates the privacy and usage of network space but also causes

operational disruption and financial loss [5]. In fact, several industrial IoT systems have been attacked, such as a well-known attack on the Ukrainian power grid in 2015 [6], where cyber criminals attained remote access to the grid's control unit and disrupted power to over 230,000 users. In 2018, a Taiwanese chip manufacturer with an IIoT network was attacked [7], resulting in damages of approximately USD 170 million. Hence, although there is no chance of changing the increased dependence on digitalization and automation, industrial organizations are still seeking enhanced methods to secure their IIoT networks. It is estimated that IIoT enterprises will spend up to USD 90 trillion by 2030 if they fail to find effective mitigation strategies to prevent cyber attacks on the IIoT network [8]. Therefore, it is vital to protect infrastructures and services, as the volume of IIoT devices in every industrial organization is increasing daily [9].

An IDS has a critical role in enhancing the security of the IIoT network to ensure the integrity of the information and the privacy of the data transmitted. An IDS aims to automatically detect, report, react to, and prevent any malicious or attack activities, which can affect the security of an IIoT network [10]. IDS is considered a precise or effective method when it can obtain a high accuracy of attack detection and a low false-positive rate [5]. In addition, an IDS should determine when the hackers begin probing devices, which is the initial step in generating a secure IIoT [11]. A few years ago, deep learning (DL)-based IDS, especially the Deep Neural Network (DNN) model was considered a potential method for IDS, for example, Recurrent Neural Network (RNN), Long-Short Term Memory (LSTM), and Gated Recurrent Unit (GRU) models. However, these DL methods have not been effective in detecting attack data with an imbalanced distribution. Studies [12–14] have applied variant RNN models on the KDD cup dataset. Although the average detection rate (DR) obtained from these methods was over 98%, the average User to Root (U2R) attack type detection was still below 50% or even not detected because of the very small amount of U2R samples compared to the other attack-type samples. Next, Le et al. [15,16] built an IDS model based on RNN, LSTM, and GRU models using two datasets, the NSL-KDD and ISCX datasets. Their experimental results showed that the SFSDT-GRU model obtained the best performance compared to variant RNN models. In particular, the model achieved a detection attack rate of 91.8% and a U2R attack detection accuracy of 90%.

In recent years, machine learning (ML) has also gained increasing attention and developed applications to detect malicious activity on a target network, because this technology can balance performance efficiency and computational cost for next-generation IoT networks. Researchers have successfully developed advanced IDS methods based on the ML method, which have achieved a promising attack detection performance [17]. Still, the major issue of existing IDS datasets is the huge volume both in the number of network traces and feature space dimensions. Moreover, one of the challenges in the IIoT IDS dataset is the imbalanced distribution in the number of samples for each attack type. This has caused previous ML or DL models to not obtain a high performance in detecting particular attack types. In this paper, we propose an ML-based IIoT IDS method approach that aims to improve the performance of the attack detection of different types with an imbalanced distribution of data. The model is trained using the latest and benchmark intrusion detection IIoT datasets that contain an imbalanced distribution of attack type data. Hence, the main contributions of this study are as follows.

- We built an XGBoost model to improve the detection of imbalanced distribution attack types using two benchmark IIoT IDS datasets, the X-IIoTID and TON_IoT. The raw datasets were preprocessed in several steps, including normalizing features, encoding labels, and splitting the training and testing data.
- We evaluated the proposed method with imbalanced multiclass classification by measuring two performance metrics, which were the confusion matrix and the learning curve.
- We compared the proposed method's results with other related methods. The experimental results showed that our model enhanced the performance of attack detection

for imbalanced multiclass classification in IIoT-based IDS datasets and outperformed other previous models on the same datasets.

The remainder of this paper is organized as follows. Section 2 describes the materials and methods. Section 3 presents the results of the proposed method with the imbalanced multiclass classification and performance learning curve results and then discusses the performance comparison. Finally, Section 4 provides the conclusions of the study and future work.

2. Materials and Methods

This section provides (1) a summary of the related research work in ML-based IoT/IIoT IDS methods, (2) the IIoT datasets used and their imbalanced distribution of attack type data, and (3) the proposed XGBoost model to solve the imbalanced multiclass classification.

2.1. ML-Based IoT/IIoT IDS Context

Numerous cyber attacks target industrial enterprises around the world. Therefore, it is necessary to build an effective IDS to protect industrial systems by fighting against attacks automatically and intelligently. There have been many ML-based IDS methods proposed to achieve this goal. ML-based IDS classification techniques learn from labeled input and evaluate new observations in the binary or multiclass format. Some recent methods used for IDS classification include Support Vector Machine (SVM), Naïve Bayes (NB), k-Nearest Neighbors (kNN), Gradient Boosting Machines (GBM), Random Forest (RF), Decision Tree (DT), Logistic Regression (LR), Linear Discriminant Analysis (LDA), Classification and Regression Trees (CART), Neural Network (NN), etc.

For a general network, Al-Khateeb et al. [18] proposed an anomaly detection method based on an NB classifier. This method was evaluated using modeled data to predict anomalous behaviors. Le et al. [19] applied an RF model to detect types of DoS attacks in wireless sensor networks (WSNs). Sornsuwit et al. [20] proposed a hybrid ML method to improve detection of cyber threats using two datasets: KDD Cup and UNSW-NB15. Hui Wu et al. [21] proposed an ML-based method to detect cyber attacks, such as DoS, DDoS, and malware with high performance accuracy.

For an IoT/IIoT network, Khraisat et al. [22] built a hybrid ML model based on an SVM model to detect zero-day IoT network attacks. Similarly, Ullah et al. [23] proposed a hybrid ML model based on DT and RF to detect real-time IoT network attacks. Le et al. [24] proposed ensemble trees models comprising DT and RF to detect attacks on IoT-based IDS datasets. Alsamiri et al. [25] examined several ML models to detect attacks and based on the experimental results selected the model most efficient on IoT network data. Pacheco et al. [26] proposed an ML-based IDS method to detect IIoT node attacks with a high detection accuracy rate and low false alarm rate.

For the X-IIoTDS dataset, Al-Hawawreh et al. [27] implemented three IDS models, including Asynchronous Peer-to-Peer Federated Learning (AP2PFL)-Multilayer Perceptron (AP2PFL-MLP), AP2PFL-DNN, and Data Purifying Module–Diagnostic and Decision Module (DPM–DDM) models using the X-IIoTID and NSL-KDD datasets. The experimental results showed that the DPM–DDM model obtained average F1 scores of 97.41% and 89.93% on X-IIoTID and NSL-KDD, respectively, which outperformed the other two models. However, the DPM–DDM model obtained low detection rates for targeted ransomware state data on the two datasets. In the X-IIoTID dataset, the F1 score was 64.66% for the "exploitation" attack. Furthermore, in the NSL-KDD dataset, the F1 score was 55.81% for the "Weaponization" attack. Al-Hawawreh et al. [28] applied several learning models on the same dataset. The experimental results showed that the DT model obtained the best F1 scores of 97.27% (for class 1 output with 9 attack types) and 93.80% (for class 2 output with 18 attack types). However, the DT model had low detection rates for several attack types, such as "RDOS" (76.77%), "Shell" (67.62%), and "Modbus_read" (79.94%) of class 2 output.

