Anomaly Detection in IoT Using Extended Isolation Forest

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Abstract. The emergence of various smart services delivered by heterogeneous Internet of Things (IoT) devices has made daily human-life easy and comfortable. IoT devices have brought enormous convenience to various applications, no matter the IoT systems include homogeneous devices like in most sensor networks or heterogeneous devices like in smart homes or smart business applications. However, several known communication infrastructures of IoT systems are at risk to various security attacks and threats. The practice of discovering uncommon occurrences of conventional behaviors is known as anomaly detection. It is an essential tool for detecting fraud as well as network intrusion. In this work, we provide an anomaly-based model on the Extended Isolation Forest method. In our work, the available dataset 'UNSW_2018_IoT_Botnet_Final_10_best_Testing' has been used for the experiment. Performance indicators, including accuracy, precision, recall, and F1-Score, are used to validate the performance of our suggested system. We get an Accuracy Score of 93% and F1-Score of 96% through the experiment. In addition, the most important top 12 features have a more substantial impact on correct prediction for anomaly identification and have also been identified in this study.

Keywords: Anomaly detection · Isolation forest · Extended isolation forest · Iot security · Feature set

1 Introduction

With the lightning-fast development, the Internet is now not limited to PCs and Laptops; It has inspired a new phenomenon known as the Internet of Things (IoT). The primary purpose of this technology is to simplify people's lives by automating existing device infrastructure and entering all individuals' lives. Web services or interfaces are used to connect IoT devices to the Internet. However, some well-known IoT communication infrastructures are vulnerable to various security risks and assaults, putting IoT networks at risk. Thus, securing the IoT devices and the networks associated with the IoT system is necessary. Several security and privacy features for IoT applications have been developed and

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implemented, but many problems remain open. Thus, the adoption of security and privacy for IoT devices is the researchers' top objective. The denial-of-service (DoS) attacks, distributed denial-of-service (DDoS) attacks, botnet, access control, identity management, governance frameworks, etc., are the serious concern in the security field of IoT [16]. Among all risks, DoS and DDoS (which are advanced versions of DoS and more difficult to prevent) cyberattacks, perhaps, are the most deadly and devastating security issues for gaining control of IoT nodes [2,9]. As a result, detection of these attacks on IoT devices has piqued the interest of experts in recent years. The three levels of an IoT architecture are the perception layer, network layer, and application layer. Malicious physical attacks on devices with sensors and unauthorized access to equipment on the Perception layer are the most common attacks, whereas, in the Network layer, the most attacks are DoS, DDoS, gateway attacks, routing attacks, information theft, information gathering, etc. Panja et al. [15] depicted different threats and attacks concerning the layers of IoT systems. However, a detection system is necessary to identify these attacks in the IoT network, known as Intrusion Detection System (IDS) [19]. IDS is classified as a Signature-based Intrusion Detection System (SIDS) and an Anomaly-based Intrusion Detection System (AIDS). In between these, SIDS, although it performs well on previously known attacks, is not dynamic because it fails on unknown attacks [1]. AIDS, on the other hand, using network parameter learning algorithms, is capable of dealing with that scenario [14]. However, Communication to IoT devices is occasionally misclassified as anomalous traffic by threshold-based anomaly detection systems, which cannot respond to different patterns of attacks. [3]. In contrast, anomaly detection methods based on machine learning performed better in reducing false positives.

The remaining part of the paper is laid out as follows: A survey of relevant work has been provided in Sect. 2. In Sect. 3, we explored our objective and motivation for doing this work. In Sect. 4, a brief description of Isolation Forest (IF) and Extended Isolation Forest (EIF) has been given. The entire methodology of our work has been described in Sect. 5. Finally, the conclusion part has been discussed in Sect. 6.

