Detection of Mirai Malware Attacks in IoT Environments Using Random Forest Algorithms

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Abstract – The potential for Cyber-attacks against Internet of Thing (IoT) Infrastructure is enormous as devices run on pre-existing network infrastructure, for example Mirai Malware Attack. Network Forensics investigations require the Random Forest Algorithm which is used to perform classification and detection techniques for the Mirai Malware attack. The trials have been carried out using 5 attack scenarios and device types. The experimental results show that the RF algorithm achieves optimal performance with an average accuracy value of 95.01%, recall 90.82%, F1 Score 93.85% and the best precision value 99.23%. Besides, the Random Forest algorithm is suitable for very large data processing. The contribution of this research is to provide a recommendation that the RF Algorithm can be used to classify and identify Mirai malware attacks on the Internet of Things infrastructure.

Keywords – IoT, Mirai Malware, Random Forest Algorithm, IOT Environment.

1. Introduction

The growth of various electronic devices connected to the Internet is quite good evidence of Internet of Things technology.

Electronic devices commonly used in households, industrial automation, and smart city infrastructure are now all connected to the Internet [1]. The security risks generated by technology development are also increasingly high. Threats to the Internet of Things (IoT) target various hardware devices, including IP cameras, home routers, and smart devices [2]. Distributed Denial of Service (DDoS) attacks are one of the most interesting types of attacks in cyberspace, where Crackers manipulates a number of devices capable of accessing the internet known as botnets and then makes simultaneous requests to servers or various servers to ensure service, so flood the server and make it ignore requests from legitimate users [3]. Malware is a malicious program [4], one of the most dangerous malware in recent years is Mirai malware, it has even been used for the biggest DDoS attacks ever recorded [5]. DDoS attacks using the Mirai botnet and launched by IoT devices tend to be large and annoying, so overcoming the Mirai botnet threat is an urgent problem. Machine learning is a solution to creating a mechanism for detecting and identifying new types of attacks, this technique provides anomalous based intrusion detection functions in IoT networks [6]. Random Forest is a machine learning classification algorithm that has been proven to perform well in conducting classification compared to other classification algorithms [7] and the random forest has the best performance for anomaly detection [8].

In this research, we used a public dataset from the UCI Repository entitled detection of IoT botnet attacks N BaIoT. The data tested was only a Mirai malware attack on the internet of things device which is a type of security camera. The N BaIoT dataset is collected from raw network traffic data (in pcap format) using port mirroring on the switch through which the organizational traffic typically flows [9]. Each security camera device has 6 datasets, one dataset is a type of normal traffic, five other types of attack traffic files, including Scan, ACK, SYN, UDP and UDPPain.

DOI: 10.18421/TEM103-27

<https://doi.org/10.18421/TEM103-27>

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Received: 23 April 2021.

Revised: 08 July 2021.

Accepted: 14 July 2021.

Published: 27 August 2021.

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The amount of data for each dataset is very large. Therefore, in this paper, we propose machine learning methods using Random Forest (RF). This method is not only proved to be stronger [8] but also produced a high level of accuracy [10]. We also propose a sampling and features selection process to produce maximum accuracy. Sampling is used to balance the unbalanced data on a type of attack. The key goal of this research is the application of random forest algorithms in detecting Mirai malware attacks, including Scan, ACK, SYN, UDP and UDPplain on the internet of things device (security cameras) and also measuring accuracy.

traffic file, unbalanced data poses a big challenge for Random Forest techniques [7]. Whereas, Feature Selection (FS) is the process of selecting a subset of feature sets or attributes from a given data set while ignoring irrelevant or irrelevant features [11].

2. Research Method

In this study, (Fig. 1) is proposed as a research flow stages, there are 4 main stages, namely: Data Collection, Data Processing, Modeling, and Testing.

Figure 1. Research process flow

2.1. Data Collection

Data collection is the first stage in the research, namely the process of collecting data from various sources [12], the source of which we use is only a

public dataset from the UCI Repository. All information in the dataset is collected and arranged based on function and type. The process of collecting data in this research is described in Figure 2.