For the TON_IoT dataset, Alsaedi et al. [29] applied several learner methods such as LR, LDA, kNN, RF, CART, NB, SVM, and LSTM models on the TON_IoT dataset. The

experimental results showed that the CART algorithm achieved the highest average F1 score of 81.14%. However, the CART model obtained poor F1 scores for two IoT devices' data, including Light_Motion with 43% and Thermostat with 57%. Next, Kumar et al. [30] proposed a Trustworthy Privacy-Preserving Secured Framework (TP2SF) with gradient tree boosting systems for an intrusion detection module inside ToN-IoT and BoT-IoT. The TP2SF model obtained a 95.28% F1 score on the ToN-IoT dataset. However, this study did not mentioned the detection rate for each IoT device and each attack type. Then, Booij et al. [31] applied GBM, RF, and NN models on the TON_IoT dataset. The RF model obtained the highest F1 score of 97.264% compared to the GBM and NN models. However, similar to [30], the authors did not detail the performance results for the detection rate of each IoT device as well as each attack type.

2.2. IIoT Datasets and the Imbalanced Multiclass Problem

There are several representative IIoT datasets that can validate IDS in network traffic, including N-BaIoT, UNSW-NB15, BoT-IoT, etc. However, these datasets cannot be used to validate IDS in a different environment, such as an IoT system or host. Hence, they have several drawbacks as shown in Table 1 below.

Table 1. Other existing related IoT-based IDS datasets.

Dataset	Features	Limitation
N-BaIoT [32]	An IoT environment simulation was set up to collect normal status and botnet attacks. This simulation included some IoT devices such as access points, wifi, wired connection, and a router. A small-scale network-based Wireshark for network traffic collecting aimed to reduce many packets in the high-bandwidth network.	There were no telemetry data from IoT sensors and data traces of operating systems.
UNSW-NB15 [33]	The dataset was created in a network traffic simulation using an IXIA traffic generator and was saved in four CSV files. This dataset contained a normal vector and nine attack vectors. Each vector had 47 features and the class target feature.	The dataset did not contain security events against operating systems and IoT networks.
Bot-IoT [34]	Large-scale raw packets from different virtual machines were collected. This dataset contained malware events and various botnet attacks with various data features.	The dataset did not contain hacking vectors against traces of operating systems and IoT systems.

In this work, we chose two recent IIoT-based IDS datasets on which to perform experiments, the TON_IoT and X-IIoTDS. These datasets have addressed the main limitations of the existing related datasets above. Furthermore, they are suitable for the requirements of the IIoT network. These datasets were collected from IIoT network systems with both normal and attack scenarios. The datasets were collected from the new IIoT connectivity protocols, network traffic, logs, security mechanisms, host resources, and especially recent

attack tactics. The obtained data are the labeled network data and host data, which reflect a realistic and complete IIoT network.

First, TON_IoT [29] was collected from a new testbed at the IoT Lab. To mimic the scalability and complexity of the IIoT network, they set up connected physical systems, virtual machines, hacking platforms, cloud and fog platforms, and IIoT sensors. The obtained datasets comprised telemetry of IIoT sensors, operating systems data of Windows 7 and 10, Ubuntu 14 and 18 TL, and network traffic data. The datasets were saved in CSV files. This paper focused on the telemetry IoT device dataset logged in a CSV file. Seven IoT device data were collected, including IoT_Fridge, IoT_Garage_Door, IoT_GPS_Tracker, IoT_Modbus, IoT_Motion_Light, IoT_Thermostat, and IoT_Weather. Table 2 describes the distribution of each class type in each IoT device from the TON_IoT dataset.

As shown in Table 2, "xss" and "scanning" had the smallest ratio distribution of the number of samples compared to the other attack types. For example, in the IoT_Garage_Door dataset file, while the "scanning" attack type had the smallest amount with 2.15% and the "xss" attack type had 4.7%, each other attack type ("ddos", "password", "backdoor", and "injection") had the largest with 20.33% and the "ransomware" attack type had 11.83%. This was similar to the other IoT device dataset files.

Second, X-IIoTID [28] was created by careful simulation of techniques and procedures, recent tactics of attackers, and the realistic activities of IIoT systems. The simulation included IoT devices such as sensors, controllers, actuators, mobile, edge, and cloud traffic. In addition, it contained the behaviors of the connectivity protocols, such as MQTT, CoAP, and WebSocket. Furthermore, some communication patterns were also included, for example, M2M, Human-to-Machine (H2M), and Machine-to-Human (M2H) with large volume network traffic and events. The dataset contained 68 features, with a subcategory attack (class 2) and a sub-subcategory attack (class 1). Table 3 shows the distribution of the attack type of the X-IIoTID dataset.

Table 2. Type class output distribution of the TON_IoT dataset.

Device	Target Value	Number of Samples
IoT_Fridge	normal	35,000
	ddos	5000
	injection	5000
	backdoor	5000
	password	5000
	ransomware	2902
	xss	2042
IoT_Garage_Door	normal	35,000
	ddos	5000
	password	5000
	backdoor	5000
	injection	5000
	ransomware	2902
	xss	1156
	scanning	529
IoT_GPS_Tracker	normal	35,000
	password	5000
	backdoor	5000
	injection	5000
	ddos	5000
	ransomware	2833
	xss	577
	scanning	550

Table 2. *Cont.*

Device	Target Value	Number of Samples
IoT_Modbus	normal	35,000
	injection	5000
	backdoor	5000
	password	5000
	xss	577
	scanning	529
IoT_Motion_Light	normal	35,000
	ddos	5000
	password	5000
	injection	5000
	backdoor	5000
	ransomware	2264
	scanning	1775
	xss	449
IoT_Thermostat	normal	35,000
	password	5000
	injection	5000
	backdoor	5000
	ransomware	2264
	xss	449
	scanning	61
IoT_Weather	normal	35,000
	password	5000
	backdoor	5000
	ddos	5000
	injection	5000
	ransomware	2865
	xss	866
	scanning	529

Table 3. Class output distribution of the X-IIoTDS dataset.