2 Related Study

Anomaly detection focuses on patterns in data that deviate from the expected pattern. Anomaly detection techniques can be used to distinguish malicious traffic from legitimate traffic. In this section, we discuss various machine learning-based anomaly detection systems in the IoT presented by different researchers. Many researchers used supervised machine learning approaches in their models to detect anomalies in IoT networks. As a result, unsupervised machine learning algorithms in IoT networks may be used to discover anomalies. Supervised learning works by training sample data from a data source that already has a

categorization. The capacity to acquire and organize information using an unlabeled dataset is referred to as unsupervised learning.

Doshi et al. [6] suggested a DDoS identification for consumer IoT systems based on a machine learning algorithm. The authors proposed an unsupervised machine learning pipeline for DDoS detection in IoT traffic that includes some steps like data gathering, feature extraction, and binary classification. The pipeline has been designed to operate on network middleboxes, such as routers, network switches, or firewalls, to detect DDoS attack origins on nearby IoT devices spontaneously. It's the earliest network anomaly detection technique that emphasizes IoT-specific properties and recognizes IoT bots at the level of localized networks.

Vishwakarma et al. [21] proposed a honeypot-based malware identification strategy that uses machine learning techniques. All the data acquired by the IoT honeypot is used as a dataset asset. These datasets are for the training of functional and adaptive machine learning models. The approach is effective for starting when dealing with zero-day DDoS attacks.

Diro and Chilamkurti [5] proposed a deep learning-based IDS that depends on stateless and stateful properties to distinguish malicious traffic from regular traffic on the IoT network. The approach primarily safeguards IoT devices.

Thamilarasu and Chawla [18] developed a deep learning-based approach to identify different types of attacks in IoT, such as blackhole, opportunistic, DDoS and sinkhole, and also wormholes. The model has a 97% true positive rate and a 95% average accuracy against all types of attacks.

Hussain et al. [8] proposed a machine learning-based IDS to detect attacks like DOS, data type probing, malicious control, malicious operation, scan, etc., for the IoT devices used in a smart home.

Das et al. [4] proposed an unsupervised machine learning-based technique to develop an anomaly detection mechanism with notable performance in detecting DDoS attacks. This work aims to enhance the precision of DDoS attack detection and minimize the number of false positives. For testing, the authors utilized the NSL-KDD data set sample and 12 feature sets from earlier research to compare their composite outcomes to those of their individuals and other current models.

Nakahara et al. [13] proposed an integrated strategy that uses a white list and machine learning to remove regular communication from intrusion detection while examining additional communications using an Isolation Forest (IF) algorithm. They also compared the outcomes of anomaly detection with and without the white list to show that the recommended technique is effective.

Nakahara et al. [12] designed a method that sends statistical information from the home gateway to an analysis server to detect irregularities in IoT devices in the home network. Despite the fact that the statistical information employed in anomaly identification has been limited, they have also proven the abnormalities of numerous devices in the experiment. With Isolation Forest (IF) and K-means clustering, they proposed a method that might minimize the data quantity needed for the analysis by over 90% while still achieving high precision.

Tyagi and Kumar [20] investigated various supervised learning classifiers for anomaly and threat detection in IoT environments, including K Nearest Neighbor (KNN), Support Vector Machine (SVM), Logistic Regression (LR), Decision Tree (DT), Multilayer Perceptron (MLP), and Random Forest (RF). The authors demonstrated that both DT and RF are more accurate than the rest classifiers applied. The suggested study uses the BoT IoT dataset to derive a unique IoT-specific feature set that identifies various types of attacks. The extracted set of features is independent of attack characteristics but dependent on the IoT network. As a consequence, these features can aid in the detection of any questionable behavior in an IoT network using a machine learning model.

Seifousadati et al. [17] proposed a DDoS attack detection methodology combining machine learning and data mining approaches. To identify traffic on the network that is not real, the authors used famous machine learning methods, notably Naïve Bayes, Support Vector Machine (SVM), AdaBoost, XGBoost, K Nearest Neighbor (KNN), and Random Forest.

