Monitoring and Detection Time Optimization of Man in the Middle Attacks using Machine Learning

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Abstract—The internet of things (IoT) is growing with the advancement of technology. Many vendors are creating IoT devices to leverage the quality of life of consumers. These devices include smart grid, smart homes, smart health care systems, smart transportation, and many other device applications. IoT devices interact with the environment and each other using sensors and actuators. However, the widespread proliferation of IoT devices poses many cybersecurity threats. The IoT devices' interconnection opens the door to attackers who try to gain unauthorized access to the devices. For many IT networks, establishing trust and security during the devices' regular operation is challenging. Further, devices may leak vital information, which is a huge concern in cybersecurity. Prior research has shown that security breaches have increased by 67% in the past five years, and 95% of HTTPs servers are vulnerable to Man in the Middle (MIM) attacks. This paper explores the new attacks dataset from the HCRL (Hacking and Countermeasure Research Lab) collected from real-life internet of things devices that incorporated smart cameras, laptops, and smartphones [1]. We then apply three machine learning algorithms that include the Random Forest, Logistic Regression, and Decision Tree to evaluate our model's performance. Our results show that the overall detection accuracy is 98-100%, which more promising than traditional Intrusion Detection System (IDS)

Keywords— Internet of Things (IoT), cybersecurity, Intruusion Detection System (IDS), Random Forest (RF), Decision Tree (DT), Logistic Regression (LR),Man In The Middle (MIM) attacks.

I. INTRODUCTION

The internet of things has been around for decades now, and it has tremendously affected users' quality of life[2]. Moreover, with the rapid growth of technology, people tend to get more IoT devices connected to their home networks to facilitate their daily activities [3]. For instance, a smart garage door opener will automatically open the door to its intended users without requiring any physical contact with the door. These devices' significances and benefits are tremendous, and also these devices talk to each other using several communication protocols such as Wi-Fi, Bluetooth, Z-Wave, and ZigBee [4], [5]. As shown in Figure 1, the IoT market revenue will reach up to 600 billion by 2022.

The significance of IoT cannot be overstated. Everything is getting connected to the internet, ranging from smart, smart, smart, smart, and smart cities[6]. For example, the smart grid system might have more than five million nodes interconnected and exchanged confidential information, which could be an attack surface for a hacker. People do not need to manually access their devices; everything is done via smartphones in just one click [7]. Users' can connect to their home network from anywhere and access the devices. For instance, in smart healthcare, a doctor in the hospital can diagnose and prescribe medication to patients remotely without their physical presence [8],

[9]. It is almost impossible to live without smart devices, which leads to the critical need for IoT in our life. Those devices must be tied to a network with Internet connectivity to operate correctly. However, with the diverse type of communication networks, an unauthorized user can easily access the user's network and perform malicious activities[10].
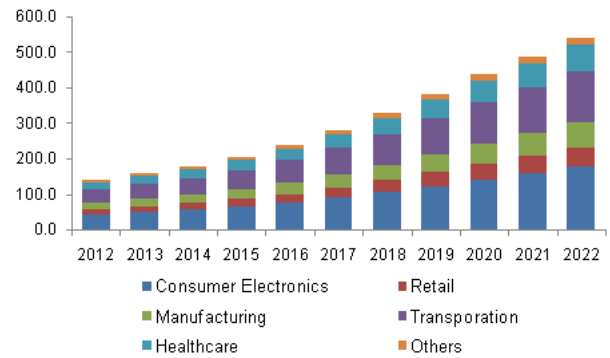

Fig. 1. North America IoT Market revenue

The intruders are always seeking techniques to penetrate the network and comprised the system. The consequences are tremendous and can put any host device connected to the network at risk and private information such as passwords, bank credentials, social security number, and patient records. Moreover, giving the fact that most of the network today has many devices that can be controlled remotely, monitoring the network traffic from anywhere is a huge concern in the cybersecurity area [11]. Usually, the consumer will rely on the service provider's network to assure the security of their devices. Unfortunately, most of the gateways available in the market, like routers, do not have an intrusion detection system built-in to protect the potential users' against any cyber threat. The network system in place does not have an efficient mechanism to differentiate between Man in the Middle attack type with other cyber threats [12]. Therefore, industry, government, and researchers should work closely together to address the security vulnerabilities related to internet usage of things devices and networks. Although the Intrusion Detection Systems (IDS) are widely used to respond to network attacks, it is still not sophisticated enough to handle attacks from the vast network. Machine learning is a subset of artificial intelligence that utilizes algorithms to recognize patterns from data [13]. The algorithms provide the ability to extract meaningful features from the data for further analysis. The result of the analysis will then be used for future prediction [14]. With a massive amount of data generated by the internet of things devices, it is significant to use

machine learning to learn the network traffic behavior, which could be relevant to detect an attack in the system [15]. Vendors could then utilize the result of the prediction and analysis to build more secure systems. On the other side, researchers could exploit that to further their work. The main contributions of this paper are as follows:

1) We propose a testbed architecture that could be used to launch the MIM in the lab environment with many sets of Internet of Things that include the smart thermostat, the ring video camera, the light bulb, smart glucometer, smart infusion pump, smart cardio, smart blood pressure monitor, and Amazon Echo device.
2) We explore the new attacks dataset from the HCRL (Hacking and Countermeasure Research Lab) collected from real-life internet devices that incorporated smart cameras, laptops, and smartphones.
3) We build our model using three machine learning algorithms that include Random Forest, Decision Tree, and Logistic Regression to optimize the network's detection time and have an overall accuracy that ranges between 98-100%

The rest of this paper is organized as follows. An overview of the motivation is presented in section II, a literature review of the related works and gaps is presented in section III, while section IV presents the methodology utilized to optimize the detection time of the attacks. Section V shows the results and analysis. Lastly, Session VI elaborates on the future work and conclusion.

II. MOTIVATION

In his article titled "80 Eye-Opening Cyber Security Statistics for 2019", Hashedout published a disturbing report summarizing cybersecurity statistics for 2019, which shows that security breaches have increased by 67% past five years .Among their 80 statistics list, there are MIM attacks, which, according to IBM's X-Force Threat Intelligence Index 2018, more than a third of the inadvertent exploitation of weaknesses involved MIM attacks. Also, 95% of HTTPS servers are vulnerable to MIM, according to NetCraft. MIM attacks consist of intruders intercepting traffic between two parties, the source, and destination, posing as a legitimate source at the destination and masquerading as the source's legitimate destination [16].
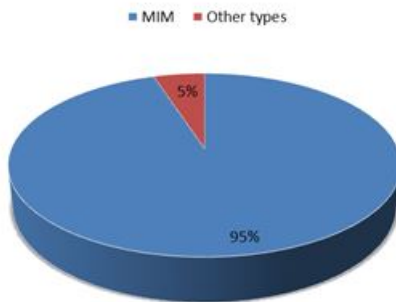

Fig. 2. MIM Attacks Statistics

The MIM attack is made without both the attacker source and the victim destination suspecting the communication channel's corruption. The Internet of Things devices, with their low computational power, low memory, can barely handle high-level encryption algorithms, thus the exposure to critical cyber-attacks due to the presence of backdoors [17]. Therefore, protecting the network system with adequate security prevention mechanisms such as IDS (Intrusion Detection System), firewalls do not guarantee the prevention or mitigation of cyber threats [18].

III. RELATED WORK

The Internet of Things has significantly leveraged the consumer's quality life. Besides, with the vast amount of benefits that range from interconnecting the devices in any given network, being able to monitor the devices without any physical presence, and the capability of the user's to integrate end devices in their network setup independently of the manufacturers[19]. However, the majority of those IoT devices' present some limitations in terms of security features which often open backdoors to hackers who can infiltrate into the network using the devices. Man in the Middle attack is known as one the most common attack used by hackers to harm the system. Many researchers have proposed some methods to detect the MIM attack in the network; however, their solution is not always suitable for constraint devices with very low computational power [20], [21], [22], [23].

Dong et al.[15] developed a technique to detect and localize the MIM in the wireless sensor network based system which is does not shown promising results when applying to the attacks coming from Internet of Things devices. Liu et al. [24], [25] have conducted their experiment using Internet of Things devices data and applied some machine learning algorithms such as KNN, Logistic Regression (LR), and Random Forest to detect anomaly in the IoT Network; however, the data collection and pre-processing phase lack clarities. The authors implemented the SVM (Support Vector Machine) algorithm which gave them the overall accuracy of 70%, which is not promising. Also, the Logistic Regression which was 86%. This paper presents more details about the data acquisition and pre-processing phase. We also implement the Decision Tree algorithm to produce results with the accuracy close to 100%.