Output	Target Value	Number of Samples
Class 1	Normal	421,417
	RDOS	141,261
	Scanning_vulnerability	52,852
	Generic_scanning	50,277
	BruteForce	47,241
	MQTT_cloud_broker_subscription	23,524
	Discovering_resources	23,148
	Exfiltration	22,134
	insider_malcious	17,447
	Modbus_register_reading	5953
	False_data_injection	5094
	C&C	2863
	Dictionary	2572
	TCP Relay	2119
	fuzzing	1313
	Reverse_shell	1016
	crypto-ransomware	154
	MitM	117

Table 3. *Cont.*

Output	Target Value	Number of Samples
Class 2	Normal	421,417
	RDOS	141,261
	Reconnaissance	127,590
	Weaponization	67,260
	Lateral_movement	31,596
	Exfiltration	22,134
	Tampering	5094
	C&C	2863
	Exploitation	1133
	crypto-ransomware	154

As shown in Table 3, the smallest number of samples belonged to the "crypto-ransomware" and "MitM" attacks for the class 1 target. Furthermore, for the class 2 target, while "RDOS" and "Reconnaissance" attacks had the largest amounts of data with 35.39% and 31.97% respectively, the two attack types "Exploitation" and "crypto-ransomware" had the smallest data ratios of 0.28% and 0.038% respectively.

In summary, the imbalance of the data distribution is a challenge for the IIoT IDS datasets, and this is the main reason for the decreased performance accuracy for the attack detection of IDS ML or DL models.

2.3. The Proposed Method

This section provides the high-level architecture of IIoT with the attached ML-based IDS method and the proposed XGBoost IDS method for the IIoT datasets to solve the imbalanced multiclass classification issue.

Firstly, Figure 1 illustrates an IIoT high-level architecture, including three main layers: the IIoT perception layer, the IIoT network and processing layer, and the IIoT application layer [35,36].

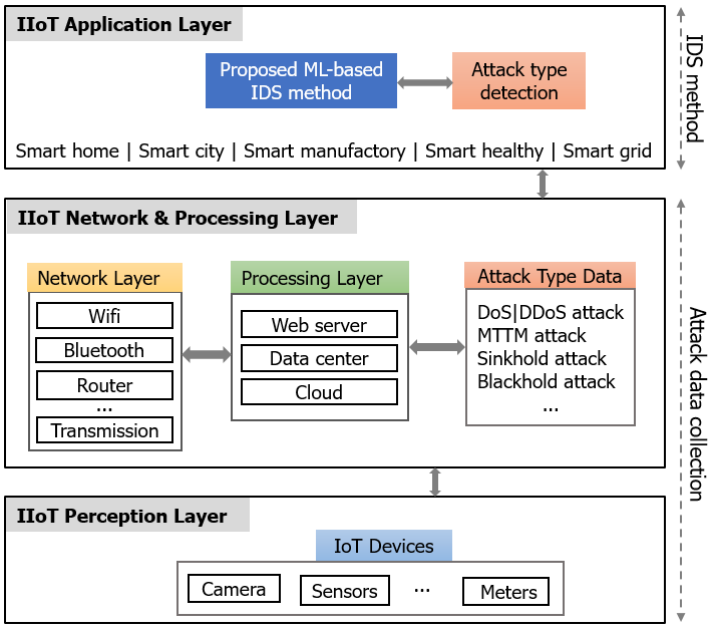


Figure 1. ML-based IDS method inside the high level IIoT network architecture context.

In particular, the perception layer contains IoT devices, for example, IoT sensors, cameras, meters, etc. These devices have the main function of gathering sensory data, tracking the environment, and transporting raw materials. The next layer is the network layer, which might have different connectivity networks, such as LoRa, 6LoWPAN, Bluetooth,

WiFi/IEEE 802.15.4, and NarrowBand-IoT. These connectivity networks have responsibility for transferring the sensory data from IoT devices in the perception layer to the network and processing layer [36,37]. The network and processing layer contains servers and databases for different types of attacks, for example, Ransomware, Distributed Denial of Service (DDoS), Man-in-the-Middle (MiT), etc. These attacks can block the connection, steal, or delay the transmitted data bytes [38–40].

In addition, the application layer ensures the meeting of the application-specific needs of the end user, such as a smart city, smart home, smart grid, smart factory, smart healthcare system, and ad hoc vehicle networks (VANET) [41]. Hence, Figure 1 contains an IDS network architecture ML-based solution in the application layer.

Secondly, Figure 2 shows the proposed XGBoost model for the imbalanced multiclass classification in the IIoT-IDS datasets. There are three main components: preprocessing, XGBoost-based IIoT IDS, and classification evaluation.

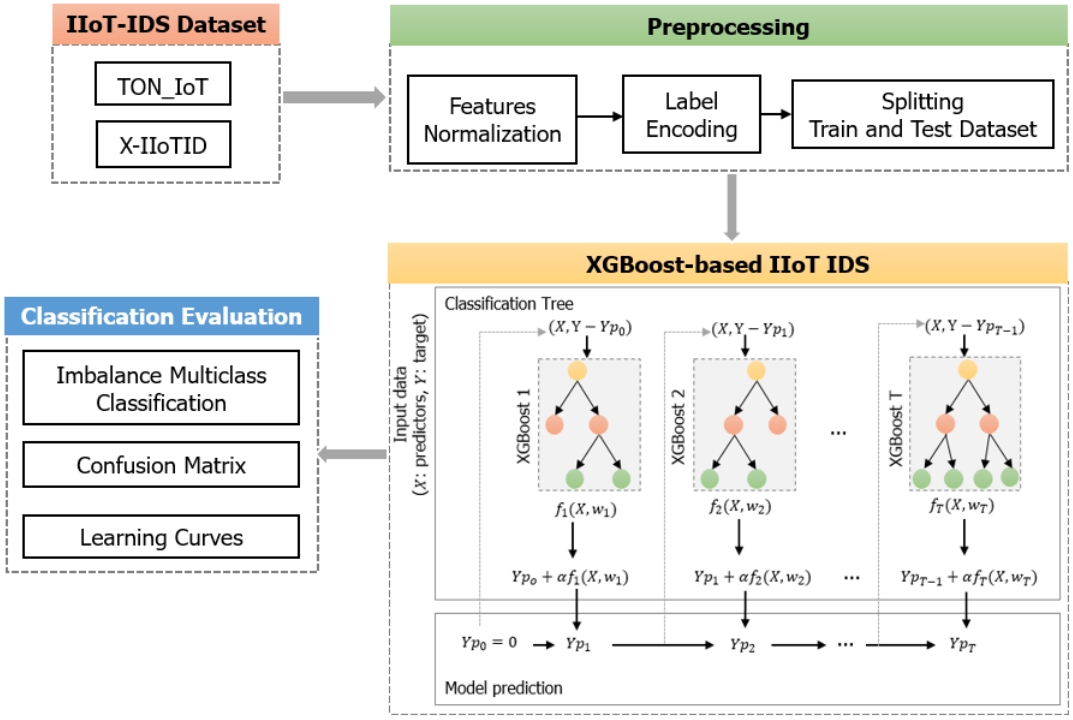


Figure 2. The proposed XGBoost for imbalanced multiclass classification.