Hariri et al. [7] presented a method for detecting anomalies, namely the 'Extended Isolation Forest' (EIF) algorithm. EIF corrects problems with anomaly scores assigned to specific data points. The researchers explored the challenge by employing heat maps for anomaly scores, which suffer from artifacts generated by the criteria for the branching operation of a binary tree. The researchers thoroughly defined the problem and graphically displayed the method through which it happens. They recommended two techniques: randomly modifying the data before creating each tree, which results in averaging out the bias and enabling data slicing to employ hyper-plane with randomized slopes.

3 Motivation of Our Work

IoT plays a crucial part in our daily lives in the modern age. It is now used in a wide range of fields, such as home automation, smart cities, self-driving cars, smart grids, hospitals, farms, and so on. Anomaly detection in IoT is an ongoing research theme because IoT devices are prone to be attacked through different weak points. Machine Learning algorithms have become very popular and efficient in detecting anomalies, which attracted the attention of researchers. However, we have reviewed the works of many researchers where we found that some of the machine learning-based anomaly detection systems [5,11] are not suitable for IoT environments. Furthermore, anomaly Detection in IoT networks is mostly based on supervised machine learning approaches. However, in the case of unsupervised learning, the lack of guidance for the learning algorithm could sometimes be advantageous because it enables the system to search back for patterns that were not even previously examined. Thus, we planned to use unsupervised machine learning in this work. We have used the Extended Isolation Forest (EIF) algorithm, proposed by [7] for detecting an anomaly. The basic idea of Extended Isolation Forest (EIF) is similar to the Isolation Forest (IF) algorithm. In an Isolation Forest technique, data is taken from a sample of a sample and prepared in a tree structure that depends on random cuts in the

values of randomly selected attributes in the data set. Data samples that extend deeply into the branches of a tree are less probable for being anomalous, whereas smaller branches are more probable for being anomalous. Extended Isolation Forest splits data using hyper-planes with random slopes (non-axis-parallel) to create binary search trees. However, as branch splits in isolation forests are frequently horizontal or vertical, it generates bias and causes abnormalities in the anomaly score map. Extended Isolation Forest, on the other hand, as choose a branch cut with a randomized slope at every branching point, eliminates the bias.

4 Isolation Forest (IF) and Extended Isolation Forest (EIF)

In this part, we provides a brief overview of the Isolation Forest (IF) and Extended Isolation Forest (EIF) algorithms, which are widely applied for anomaly detection.

Isolation Forest (IF) is an unsupervised learning method for anomaly detection which follows the process of randomly partitioning data points to isolate the anomaly from the normal instances.

- The algorithm chooses a random sample of sampled data to build a binary tree and ensemble iTree from a given dataset. The binary tree is built to isolate all the points and measure their individual path length from the root. It detects anomalies in the iTrees that are closer to the root and considers normal point that is deeper in the tree. A diagrammatic view of iTree has been given in Fig. 1.
- In order to construct an iForest, one arbitrarily sample determine a portion of the data set to generate iTrees, and it has been discovered that 256 is really a reasonable quantity of data for subsequent sub-sampling.
- iForest does not use density or distance calculations to identify anomalies; thus, this step eliminates the processing cost compared to the distance measure involving grouping, which requires linear time complexity.
- iForest need a small quantity of memory and uses the combined idea if some iTrees do not produce valid results because the integrated algorithm converts weak trees into valid trees. Because of all these benefits, iForest is proficient in detecting anomalies involving complex and large datasets.
- The Eq. 1 for calculating anomaly score for iTrees is [7]:

$$S(x, n) = 2^{\frac{(-E(h(x)))}{c(n)}} \tag{1}$$

where, $E(h(x))$ is the number of edges in a tree for a certain point (x).

$$c(n) = 2H(n-1) - \frac{2(n-1)}{n} \tag{2}$$

where, in Eq. 2, $c(n)$ is the normalization constant for a dataset of size n and $H(i)$ is a harmonic number can be evaluate by $ln(i) + 0.5772156649$ (Euler's constant) and n is the number of points used to develop of trees.