Figure 2. Data Collection Flowchart

2.1.1. IoT Devices

The selected IoT device is 4 IoT devices of the type of security cameras from 2 different brands. The details of the datasets such as name and type devices

are shown in Table 1 and for detailed specifications such as ports and wireless support are shown in Table 2.

Table 1. IoT Devices

Code	Device Name	Type
pro7	Provision PT-737E	Security Camera
pro8	Provision PT-838	Security Camera
sam2	SimpleHome XCS7-1002-WHT	Security Camera
sam3	SimpleHome XCS7-1003-WHT	Security Camera

Table 2. IoT Device Specifications

Code	Wireless Support	Port	Camera Quality	Pan/ Tilt	iOS/ Android App	2 Way Audio
Pro7	802.11b/g/n	80 (UDP)	1MP (720p)	280°/ 80°	✓	✓
Pro8	802.11b/g/n	80 (UDP)	2MP (1080p)	355°/ 120°	✓	✓
Sam2	802.11b/g/n	80 (UDP)	1MP (720p)	355°/ 120°	✓	✓
Sam3	802.11b/g/n	80 (UDP)	1MP (720p)	-	✓	-

2.1.2. Type of Attack

There are 5 types of Mirai malware attacks, four of the five types of attacks are Distributed Denial of Services (DDoS) attacks. The details of the datasets are shown in Table 3.

Table 3. Type of Attack

Attacks	Description
Scan	Automatic scanning for vulnerable devices
ACK	Ack flooding
SYN	Syn flooding
UDP	UDP flooding
UDPplain	UDP flooding with fewer options, optimized for higher packets per second

2.1.3. Datasets

There are 6 datasets in each device, consisting of 1 dataset of normal traffic (Benign) and 5 datasets of Mirai attack traffic (Scan, ACK, SYN, UDP, and UDPplain). The details are shown in Table 4.

Table 4. Datasets

Code	Benign	Scan	ACK	SYN	UDP	UDPplain
pro7	✓	✓	✓	✓	✓	✓
pro8	✓	✓	✓	✓	✓	✓
sam2	✓	✓	✓	✓	✓	✓
sam3	✓	✓	✓	✓	✓	✓

2.1.4. Packet Stream

There are 8 statistics extracted from the stream package, the details of the packet stream dataset are shown in Table 5.

Table 5. Packet Stream

Packet Stream	Description
Weight	The weight of the stream
Mean	The mean of the stream
Variance	The variance of the stream
Std	The standard deviation of the stream
Magnitude	The number of square roots between two streams' means
Radius	The number of square roots between two streams' variances
Covariance	The covariance is estimated between two streams
Pcc	The correlation coefficient is estimated between two streams

2.1.5. Aggregation Stream

Table 6 shows the details of aggregation streams. These five aggregations are the latest traffic summary statistics:

Table 6. Agregation Stream

Code	Aggregation	Description
MI	Host-MAC&IP	Statistics summarizes the latest traffic from packet's host (IP + MAC)
H	Host-IP	Statistics summarizes the latest traffic from packet's host (IP)
HH	Channel	Statistics summarizes the latest traffic from packet's host (IP) to packet's destination host.
HH_jit	Network Jitter	Statistics summarizes the jitter of the traffic from packet's host (IP) to packet's destination host.
HpHp	Socket	Statistics summarizes the latest traffic from packet's host+port (IP) to packet's destination host+port.

2.1.6. Time Frame

There are 5-time frames contained in the features in the dataset, time frame 5 times is used to detect Mirai malware in real time. The details of the time frame of the dataset are shown in Table 7.

Table 7. Time Frame

Code	Time Frame
L5	1 minute
L3	10 second
L1	1.5 second
L0.1	500 millisecond
L0.01	100 millisecond

2.1.7. Feature

Table 8 shows the details of the features contained in each dataset, these features consist of 23 main

features and 5-time frames (1 minute, 10 seconds, 1.5 seconds, 500 milliseconds and 100 milliseconds), the number of features in each dataset is 115 features.