- The data processing. We performed feature normalization, label encoding, and splitting of the training and testing datasets from the original TON_IoT and X-IIoTID. In the feature normalization, we used a min–max scale for input features following the formula:

$$X_i^N = \frac{X_i^N - min(X_i^N)}{max(X_i^N) - min(X_i^N)} \quad (1)$$

In the label encoding, we processed the multiclass output values in order to convert non-numerical type data to numerical data for the ML model to learn. We encoded target labels (Y) with a value between 0 and ($n\_classes - 1$), where $n\_classes$ is the number of different values in Y. We used the LabelEconder function of the Sklearn library in Python language to process this task. The ratio between the training data and testing data determined the number of sampling data separately used for the training and testing processes of the proposed method. In splitting the training and testing data, we divided the data with a ratio of 70:30, respectively.

- XGBoost-based IIoT IDS. XGBoost is one representative of the sequence model XGBoost. We chose the XGBoost model because of its advantages, including learning from its mistakes, fine-tuning extensive hyperparameters, scaling imbalanced data, and processing null values. The sequential ensemble method is known as boosting, which attempts to correct the mistakes of the previous models in their sequences. XGBoost is a kind of boosting algorithm that has been proven to boost weak learners in both classification and regression problems. The trees in XGBoost can create a new tree by considering the previous prediction value for the given input data of the tree and then maximize the gain in prediction. We present the main concept of XGBoost-based IIoT IDS datasets in Algorithm 1.
  In Algorithm 1, the training process is iterative to add a new tree, which can fix prior tree mistakes and residuals. After that, this process combines the previous trees to generate the final prediction. The prediction value is shown in Equation (2).

$$Yp_T(X) = Yp_{T-1}(X) + \alpha * f_T(X, w_T) \tag{2}$$

  where Yp_T is the prediction output of the Tth, α is the learning rate parameter, and f_T is a function that is trained to predict the weight w_T of the Tth.
  Based on the most significant gain loss, the model selects a leaf node; meanwhile, the model continuously measures the node loss during the training process. The model adds a tree each time by learning a new function $f_t(X, w_t)$ to fit the residual of the last prediction. After training, the T tree is obtained, which contains the corresponding leaf node with the corresponding score. Finally, by adding the related scores of each tree, the predicted value is calculated. In order to avoid over-fitting issues, XGBoost needs to find the optimal solution to balance the decline of complexity and the object function. Hence, XGBoost takes the Taylor expansion of the loss function up to the second order and adds a regularization term. Therefore, the XGBoost model prediction is shown in Equation (3).

$$Yp_t = \sum_{t=1}^{T} f_t(X_t) \tag{3}$$

  where T is the number of decision trees, $f_t(X_t)$ is the function of the input in the t-th decision tree, and Yp_t is the predicted value.
  The training objective function of XGBoost includes two parts, which are the training error and regularization as shown in Equation (4).

$$Xp_t = \sum_{i=1}^{n} L(Y_i, Yp_i) + \sum_{t=1}^{T} re(f_t) \tag{4}$$

  where $\sum_{i=1}^{n} L(Y_i, Yp_i)$ is used to measure the difference between the predicted value and the real value of the loss function. $\sum_{t=1}^{T} re(f_t)$ is the the weak learner's regularization term, and $re(f_t) = \gamma N + \frac{1}{2}\lambda|s|^2$, where N is the number of leaf nodes, s is the score of the leaf nodes, γ is the leaf penalty coefficient, and λ ensures that the score of the leaf node is not too large.
  Taylor expansion on training object: in the above step t-th object function, the previous $t-1$ prediction function y head can be considered as a variable t-th weak learner, and $f_t(X)$ is the delta change; so, XGBoost uses a second order Taylor expression to approximate the step t-th object function:

$$Xp_t = \sum_{i=1}^{N} \left(L(Y_i, Yp_{t-1} + g_i f_t(X_i) + \frac{1}{2} h_i f_t^2(X_i) \right) + \sum_{i=1}^{t} re(f_i) \tag{5}$$

  where g_i is the gradient, which is the first derivative, and h_i is the hessian, which is the second derivative.

$$g_i = \partial Yp_{t-1} L(Yi, Yp_{t-1}) \tag{6}$$

$$h_i = \partial^2 Yp_{t-1} L(Yi, Yp_{t-1}) \tag{7}$$

In the equation above, at the current t-th step, the $t-1$ step prediction y head and all before t regularization are known values; so, they are constant values in the t-th step object function. We remove the constant terms (because they do not impact the object function optimization), and we obtain:

$$Xp_t = \sum_{i=1}^{n} \left(g_i f_t(X_i) + \frac{1}{2} h_i f_t^2(X_i) \right) + re(f_t) \tag{8}$$

The tree mapping function definition is as follows:

$$I_j = \{ i | q(X_i) = j \} \tag{9}$$

where j represents a tree's j-th leaf; I_j represents a set containing all data instances, which are located in the tree's j-th leaf; and $q(x_i)$ represents a function that maps the data instance x_i into a tree leaf and returns the leaf index:

$$f_t(X) = w_q(X) \tag{10}$$

where w_i represents the i-th leaf score (weight or output). So, $f(X)$ actually represents a tree output, for instance, X.
Next, we rewrite the object function with regularization:

$$X(t) = \sum_{i=1}^{n} \left(g_i f_t(X_i) + \frac{1}{2} h_i f_t^2(X_i) \right) + \gamma T + \frac{1}{2} \lambda \sum_{j=1}^{T} w_j^2 \tag{11}$$

$$= \sum_{j=1}^{T} \left((\sum_{i \in I_j} g_i) w_j + \frac{1}{2} (\sum_{i \in I_j} h_i + \lambda) w_j^2 \right) + \gamma T \tag{12}$$

where T is the number of leaves in the t-th weak learner tree $f_t(X)$; and γ and λ are regularization hyperparameters.
The optimized object function is as follows: Now, the t-th step object function is a function of w_i, g_i, and h_i, whose values are known, because they related to the loss function and step $t-1$ prediction values. So, we can use the following equation to obtain the best w_i to minimize the object function:

$$\partial_{wi} Xt = 0 \tag{13}$$

The optimal w is:

$$w_j = -\frac{\sum_{i \in I_j} gi}{\sum_{i \in I_j} h_i + \lambda} \tag{14}$$

Furthermore, the corresponding minimal object value is:

$$Xt = -\frac{1}{2} \sum_{j=1}^{T} \frac{(\sum_{i \in I_j} g_i)^2}{\sum_{i \in I_j} h_i + \lambda} + \gamma T \tag{15}$$

The slitting criteria for the weak learner is as follows: Firstly, we obtain the t-th step object function. Next, we build the t-th tree. This tree should be constructed to reduce the object function value as much as possible. To build this tree, we only allow a node split and search for the best split, which causes the greatest reduction. Hence, in each split, we measure the objective function value reduced by the tree object function value (After Node Split)-(Before Node Split).