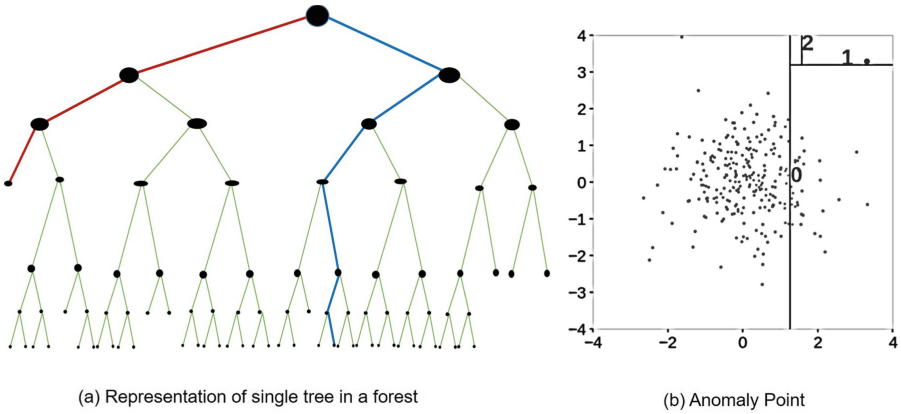

Fig. 1. A diagrammatic view of iTree

– In iForest, the branch cuts either vertical or horizontal; this may lead to a bias and distortions to the anomaly scoring map.

Extended Isolation Forest (EIF) chooses a branch cut with a randomized slope at every branching point; thus, it can eliminate the bias.

– The core notion of EIF is the same as IF; however, it is dependent on the randomness of feature selection. Because specific points are 'few and unusual,' they stand out rapidly compared to random choices.
– iForest needs two pieces of records for branch cuts: a) a random characteristic or coordinate, and b) a random value for the feature from the record's variety of possible values. EIF requires two fact segments, but those are: 1) a random slope for the branch reduce and 2) a random intercept for the branch reduce, each of which can be picked from the training data's boundary of accessible values.
– Choosing a random slope for the branch reducing for an N-dimensional data set is equivalent to picking a normal vector, $\overrightarrow{n}$, evenly over the unit N - Sphere. This is simply performed by selecting a random integer from the usual normal distribution N (0, 1) for each of $\overrightarrow{n}$ coordinates. As a result, the N-point spheres are evenly distributed. For the cut-off, $\overrightarrow{p}$, We simply select values from a uniformly distributed set that spans the range of values available at every intersection.
– The branching criterion for data partitioning at a specific point $\overrightarrow{x}$ will be defined after these two pieces of information are identified, as follows:
  1. If the condition is met, the data $\overrightarrow{x}$ is sent to the left-sided branch; else, it is sent to the right-sided branch.
  2. At this point, a new generalization hyper-parameter, extension-Level, is introduced. The function of extension Level is to force random items of $\overrightarrow{n}$ to be zero. The value of the extension-level hyper-parameter ranges from 0 to P-1, where P denotes the number of features. A value of 0

indicates that all gradients will be parallel in all directions, which is the behavior of an Isolation Forest. The more extension levels there are, the more parallel the divide is with the number of extension-level axes. The term "full extension" refers to a level of extension equal to P-1. This means that the branching point's slope will be randomized at all times.

EIF algorithm can fully replace the IF algorithm since it allows leveraging generalization by employing the extension-Level hyper-parameter. However, even if enough uses of EIF algorithm would exist, IF algorithm will remain in use due to its interpretability. Since the IF uses Binary Search Tree (BST), it is easy to interpret, but the interpretability of EIF is irretrievably lost with the adjustment of branching.

5 Methodology

5.1 Proposed Study

Algorithms for machine learning that are most widely used for anomaly detection were determined by reviewing related works by other researchers. In terms of effectiveness and speed, we proposed a model in our paper. The dataset titled "UNSW_2018_IoT_Botnet_Final_10_best_Testing", has been used for the experiment. After preprocessing the data, we evaluated the most common machine learning method for anomaly detection and recorded the results.