The previous approach is different from the one discuss in this paper which main focus is to optimize the detecting time of MIM attack.Bagaa et al.[26] have designed a machine learning security framework to leverage cyber threat in Software Define Networking system which again barely detect attacks from Internet of Things devices in the network. Hussain et al. [22]have investigated on different possibilities to apply machine learning technique to solve IoT security network which target technologies such as Software Defined Network, Cloud Computing, and Fog computing.

N. Santhosh [27] has carried out some research related to the usage of machine learning technique to solve the security issue faced by Internet of Things devices. Their experimental results do not incorporated appropriate features selection mechanism which could not be applied to a large scale network of Internet of Things devices. N. Gupta et al.[21] have created a firewall based system to improve the security of internet of things devices. The firewall is built using a Raspberry as a gateway to monitor the network traffic and secure the communications patterns through the cloud database. The proposed firewall based system presents some security limitations because any third party can eavesdrop into the communication, then compromise the entire cloud database. Another limitation of this work is related to the scalability due to the fact a Raspberry Pi is not powerful enough to handle complex encryption algorithm.

IV. METHODOLOGY

The paradigm of the Intrusion Detection System (IDS) is not explicitly and formally defined in the literature. Besides, traditional tools such as firewalls and anti-virus are not designed to detect MIM coming from IoT devices. Consumers usually rely on routers to protect their home network against cyber threats and do not necessarily consider IoT devices a second entry point for hackers [28]. In this work, we develop a model that focused on anomaly detection, particularly the Man-in-the-Middle attack, given that in the last five years, statistics show that 95% of HTTP servers are vulnerable to these attacks, hence our motivation. A benefit with this perspective is that it manages to optimize the Man-In-The-Middle attack's monitoring and detection time. To experiment, we use three

Machine Learning algorithms in the data set for accurate real-time anomaly detection. The approaches include Random Forest (RF), Logistic Regression (LR), and Decision Tree. We then apply binary classification by classifying Man-In-The-Middle attacks as one (1) and zero (0) as the normal packet.

A. Data Acquisition Phase

In this work, we are developing and experimenting with our models on the intrusion dataset on the IoT network, created by a group of researchers from the Hacking and Countermeasure Research Lab [see article that produced the dataset]. This dataset is publicly available and developed explicitly for academic use only. The dataset employs two typical smart home devices - SKT NUGU (NU 100) and the EZVIZ Wi-Fi camera (C2C Mini O Plus 1080P). Both devices were connected via Wi-Fi with other smartphones and laptops to create the data. All devices, including some laptops and smartphones, were connected to the same wireless network. Packet files were captured using the monitor mode of the wireless network card. To maintain the privacy of the users, Aircrack-ng was utilized to remove wireless headers. ll attacks except for the Mirai Botnet category are packets captured when simulating attacks using tools such as Nmap. In the case of the Mirai Botnet category, the attack packets were generated on a laptop and then manipulated to appear as if they came from the IoT device. The dataset consists of 42 raw network packet (pcap) files at different times; including six pcap files containing Man-In-the-Middle attack[1].

Table I provides an overview of the dataset set. Each pcap file contains 7 features. The first feature is the sequence number of the packet; the second feature is the time, which represents the transmission time of the packet; the third feature is the source IP address of the packet; the fourth feature is the destination IP address of the packet; the fifth feature is the protocol in which the packet is transmitted; the sixth feature is the length of the packet, measured in bytes; the seventh feature is Info, which contains additional details corresponding to the packet. The dataset used containing the man-in-the-middle attack has 194184 observations.

TABLE I
TABLE OF THE DATASET

	CATEGORY	SUB-CATEGORY	# OF PACKETS
0	Normal	Normal	1,756,276
1	Scanning	Host Discovery	2,454
2	Scanning	Port Scanning	20,939
3	Scanning	OS/Version Detection	1,817
4	Man in the Middle (MITM)	ARP Spoofing	101,885
5	Denial of Service (DoS)	SYN Flooding	64,646
6	Mirai Botnet	Host Discovery	673
7	NaN	NaN	NaN
8	Mirai Botnet	Telnet Bruteforce	1,924
9	Mirai Botnet	UDP Flooding	949,284
10	Mirai Botnet	ACK Flooding	75,632
11	Mirai Botnet	HTTP Flooding	10,464

The dataset contains 42 raw network packet files recorded at various time intervals. Each pcap file for the Man-in-the-Middle attack contains up to 65768 packets. In this dataset, a description file is provided specifying the filtering rules for separating attack packets from benign packets. In addition, the dataset includes 5 main categories and 11 subcategories. The 5 categories include one category of normal transmissions and 4 groups of cyber-attacks. The

4 groups of attacks cover the most common attacks for IoT networks, i.e. scan attacks, Man in the Middle (MIM) attacks, Denial of Service (DoS) attacks and Mirai Botnet attacks. In addition, 11 subcategories are derived from the 5 main categories, including 1 subcategory for non-normal transmission and 10 unique attack types. In this paper, we have exploited only Man-in-the-Middle attacks, which is the focus of our work.