$$G = \frac{1}{2}\left(\frac{(\sum_{i\in I_L} g_i)^2}{\sum_{i\in I_L} h_i + \lambda} + \frac{(\sum_{i\in I_R} g_i)^2}{\sum_{i\in I_R} h_i + \lambda} - \frac{(\sum_{i\in I} g_i)^2}{\sum_{i\in I} h_i + \lambda}\right) - \gamma \quad (16)$$

Gain (G) is how many object's function values are reduced in the split. I_L is a left splitting child leaf; I_R is a right splitting leaf; and I is the parent leaf.
For simplicity, each leaf can calculate its Similarity Score (SS):

$$SS = \frac{(\sum_{i\in I} g_i)^2}{\sum_{i\in I} h_i + \lambda} \quad (17)$$

The splitting gain can be expressed as:

$$Left(SS) + Right(SS) - Parent(SS) \quad (18)$$

Based on the chosen loss function, g_i and h_i are 1-order and 2-order derivatives to calculate tree node similarity and tree leaf output w_i. For classification, the loss function is a custom log loss function (as shown in Equation (19).

$$L = Y_i log(p_i) + (1 - Y_i) log(1 - p_i) \quad (19)$$

where $p_i = sigmoid(Y_i)$ is the output class probability, calculated via log transformation on the tree output prediction Y_i.

- Classification evaluation metrics. Cortés-Leal et al. [42] used a performance metric to mitigate IIoT attacks through measuring the impact of the energy consumption during transmission in IoT and WSN environments. However, we considered other performance metrics, since they suited the ML approach in this work. In particular, we used a confusion matrix (CM) and learning curves to evaluate the performance of our proposed model. A CM contains true positive (TP), true negative (TN), false positive (FP), and false negative (FN). Based on these values of CM, we calculated other performance evaluation metrics, including precision (P), recall (R), and the F1 score.
The precision (P) is used to measure the accuracy of the model for classifying a sample as positive.

$$P = \frac{TP}{TP + FP} \quad (20)$$

The recall (R) is used to measure the ability of the model to detect positive samples.

$$R = \frac{TP}{TP + FN} \quad (21)$$

The $F1$ score is the harmonic mean of P and R, which is calculated following Equation (22).

$$F1 = 2 \times \frac{P \times R}{P + R} \quad (22)$$

The learning curve performance represents the efficiency of the model during training time with instances. The cross-validation score will represent the evaluation performance of the learning curve.

Algorithm 1: XGBoost-based IDS model.

input : Input features (X, Y),
A loss function L,
The learning rate α,
The number of terminal node T

output: Output prediction (Y_p)

Initialize function $f_0(X) = argmin_\theta \sum_{i=1}^{n} L(y_i, \theta)$
while $i <= M$ **do**
  $g_m(X_i) \leftarrow \frac{\partial L(Y_i, f(X_i))}{\partial f(X_i)}$
  $h_m(X_i) \leftarrow \frac{\partial^2 L(Y_i, f(X_i))}{\partial f(X_i)^2}$
  Determine the structure $\{R_{jm}\}_{j=1}^{T}$ by selecting splits which maximize
  $Gain(G) \leftarrow \frac{1}{2}(\frac{G_L^2}{H_L} + \frac{G_R^2}{H_R} - \frac{G_{jm}^2}{H_{jm}})$
  Determine the leaf weights ${w_{jm}}_{j=1}^{T}$ for the learned structure by
  $w_{jm} \leftarrow -\frac{G_{jm}}{H_{jm}}$
  $f_m(X) \leftarrow \alpha \sum_{j=1}^{T} w_{jm} I(X \in R_{jm})$
  $f_m(X) \leftarrow f_{m-1}(X) + f_m(X)$
  $i+ \leftarrow 1$
end
return $Y_p = f(X) = f_M(X) = \sum_{m=0}^{M} f_m(X)$

3. Results and Discussion

This section provides the performance evaluation results of the proposed method. In particular, Section 3.1 shows how the proposed method can solve the imbalanced multiclass classification problem. Section 3.2 presents the performance learning curves. Furthermore, we compare the performance classification of the proposed method with other related methods in Section 3.3.

3.1. Imbalanced Multiclass Classification

We computed and visualized the multiclass classification of the proposed method using a CM and a classification report. For the X-IIoTID dataset, we visualized the performance results with precision, recall, and F1 measurements by classification reports for class 1 and class 2 as shown in Figures 3 and 4, respectively.

The X-IIoTID dataset included two output class labels: class 1 and class 2. Although class 1 and class 2 contained output class labels, which were not balanced samples, the proposed method still obtained the best accuracy on the three types of measurement metrics. The proposed method obtained almost 100% on the precision, recall, and F1 metrics with 18 multiclass outputs of class 1 (see Figure 3) and 10 multiclass outputs of class 2 (see Figure 4).

For the TON_IoT dataset, we visualized the performance of the multiclass classification by CM as shown in Figure 5. Although the two attack types of "xss" and "scanning" had the smallest amount of IoT device data compared with the other attack types, the proposed model still detected approximately 100% accurately. Furthermore, the proposed method also obtained the best precision and recall as well as the F1 score on the balanced attack data distribution, including ["crypto-ransomware", "Exploitation", "C&C", "Tampering", "Exfilltration", "Lateral_movement", "Weaponization", "reconnaissance", and "RDOS attacks"].

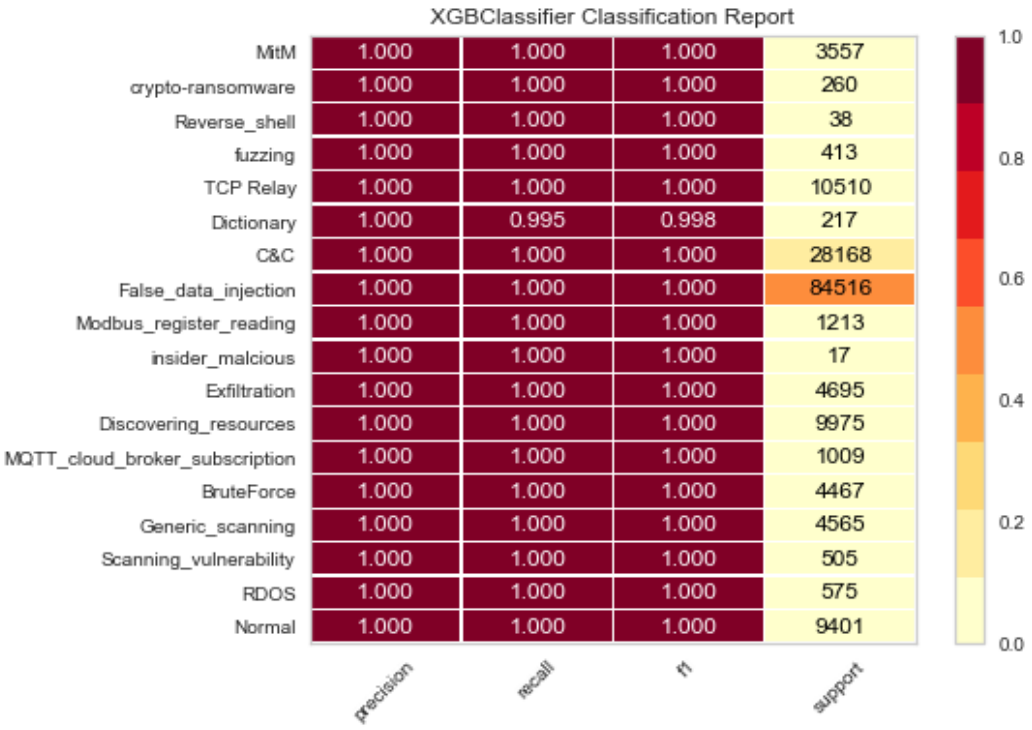


Figure 3. Classification report result for class 1 of the X-IIoTID dataset.