Table 8. Feature

Code	Time Frame	Packet Stream							
		Weight	Mean	Variance	Std	Magnitude	Radius	Covariance	Pcc
MI	L5	✓	✓	✓					
	L3	✓	✓	✓					
	L1	✓	✓	✓					
	L0.1	✓	✓	✓					
	L0.01	✓	✓	✓					
H	L5	✓	✓	✓					
	L3	✓	✓	✓					
	L1	✓	✓	✓					
	L0.1	✓	✓	✓					
	L0.01	✓	✓	✓					
HH_jit	L5	✓	✓	✓					
	L3	✓	✓	✓					
	L1	✓	✓	✓					
	L0.1	✓	✓	✓					
	L0.01	✓	✓	✓					
HH	L5	✓	✓	✓	✓	✓	✓	✓	✓
	L3	✓	✓	✓	✓	✓	✓	✓	✓
	L1	✓	✓	✓	✓	✓	✓	✓	✓
	L0.1	✓	✓	✓	✓	✓	✓	✓	✓
	L0.01	✓	✓	✓	✓	✓	✓	✓	✓
HpHp	L5	✓	✓	✓	✓	✓	✓	✓	✓
	L3	✓	✓	✓	✓	✓	✓	✓	✓
	L1	✓	✓	✓	✓	✓	✓	✓	✓
	L0.1	✓	✓	✓	✓	✓	✓	✓	✓
	L0.01	✓	✓	✓	✓	✓	✓	✓	✓

2.1.8. Organization of Features

Table 9 shows the organization of feature datasets based on package statistics in Table 8. This Feature Organization has 4 groups.

Table 9. Organization of Features

Aggregate (packet src, dst)	Statistic Packet with Matrix			
	Count	Jitter	Outbound Size	Combined Size
MI	weight		mean, variance	
H	weight		mean, variance	
HH	weight	weight, mean, variance	mean, variance	magnitude, radius, covariance, pcc
HpHp	weight		mean, variance	magnitude, radius, covariance, pcc

2.2. Data Processing

Data processing is the second stage in research, namely processing datasets with large amounts of data and unbalanced data, becoming datasets that can

be used for the testing process. Data processing in this research is described in Figure 3.

Figure 3. Data Processing Flowchart

Figure 3 shows the stages of data processing, the beginning of the process of entering a dataset of normal traffic and attack traffic, and the combination produces an unbalanced dataset, then the dataset is sampled so that the combined dataset of traffic and attack traffic becomes a balanced dataset. However, the dimensionality dataset is still high, then the feature in the dataset is selected so that the dataset becomes low dimensionality and the accuracy level becomes optimal.

2.2.1. Sampling

Sampling is the process of randomly selecting data to make subsets. This sampling aims to cut a lot of data into a little, a little data processing process

results in a faster machine learning process. Random sampling is a sampling method that uses calculations based on "random numbers" [13]. The formula used for sampling can be seen in equation (1) below:

$$\frac{(\text{Total number of examples})}{(\text{sum of ratios})} \times \text{ratio of this partition} \quad (1)$$

2.2.2. Feature Selection

Features Selection aims to select the most important features for a random forest in the classification of benign traffic and malicious traffic. Classification is used to map input data to predetermined class labels [14]. Features selection selects the 5 best features of 115 features. Random Forest is used as a selection process based on Tree Importance from 100 decision trees with a depth of 10, the processing criteria used by random forest is the Gini index.

2.3. Modeling

Modeling is the third stage in research. Modeling is the process of designing a model for feature selection (Figure 4), testing and anomaly detection (Figure 5). Process flow stages of research can be described in Figure 1.

Figure 4. Feature Selection Model

The modeling in Figure 4 shows how to select features. The dataset used is a dataset with the highest amount of data in normal traffic (Benign) and attack traffic (UDP) on PT-838 Provision devices. This model does not use a sampling dataset, a

combination of normal traffic and attack traffic is then processed using a random forest algorithm to find the best feature accuracy based on the Gini index criteria using the Tree Importance decision.

Figure 5. Testing Model

The modeling in Figure 5 shows how the testing process starts by selecting the normal traffic dataset and attack traffic in the training data and test data. Training data is the process of modeling the algorithm used to be studied by the system, while the test data is the modeling process that the system has learned through the training phase and it will be used to produce a certain decision. The amount of data in the training data and test data is balanced first using

sampling. Then, we choose the 5 best features to get optimal results. Then, the classification of test data based on training data will be processed. In the evaluation process model, only the performance operator is required to calculate accuracy, recall, precision, and f-measure. The anomaly detection model is also the same, only adding 1 operator is to detect outlier (Distanced).