B. Approach for Data Preprocessing

The data acquisition stage mentioned previously is essential to understand the features use in the raw data packets. The second step is called Pre-processing which is very important because it helps us to analyze and transform the data for prediction. In the case of this experiment, we need to pre-process the raw data files. Since the filtering rules have been given, we proceed as follows to process the data: In the first phase, we run the shell scripts applying the filtering rules in order to get two csv files, abnormal csv file (man-in-the-middle attack) and normal file. Then we move on to label some features, and add a column named Target, which qualifies the attack flow or not, and we do the same for the normal data. The Target column is labeled 1 for the presence of the attack and 0 for normal. Then we merge the two csv files and remove the redundant data. We perform this mechanism for all 6 pcap files containing the Man-in-the-Middle attack. In the end, we concatenate all the files into one file.
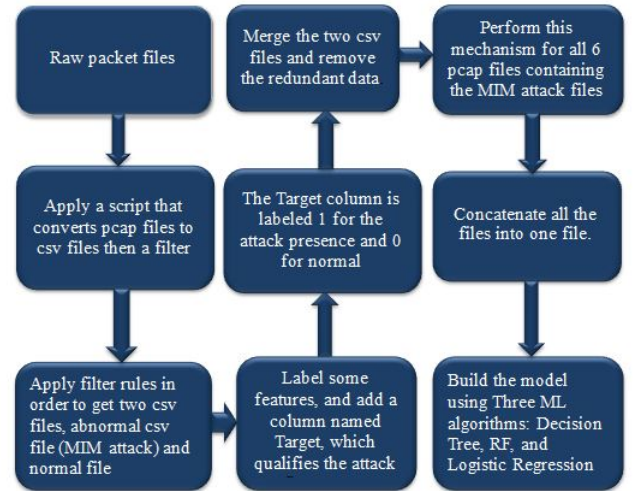

Fig. 3. Procedure for data preprocessing

This work focuses on the detection of the Man in the Middle Attack and the figure below presents the screenshot of the attack packets.
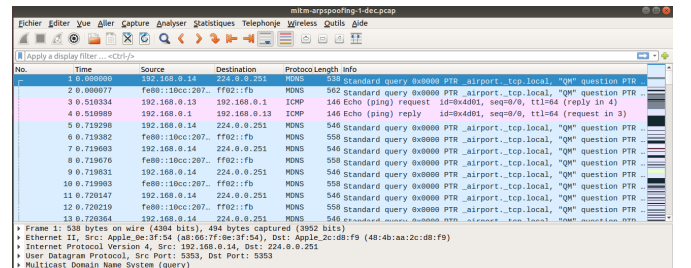

Fig. 4. mitm-arpspoofing

C. Description of the Features

The table below describes some of the important features extracted during the pre-processing phase:

TABLE II
DESCRIPTION OF THE FEATURES

Features	Description
Time	Represent the time between two consecutives packets
Source	Correspond to the sender IP
Destination	Correspond to the receiver IP
Protocol	Define the type of protocols (ARP, TCP, HTTPS, ICMP, DNS)
Length	Represent the length of each packet
Info	Correspond to the value of ACK packet
Target	Classify the attack type, where 1 means "attack present" and 0 means "no attack present"

The final output after the pre-processing operation is showed in this table 3:

TABLE III
DATASET AFTER PREPROCESSING

	No	Time	Source	Destination	Protocol	Length	Info	Target
0	18377	264.635419	26850	27110	514	67	891957	1
1	4872	35.643239	26850	27110	514	67	924549	1
2	5511	41.626743	26850	27110	514	67	928392	1
3	6970	43.890929	26850	27110	514	67	938535	1
4	9510	47.626598	26850	27110	514	67	956273	1
5	2646	26.342393	29570	31970	514	67	1277081	0