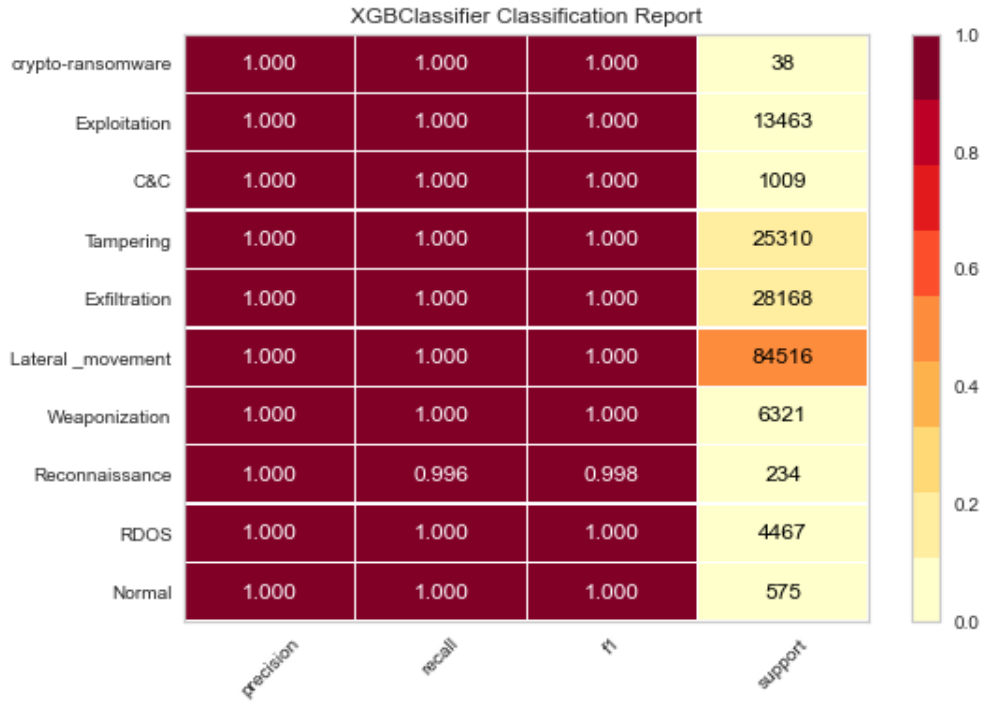


Figure 4. Classification report result for class 2 of the X-IIoTID dataset.

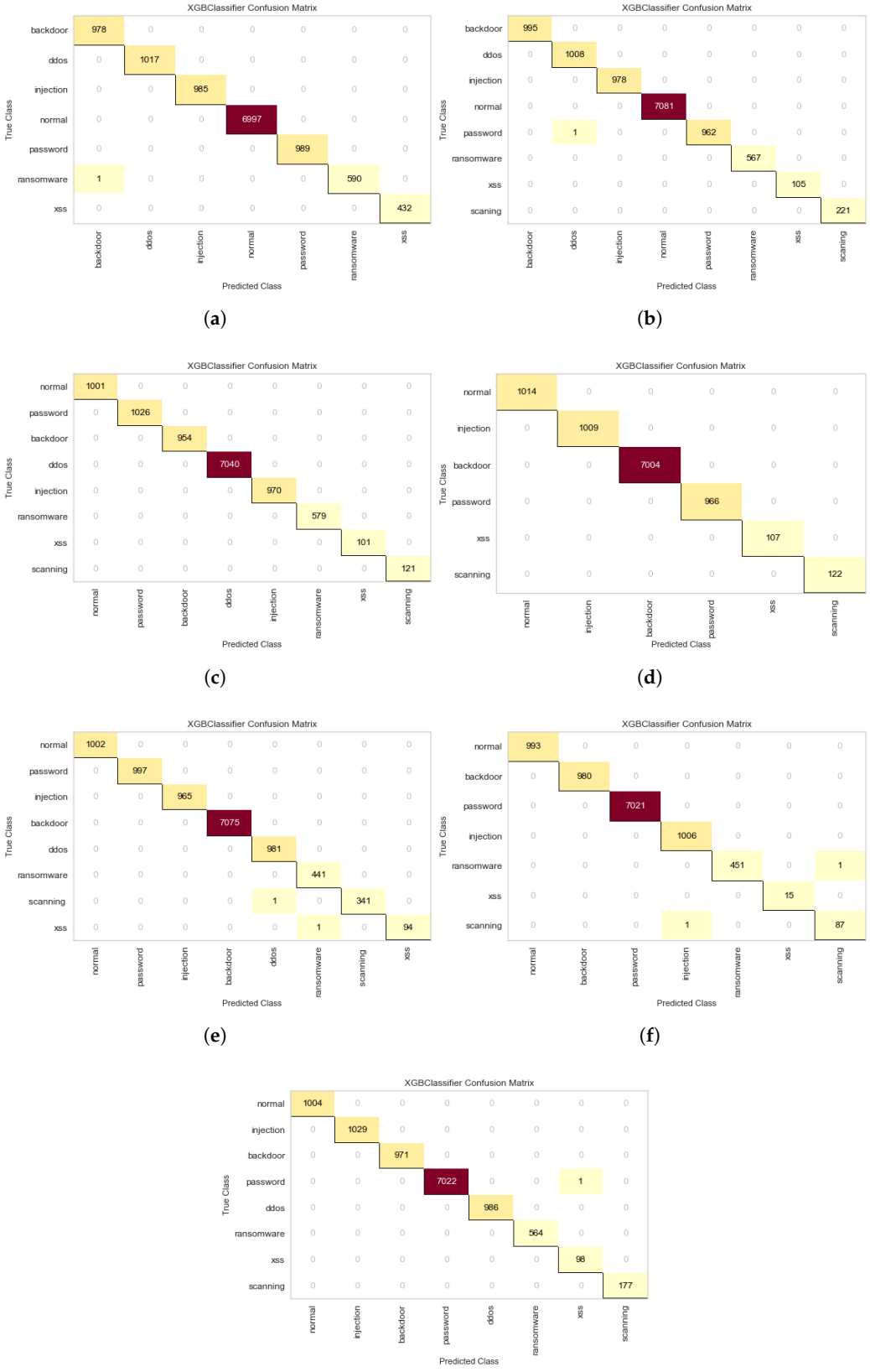


Figure 5. Confusion matrix results of the proposed method on the TON_IoT dataset. (**a**) IoT Fridge; (**b**) IoT Garage Door; (**c**) IoT GPS Tracker; (**d**) IoT Modbus; (**e**) IoT Motion Light; (**f**) IoT Thermostat; and (**g**) IoT Weather.