5.2 Dataset

The Cyber Range Lab at UNSW Canberra Cyber created an IoT dataset UNSW _2018_IoT_Botnet_Final_10_best_Testing", tested in a real-world testbed setting. [12], this dataset contains 5% of the original Bot-IoT dataset. Both simulated and real-world IoT attack traffic is included in the dataset. There are 733564 harmful entries and 107 normal entries in the sample. We consider binary classification in our experiment. The histogram of binary classification of the dataset is shown in Fig. 2, where the X-axis denotes the attack and normal class, and Y-axis denotes the frequency of data.

5.3 Data Prepocessing

We utilized the Google Colab environment for data preparation, which was designed by Google and allowed anybody to write instruction code and execute Python programs through the web browser. Consequently, researchers working on machine learning and data analysis will find it quite valuable. Therefore, we employed the Pandas, ScikitLearn, and Numpy packages in our preparation effort. In [10] researchers used different features and description which shows in the Table 1, are taken for our experiment:

The steps for data pre-processing is summarized as below:

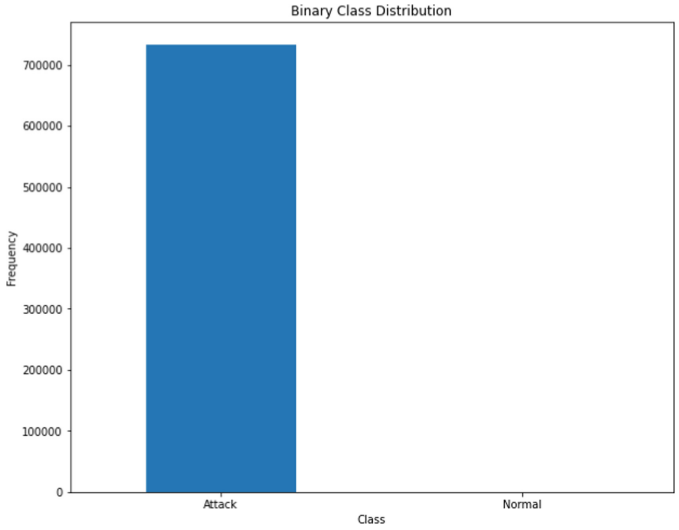

Fig. 2. Binary clasification of dataset

Table 1. Features and descriptions

Features	Description
pkSqid	Row identifier
saddr	Source IP address
Sport	Source port number
daddr	Destination IP address
dport	Destination port number
seq	Argus sequence number
stddev	Standard deviation of aggregated records
N_IN_conn_P_SrcIP	Number of inbound connection per source IP
min	Minimum duration of aggregated records
state_number	Numerical representation of feature state
Mean	Average duration of aggregated records
N_IN_conn_P_DstIP	Number of inbound connection per destination IP
drate	Destnation-to-source packets per seconds
srate	Source-to-Destination packets per seconds
max	Maximun duration of aggregated records

1. Replacing data values: There is no null values in the Dataset and contains many octal values. Therefore, we replaced octal values with a corresponding integer values.

2. Encoding categorical columns: In order to prepare the Dataset for experimental use, it is essential to convert non-numerical values into numerical values.
3. Feature Scaling: StandardScaler is used to perform Feature Scaling in Data Preprocessing. We use Standard Scalar to scale the magnitude of the feature within a certain range. Real-world data are heterogeneous and has a direct impact on performance. After scaling, data is ready to fit in the proposed model.

5.4 Evaluation Metrics

We used Accuracy Score, F1-Score, Precision, and Recall to examine the algorithm efficiency and effectiveness.