V. IMPLEMENTATION AND EVALUATION

The data set to build our model is 194184 observations, of which 92299 observations were labeled as normal data, and 101885 observations as attack data, which represents a participation of 47.53% normal packets and 52.47% attack packets. To build our models, we dissected the training and test data with 70% and 30% values, respectively. We evaluated our models' performance based on the confusion matrix, with which we used a classification report to measure the quality of the predictions from the classification algorithms. The classification report presents the main classification metrics, such as accuracy, recall, and f1 score per class. The metrics are calculated using true and false positives, true and false negatives. Hence, there are four ways to check whether our predictions are right or wrong:

- True Negative(TN): is a case in which the actual label was negative and predicted negative
- True Positive(TP): a case in which the actual label was positive and predicted positive
- False Negative (FN): Represents a case in which the actual label was positive but predicted to be negative.
- False Positive (FP): Represents a case in which the actual label was negative but predicted positive

The precision represents how accurate the predictions are in the model. It is defined as the ratio of true positives to the sum of true and false positives for each class.

Precision = TP / (TP + FP)

The recall represents the percentage of positive cases detected in the model. It is defined as the ratio of true positives to the sum of true positives and false negatives.

Recall = TP / (TP + FN) Score F1 represents the percentage of correct positive predictions. Score F1 is a weighted harmonic average of accuracy and recall such that the best score is 1.0, and the worst is 0.0.

Score F1 = 2 * (Recall * Precision) / (Recall + Precision) The accuracy is the number of correct predictions, which includes both positive and negative predictions, divided by the total number of predictions made.

Accuracy = (TP + TN) / (TP+ TN + FP + FN)

VI. RESULTS

A. Logistic Regression Approach

In this section, we present the different results of our experiments. The experiments were carried out with 10 trials for each approach. Tables 4, 5, and 6 show the results. As a result, Table 4 illustrates the logistic regression approach, which has a precision of 99%, a recall rate of 99%, and an f1 score of 99%. The performance is virtually inferior to the other perspectives. Figure 4 illustrates the confusion matrix of the logistic regression. It shows that the number of errors in class 1 is seven times greater than the number of errors in class 0, resulting in an error percentage of 1.21% for class 1 and 0.17% for class 0. The logistic regression model gives an accuracy of 98.6%.
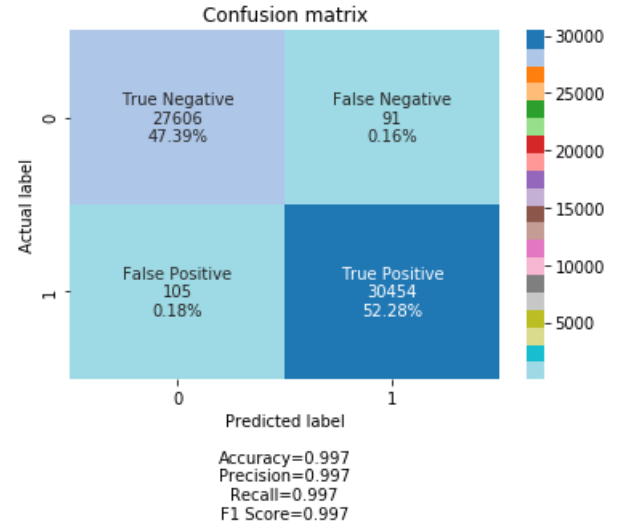

Accuracy=0.997
Precision=0.997
Recall=0.997
F1 Score=0.997

Fig. 5. Confusion Matrix Logistic Regression

1) Analysis of the confusion matrix for the logistic regression: We would analysis the confusion matrix based on the metrics values that include the True Positive, True Negative, False Positive, and False Negative.For a better performance, we would like to have our True Positive and True Negative metrics high. For this Logistic Regression case, the average f1 score is 99%.

TABLE IV
TABLE LOGISTIC REGRESSION

Classe	Precision	Recall	f1-score	Support
Classe 0	0.98	1.00	0.99	27697
Classe 1	1.00	0.98	0.99	30559
avg / total	0.99	0.99	0.99	58256