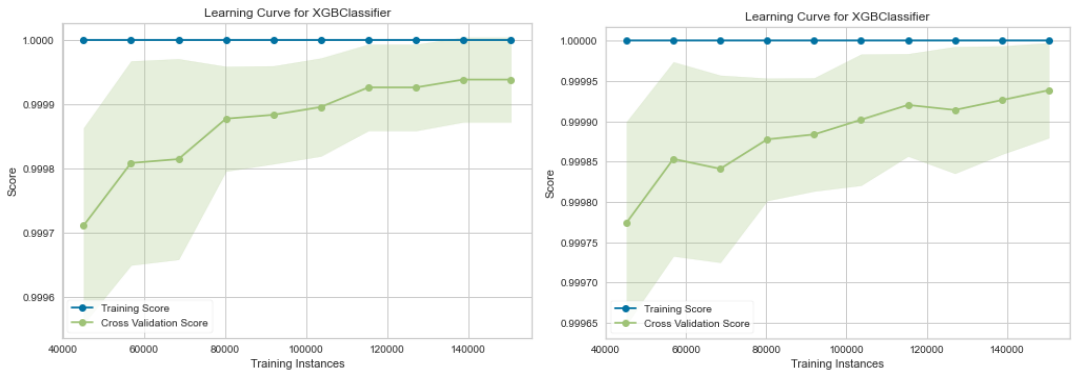
In summary, we present the average performance classification of the proposed method on the two datasets in Table 4. Three evaluation metrics were used to evaluate the proposed approach: precision, recall, and F1 score. For the X-IIoTID dataset, the average F1 score of the two output classes was 99.9%. For the TON_IoT dataset, the average F1 score of all IoT device data was 99.87%. Therefore, the proposed method can handle the multiclass data's imbalanced distribution issue.

Table 4. Average performance of the proposed method for classification.

Dataset	Output class/Device	Precision	Recall	F1
X-IIoTID	Class 1	1.0	0.9975	0.999
	Class 2	1.0	0.998	0.999
TON_IoT	IoT_Fridge	0.9995	0.999	0.9993
	IoT_Garage_Door	0.9995	1.0	0.9995
	IoT_GPS_Tracker	1.0	1.0	1.0
	IoT_Modbus	1.0	1.0	1.0
	IoT_Motion_Light	0.999	0.9953	0.9984
	IoT_Thermostat	0.995	0.9957	0.996
	IoT_Weather	0.995	1.0	0.9975

3.2. Performance Learning Curve

To further examine the robust training performance of the proposed method, we provide the learning curve measurement results. In the learning curve plot, the cross-validation score illustrated the training performance of the model. Figures 6 and 7 illustrate the learning curve results for each output class over each dataset: X-IIoTID and TON_IoT, respectively. In particular, the cross-validation score of the model on the X-IIoTID dataset achieved 99.99% (for class 1 output as shown in Figure 6a) and 99.995% (for class 2 output as shown in Figure 6b).



(**a**) (**b**)

Figure 6. Learning curve results of the proposed method on the X-IIoTID dataset: (**a**) class 1 output; (**b**) class 2 output.

Next, we provide the plotting results for the learning curve of the proposed method on the TON_IoT dataset. Most cross-validation scores for the IoT device data were approximately 100%, and the cross-validation scores for IoT Garage Door data were 97% (see Figure 7b).