3. Results and Discussion

Figure 6. Gini Index Accuracy (Increased) Random Forest Model

Figure 6, shows the results of the Gini Index Accuracy (Increase) using Tree Importance with the

Random Forest Model, five features with the highest accuracy of the Gini index is shown in Table 10.

Table 10. The Best Feature

Features
Host-MAC&IP_100ms_Mean
Host-MAC&IP_500ms_Mean
Host-IP_500ms_Variance
Host-MAC&IP_1,5s_Weight
Host-MAC&IP_1,5s_Mean

The process of testing algorithms is done using the confusion matrix, the method is shown in Table 11 below:

Table 11. Confusion Matrix

Prediction \ Actual	Attack	Normal
Attack	TP	FN
Normal	FP	TN

Positive-Positive (TP) is the amount of attack traffic that is predicted as attack traffic, False-Positive (FP) which is the amount of attack traffic predicted as normal, False-Negative (FN) traffic which is the amount of normal traffic predicted as attack traffic and True-Negative (TN), which is the with equations (2), (3), (4) and (5).

amount of normal traffic predicted as normal traffic. The results of the confusion matrix are used to measure accuracy, precision, recall, and Fmeasure to analyze the performance of algorithms in classifying to detect Mirai malware

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

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

$$\text{F - Measure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5)$$

Testing I

Testing I, tests normal network traffic (benign) and attack network traffic (Scan) on the PT-737E

Provision device. The confusion matrix of the test results is summarized in Table 12.

Table 12. Confusion Matrix Testing I

Prediction \ Actual	Attack	Normal
Attack	573	0
Normal	427	1000

Based on confusion matrix testing 1, the data of accuracy, recall, precision and F-measure are obtained, as follows:

$$\begin{aligned} \text{Accuracy} &= \frac{573+1000}{573+1000+427+0} = 78,65\% \\ \text{Recall} &= \frac{573}{573+427} = 57,30\% \\ \text{Precision} &= \frac{573}{573+0} = 100\% \\ \text{F-Measure} &= 2 \times \frac{100 \times 57,30}{100 + 57,30} = 72,85\% \end{aligned}$$

Testing II

Testing II, tests normal network traffic (benign) and attack network traffic (ACK) on the Provision PT-838 device. The confusion matrix of the test results is summarized in Table 13.

Table 13. Confusion Matrix Testing II

Prediction \ Actual	Attack	Normal
Attack	973	0
Normal	27	1000

Based on confusion matrix testing II, the data of accuracy, recall, precision and F-measure are obtained, as follows:

$$\begin{aligned}
 \text{Accuracy} &= \frac{973+1000}{973+1000+27+0} = 98,65\% \\
 \text{Recall} &= \frac{973}{973+27} = 97,30\% \\
 \text{Precision} &= \frac{973}{973+0} = 100\% \\
 \text{F-Measure} &= 2 \times \frac{100 \times 97,30}{100 + 97,30} = 98,63\%
 \end{aligned}$$

Testing III

Testing III, tests normal network traffic (benign) and attack network traffic (SYN) on the SimpleHome XCS7-1002-WHT device. The confusion matrix of the test results is summarized in Table 14.

Table 14. Confusion Matrix Testing III

Prediction \ Actual	Attack	Normal
Attack	995	0
Normal	5	1000

Based on confusion matrix testing III, the data of accuracy, recall, precision and F-measure are obtained, as follows:

$$\begin{aligned}
 \text{Accuracy} &= \frac{1000+960}{1000+960+40+0} = 98,00\% \\
 \text{Recall} &= \frac{1000}{1000+0} = 100\% \\
 \text{Precision} &= \frac{1000}{1000+40} = 96,15\% \\
 \text{F-Measure} &= 2 \times \frac{96,15 \times 100}{96,15 + 100} = 98,04\%
 \end{aligned}$$

Testing IV

Testing IV, tests normal network traffic (benign) and attack network traffic (UDP) on the SimpleHome XCS7-1003-WHT device. The confusion matrix of the test results is summarized in Table 15.