B. Decision Tree Approach

The Decision Tree is another machine learning uses to build model. The main idea behind the decision tree is to have multiple choices when it comes to making decision about what to do next.This method operates by choosing a criteria to classify attacks in the network. The number of observations is obviously the same for the Logistic Regression case. Subsequently, Table 5 illustrates the decision tree approach, which shows a 100% accuracy, a 100% recall rate, and an F1 score of 100%, only with the default hyperparameters. The performance is almost superior to logistic regression and equal to Random Forest model. Figure 6 illustrates the confusion matrix of the decision tree. It shows that our model has no prediction errors; therefore, we have a perfect model. The RF model gives an accuracy of 100%. Similarly, the max_depth (maximum depth) has not been limited for the decision tree to let the forest in the RF classifier increase the level as much as possible when needed.
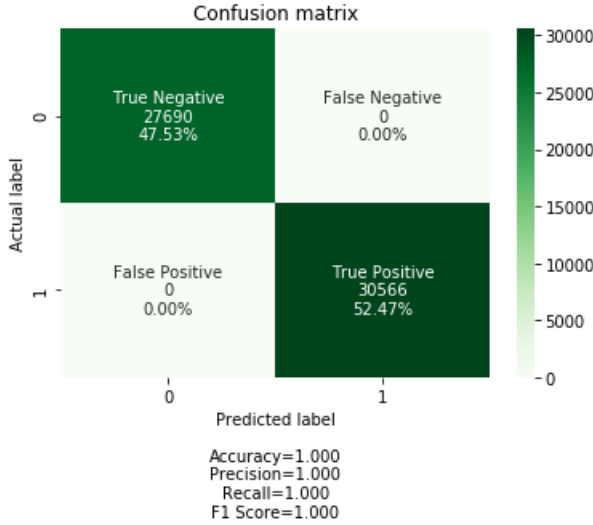

Fig. 6. Confusion Matrix Decision Tree

TABLE V
TABLE LOGISTIC REGRESSION

Classe	Precision	Recall	f1-score	Support
Classe 0	1.0	1.0	1.0	27690
Classe 1	1.0	1.0	1.0	30566
avg / total	1.0	1.0	1.0	58256

C. Random Approach

Next, Table 6 illustrates the Random Forest approach, which has 100% accuracy, a 100% recall rate, and an F1 score of 100%, only with the default hyperparameters. The performance is almost superior to logistic regression and equal to the decision tree. Figure 7 illustrates the confusion matrix of the logistic regression. The True Negative and True Positive values show that our model has no prediction any errors; therefore, we have a perfect model. The RF model gives an accuracy of 100%. The max_depth (maximum depth) has not been limited to let the forest in the RF classifier increase the level as much as possible when needed. The performance of the Random Forest model is evaluated using the confusion matrix

hyperparameters such as the precision, recall, f1 score, and the number of observations.
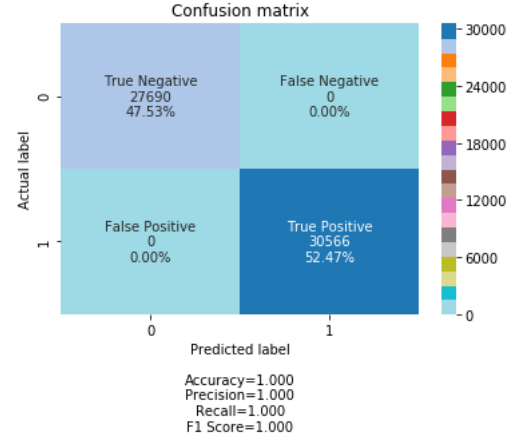

Fig. 7. Confusion Matrix Random Forest

TABLE VI
TABLE LOGISTIC REGRESSION

Classe	Precision	Recall	f1-score	Support
Classe 0	1.0	1.0	1.0	27690
Classe 1	1.0	1.0	1.0	30566
avg / total	1.0	1.0	1.0	58256

1) Comparison of our Results WITH Previous Work: Compare to the most recent work that has been done in the detection of man in the middle attack using machine learning technique [24], our approach presents better performance with an enhancement in terms of the accuracy as well.

VII. CONCLUSION AND FUTURE WORK

IoT devices are gaining popularity as technology improves, which is why attackers use them to gain illegitimate access to the network. Traditional tools have some limitations in detecting an intrusion, hence the need for our machine learning approach. In this paper, we proposed a technique based on three machine learning algorithms to optimize the detection time of the Man in the Middle attack in the network. With these three algorithms, the logistic regression approach showed an accuracy of 98.6%, the random forest showed an accuracy of 100%, and the decision tree showed an accuracy of 100% with a very high F1 score. Our results showed that the technique implemented in this paper will improve the state of the art of traditional IDS. Future work will use a Deep Learning technique to build model that will learn from data to stop propagating this attack in the network.

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