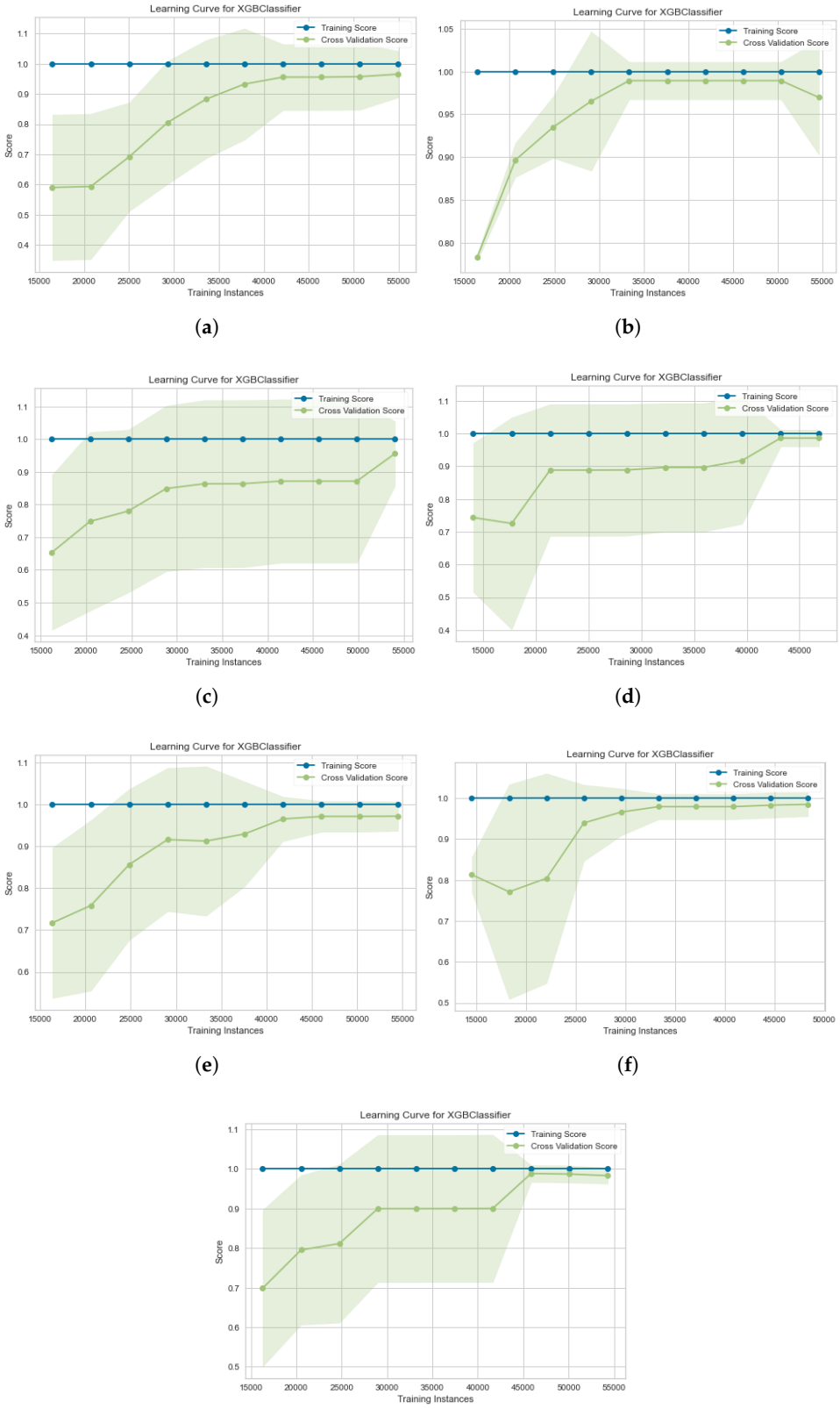


Figure 7. Learning curve results of the proposed method on the TON_IoT dataset. (**a**) IoT Fridge; (**b**) IoT Garage Door; (**c**) IoT GPS Tracker; (**d**) IoT Modbus; (**e**) IoT Motion Light; (**f**) IoT Thermostat; and (**g**) IoT Weather.

3.3. Performance Comparison

We confirmed the performance of the proposed method by comparing it with other related models used on similar public datasets. Firstly, we compared the performance of the multiclass classification via the F1 score of the proposed method with other related methods. We chose the X-IIoTID dataset with class 2 output to present the comparison results in Table 5. Indeed, the best F1 score emphasized in bold value belonged to the proposed method. While the F1 score of the Reconnaissance attack was 99.8%, the F1 scores for the other attacks achieved 100%. Hence, the attack detection performance of the proposed method was enhanced compared with the existing methods.

Table 5. Comparison of multiclass classification by the F1 score of the proposed method with other methods on the X-IIoTID dataset.

Attack Type	DPM–DDM [27]	DT [28]	Proposed Method (XGBoost)
crypto-ransomware	**100**	99.86	**100**
Exploitation	64.66	98.52	**100**
C&C	99.27	89.66	**100**
Tampering	99.72	99.47	**100**
Exfiltration	99.98	89.76	**100**
Lateral_movement	91.48	98.52	**100**
Weaponization	99.76	99.97	**100**
Reconnaissance	93	99.22	**99.8**
RDOS	99.94	99.99	**100**
Normal	-	-	**100**

Secondly, we compared the F1 score of the proposed method with other methods [29] on the TON_IoT dataset. Alsaedi et al. [29] used three methods, including the LSTM, kNN, and CART algorithm as shown in Table 6. Although the LSTM method achieved the best F1 score on the IoT device datasets, IoT_Fridge and IoT_Garage_Door, our proposed method obtained a high F1 score on both IoT device datasets and a higher F1 score on the other IoT device datasets. In particular, our method improved by 12% and 44.84% the F1 scores compared with the LSTM model's results on IoT_GPS_Tracker and IoT_Motion_Light, respectively. In addition, the proposed method enhanced by 1% and 12.75% the F1 scores compared with the CART algorithm's result on the IoT_Modbus and IoT_Weather datasets, respectively. For IoT_Thermostat data, our proposed model increased by 42.6% compared with the kNN and CART methods.

Table 6. Comparison of the F1 scores on the TON_IoT dataset.

IoT Device Data	LSTM [29]	kNN [29]	CART [29]	Proposed Method (XGBoost)
IoT_Fridge	**100**	99	97	99.93
IoT_Garage_Door	**100**	**100**	**100**	99.95
IoT_GPS_Tracker	88	88	85	**100**
IoT_Modbus	55	77	99	**100**
IoT_Motion_Light	55	43	43	**99.84**
IoT_Thermostat	54	57	57	**99.6**
IoT_Weather	80	81	87	**99.75**

Thirdly, we compared the average F1 score of the proposed method with the F1 score of other previous approaches on the TON_IoT and X-IIoTID datasets. For the TON_IoT dataset, the best F1 of the RF method achieved 97.264%, while our proposed method obtained 99.87%, an increase of 4.59%. In addition, the proposed method improved the F1 score by 2.49% compared with the best previous method, DPM–DDM, on the X-IIoTID dataset. The detailed comparison is shown in Table 7.

Table 7. Comparison average F1 score of the proposed method with other methods on two datasets.

Dataset	Method	F1
TON_IoT	LSTM [29]	76
	kNN [29]	77.86
	CART [29]	81.14
	GBM [31]	92.557
	RF [31]	97.264
	NN [31]	92.120
	TP2SF [30]	95.28
	Proposed method	**99.87**
X-IIoTID	AP2PFL-MLP [27]	92.061
	AP2PFL-DNN [27]	96.42
	DPM-DDM [27]	97.41
	DT [28]	97.27
	Proposed method	**99.9**

4. Conclusions

This paper proposed an IIoT IDS approach based on the XGBoost model. This model can solve the challenging issue of related IIoT datasets, which is the imbalance in the multi-class data distribution. The TON_IoT and X-IIoTID datasets were used for experiments to evaluate the proposed method. These datasets are benchmarks with advantages over other related IIoT datasets and contain imbalanced attack type distributions. A comprehensive set of experiments proved that the proposed method obtained the best performance in terms of F1 score. In particular, the proposed model obtained the best F1 scores of 99.87% and 99.9% in the TON_IoT and X-IIoTID datasets, respectively. In comparison with the baseline models' results, the proposed method outperformed other previous approaches on the same two IIoT datasets: TON_IoT and X-IIoTID. Therefore, we demonstrated that the proposed method could better solve the challenge of the imbalance in attack data distribution in IIoT IDS datasets compared to previous learning methods. We shall test and apply the proposed model for a specific related IIoT application in future work. In other words, the proposed method can be tuned and used in a particular context of a security application in the future.

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Abbreviations

The following abbreviations are used in this manuscript:

IoT	Internet of Things
IIoT	Industrial Internet of Things
IDS	Intrusion Detection System
ML	Machine Learning
NIDS	Network Intrusion Detection System
XGBoost	eXtremely Gradient Boosting
M2M	Machine-to-Machine
M2P	Machine-to-People
H2M	Human-to-Machine
M2H	Machine-to-Human
MitM	Man-in-the-Middle
DL	Deep Learning
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Unit
U2R	User to Root
LR	Logistics Regression
LDA	Linear Discriminant Analysis
SVM	Support Vector Machine
NB	Naïve Bayes
kNN	k-Nearest Neighbors
GBM	Gradient Boosting Machines
RF	Random Forest
NN	Neural Network
AP2PFL-MLP	Asynchronous Peer-to-Peer Federated Learning-Multilayer Perceptron
TP2SF	Trustworthy Privacy-Preserving Secured Framework
WSN	Wireless Sensor Network
DR	Detection Rate
FAR	False Alarm Rate
DDoS	Distributed Denial of Service
CM	Confusion Matrix
TP	true positive
TN	true negative
FP	false positive
FN	false negative

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