– The accuracy score is measured as the number of true predicted labels divided by the total number of labels. The formula of Accuracy Score is mentioned in Eq.(3):

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{3}$$

– The harmonic average of precision and recall is used to get the F1-Score. Because it incorporates False Positive and False Negative, it's a good measure to use in conjunction with the accuracy score. Formulas of Precision in Eq.(4), Recall in Eq.(5), and F1-Score in Eq.(6), are mentioned in the following:

$$Precision = \frac{(TP)}{(TP + FP)} \tag{4}$$

$$Recall = \frac{(TP)}{(TP + FN)} \tag{5}$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

5.5 Confusion Matrix

A confusion matrix illustrates the classifying problem's prediction outcomes. It is an evaluation tool for machine learning classification. The genuine values of the testing data are used to assess performance. In machine learning, the Confusion Matrix aids in the detection of mistakes (FP and FN) as well as the calculation of other performance metrics values. The confusion matrix comprises four parts for binary classification (True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) as given in Table.

– True Positives (TP) occur whenever a true positive label is identified as positive by the classifier.
– Whenever the classifier identifies a genuine negative label as negative, it is called a True Negative (TN).

Table 2. Confusion matrix

Confusion matrix		Actual values	
		Positive	Negative
Precicted values	Positive	TP	FP
	Negative	FN	TN

– False Positives (FP) happen whenever a classifier misinterprets a genuine negative label as a positive.
– False Negatives (FN) happen when a true positive label is wrongly classified as negative by the classifier.

A positive event is regarded a harmful occurrence, according to cyber security research, and their right categorization is considered a real positive outcome. Because a negative event is so regular, the suitable classification is true negative. An inaccuracy in categorization can lead to the wrong classification of a regular event as a harmful one. This categorization error is considered a false positive. Similarly, classifying a harmful event as a regular occurrence is considered a false negative.

5.6 Results and Analysis

After data preprocessing, n-trees(represents no of trees)= 200, sample_size= 256 and Extension-Level=1 are fitted into EIF model. After fitting data into the model, EIF predicts the score of each data instance. We take a threshold value, and any value larger than this is considered normal because EIF returns a high score for normal instances compared to anomalous instances. We have found 681548 anomalous points and 52157 normal points through our experiment,

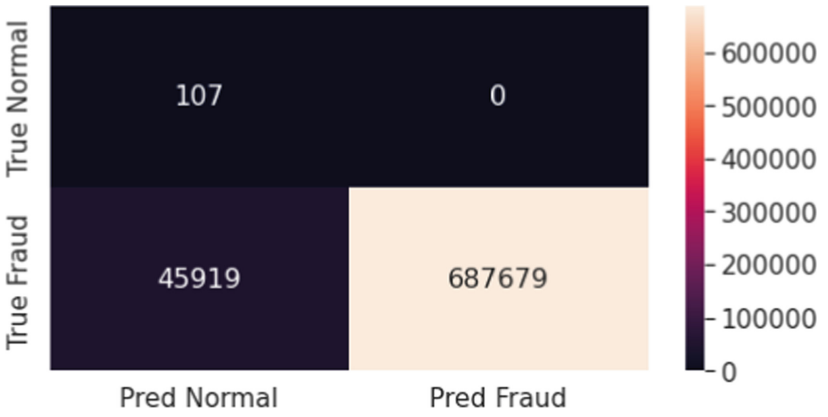

Fig. 3. Confusion matrix as per our analysis

Table 3. Anomaly detection evaluation results

EIF			
Accuracy	Precision	Recall	F1-score
93%	99%	93%	96%

which has been shown in Fig. 3. Moreover, our model accuracy is around 93% as indicated in Table 3

6 Conclusion

In this paper, we have proposed an anomaly detection model based on the machine learning algorithm 'Extended Isolation Forest (EIF)' for binary classification of 'UNSW_2018_IoT_Botnet_Final_10_best_Testing' network traffic into 'Normal' and 'Attack' classes. The proposed model's accuracy Score is 93%, and F1-Score is 96%. Our study enumerates the top 12 most crucial features for anomaly detection and has a greater influence on accurate prediction. The goal is to select the most critical features, removing any non-important features, to make the detection model more accurate and faster while preventing the overfitting of the model. We will enhance this model in the future to classify attacks according to multiple criteria (multi-level classification). In the future, we will test the performance of our approach using current and legitimate sets of data.

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