Table 15. Confusion Matrix Testing IV

Prediction \ Actual	Attack	Normal
Attack	1000	0
Normal	0	1000

Based on confusion matrix testing IV, the data of accuracy, recall, precision and F-measure are obtained, as follow:

$$\begin{aligned}
 \text{Accuracy} &= \frac{1000+1000}{1000+1000+0+0} = 100\% \\
 \text{Recall} &= \frac{1000}{1000+0} = 100\% \\
 \text{Precision} &= \frac{1000}{1000+0} = 100\% \\
 \text{F-Measure} &= 2 \times \frac{100 \times 100}{100 + 100} = 100\%
 \end{aligned}$$

Testing V

Testing V, tests normal network traffic (benign) and attack network traffic (UDPplain) on the Provision PT-737E device. The confusion matrix of the test results is summarized in Table 16.

Table 16. Confusion Matrix Testing V

Prediction \ Actual	Attack	Normal
Attack	1000	0
Normal	40	960

Based on confusion matrix testing V, the data of accuracy, recall, precision and F-measure are obtained, as follows:

$$\begin{aligned}
 \text{Accuracy} &= \frac{995+1000}{995+1000+5+0} = 99,75\% \\
 \text{Recall} &= \frac{995}{995+5} = 99,50\% \\
 \text{Precision} &= \frac{995}{995+0} = 100\% \\
 \text{F-Measure} &= 2 \times \frac{100 \times 99,50}{100 + 99,50} = 99,75\%
 \end{aligned}$$

Tests 1 to 5 produce statistical data to be evaluated, statistical data is shown in Table 17 and graph in Figure 6.

Figure 7. Testing Statistics Data

Figure 7 shows that testing 1 produces different statistical data compared to the other 4 testings. This is because training data is used for cross attack networks, using the UDP dataset. The type of UDP

attack is the same as the type of ACK, SYN and UDPplain attacks, which is the type of attack that floods the Internet of Things or into the Distributed Denial of Services (DDoS) type of attack. The test

data on testing 1 uses the Scan attack dataset, which is an attack by scanning vulnerable Internet of Things devices. Thus, the statistical data on testing 1 produces accuracy, recall, and measure which are lower than the results of another testing.

Anomaly Detection

Normal traffic and attack traffic, previously processed first from training data and test data using the random forest, as in the testing process 1 to 5, then the output is entered into detect outlier (Distanced). Scatter 3D for normal traffic and attack traffic is shown in Figure 7, while Scatter 3D outliers are in Figure 8.

Figure 8. Scatter 3D Normal Traffic (blue dots) Attack Traffic (green dots)

Scatter 3D in Figure 8 shows normal traffic (blue dot) and attack traffic (green dot). 3D Scatter consists of 3 features, on the x-axis is Host-MAC & IP 500ms Mean, on the y-axis, there is the Host-MAC & IP 500ms Mean and finally, the z-axis is Host-MAC &

IP 5s Weight. The three features are selected from the 5 best sequences from the feature selection stage (Table 10). The 3D Scatter color is then changed and based on the type of outlier or anomaly.

Figure 9. Scatter 3D Outlier False (blue dots) Outlier True (green dots)

Figure 9 shows some outliers (green dots) in normal traffic (Figure 8). Green dots are detected as outliers or anomalies found in the Host-MAC & IP_500ms_Mean and Host-MAC & IP_500ms features. Detect outlier (Distanced) is used for anomaly detection because the output is in the form of boolean (true and false), so it can be directly visualized through Scatter 3D.

4. Conclusion

An algorithm called Random Forest (RF) has been proposed to detect Mirai malware. The proposed technique produces an average accuracy value of 95.01% and produces an average precision value of 99.23%. Moreover, the selection of the right features also helps us produce high detection accuracy. Regarding testing for anomaly detection using the detect outlier (Distanced) technique, it successfully detected outliers/ anomalies in the Host-MAC & IP_500ms_Mean and Host-MAC & IP_500ms features.

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