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A STUDY OF DDOS ATTACK DETECTION METHODS

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Abstract— Distributed denial of service (DDOS) assaults are among the most serious threats to network security. This attack can cause even more destruction if it is carried out in a widespread manner. Many studies have been conducted to identify this attack. Various strategies have been examined and discussed in this. Deep learning and machine learning approaches received the majority of attention.
Keywords—DDoS, Deep Learning, Machine Learning, Attacks, Statistical.

I. INTRODUCTION

Cyber-attacks like DoS, DDoS, and a lot more which are significant security threats for Internet of Things. In most recent couple of years, DDoS attacks have been expanded altogether, which has impacted many IoT networks in the globe and has brought about misfortunes [4]. A DDoS attacks is one in which an attacker tries to hinder the approved clients exercises of a contraption and makes the gadget distant to approved clients through over the top resource usages by appropriated attack sources. In 2016, the attack on the DNS supplier, it gives a focusing on exhibit of the disturbance from designated Distributed Denial of Service attacks [5]. This specific attack used a Mirai-botnet of temperamental IoT Devices in which, in excess of 60 organizations are impacted. This is the biggest attack around then with 600 Gbps. After this attack there was another attack what breaks the record of 600 Gbps in 2018, casualty saw approaching traffic flow at a pace of 1.3 Tbps. That DDoS attack is towards Github in February 2018[6]. Similarly numerous DDoS occasions [7] happened all around the globe when more Mirai varieties were created.

Digital attacks like DDoS attacks focusing on IoT unit might make serious defilement the IoT information or organization. The Internet of Thing Devices would be about 31 billion, out of that half are defenseless and dubious against various digital attacks, as report given by Security-Today and threat-post [8][9]. Such a powerless IoT gadgets are the probable attack focus to outline botnets, these botnets then undermine the Internet of Things structure by mean of Distributed Denial of Service attacks. Likewise, greater the botnet, the further momentous the attacks can be. So, the DDoS attack location is the much essential errand, on the grounds that

DDoS attack produces attack traffic basically the same as authentic traffic and by then of time aggressors attempt to create same traffic with streak swarm. An attack movement with lacking traffic might be viewed as a real one in beginning phases [10].

II. DISTRIBUTED DENIAL OF SERVICE (DDOS) ATTACKS

DDoS attacks are alluding to the gathering of attacks wherein an invader obstructs or deny genuine clients from getting to get to their organization administrations or assets by scattered attack sources. An invader can make a botnet by utilizing feeble Net related gadgets similarly as Internet of Things gadgets, and coordinates the botnets through a control server to dispatch attacks; subsequently, setback gets colossal source-moved attacks deals bargains from the disseminated dealt gadgets, disturbing its commonplace exercises.

IoT DDoS attacks are much more problematic to defend against than traditional DDoS attacks because Internet of Things devices have limited processing power in addition bandwidth. An attacker can surely create malevolent bundles due to design flaws in the firmware of IoT devices or defects in the communication protocols. Of course, Internet of Things devices can also be employed as a potent Distributed Denial of Service attack tool in addition to causing DDoS attack damages. IoT devices' low security implementations make it easy for attackers to use them to create a widespread botnet, which is recognized as a crucial tool for setting up overflowing-based DDoS attacks. Attackers, for example, developed the ludicrous Mirai-Botnet by taking control of 65 000 IoT devices 20 hours after their original delivery and using them to launch DDoS attacks on certain IoT companies, such OVH and Dyn. [11].

A. History of DDOS [1,2,3])

David Dennis was the first person to performed DDOS attack in the 1974[3].

Table 1: History of DDoS attack

Sr. No	Attack Year	Attack Targets
1	1998	Morris worm
2	1990, 1990	IRC chat floods
3	2000	Yahoo
4	2001	Code red worm attacks
5	2002	Root servers of DNS
6	2003	Al-Jazeera
7	2004	SCO
8	2005	E-bay
9	2006	Storm pay battling
10	2007	Estonian
11	2008	Georgia president Web site
12	2009	Iranian Government Web sites, Facebook, Twitter, and Google, Russian blog
13	2010	Wordpress.com
14	2011, 2012	Sony
15	2013	South Korean Web sites, Spamhaus
16	2014	JP Morgan
17	2015	Github
18	2016	RIO Olympics

19	2017	Melbourne IT
20	2018	Github

III. DDOS DETECTION METHODS

To identify DDoS attack, numerous specialists created different methods, for example, statistical approaches (entropy varieties), machine learning techniques, deep learning techniques and so on.

A. Statistical Approaches

Estimating statistical properties of organization traffic credits is a normal method for managing DDoS attack discovery, and for the most part incorporates noticing the entropy varieties of explicit bundle header fields. Entropy-based DDoS identification approaches have become popular in logical writing since the middle of the 2000s. This is because it is thought that unanticipated variances are primarily responsible for the irregularity of traffic during a volumetric DDoS attack.

In one of the significant anticipated forms of study employing this methodology, Feinstein et al. [12] developed a DDoS detection method based on the evaluation of source IP address entropy and Chi-square conveyance. They found that, in contrast to the variations brought on by DDoS attacks, the dissimilarity in source IP address entropy and chi-square estimations brought on by changes in valid peak hour traffic bottlenecks was rather small.

Entropy change is used by Tao [13] to detect attacks during rush hour traffic. When an attack is detected, the differentiating proof structure will discourage or prohibit atypical traffic and limit the attacker's territory. To distinguish DDoS attacks from streak swarms, data distance is employed. It will be described as a DDoS attack if the information distance in the doubtful stream is not precisely in a particular edge; otherwise, it is an organization temporary clog.

Mousavi [14] suggests a technique for detecting attacks that relies on actual entropy. The study calculates entropy using the correlation between source IP addresses and objective IP addresses, and uses experience to draw a line to determine whether an attack has taken place. For the most part talking, entropy is in like manner not considered as a good measure [13] considering the way that it has decently high misleading positive or bogus negative.

In order to recognize DDoS attacks, the authors P. Bojovi'c [15] and K. Kalkan [16] developed an entropy-based scoring structure based on the objective IP address entropy and self-motivated groupings of IP and TCP layer credits. Entropy and volume traffic components are used in P. Bojovi’c technique to identify volumetric DDoS attacks.

Ahmed et al [17].'s alternative measurement method uses bundle credits and traffic stream level measures to distinguish between DDoS traffic and traffic that isn't harmful.

In any event, this strategy might not work well with online architectures. The requirement to choose an appropriate area limit is a frequent difficulty for these entropy-based approaches. AI solutions have been investigated as a means of overcoming the limitations of measurable methods of mitigating DDoS discovery.

B. Machine Learning and Deep learning Based DDoS Detection Techniques.

There are many machine learning algorithms have been created for the recognition of DDoS attacks. P. Xiao [18], proposed a strong discovery technique in view of KNN with relationship examination to identify DDoS attacks.

C. She [19] used an OC-SVM (One Class Support Vector Machine) to produce the identification plot for application-layer DDoS assaults, namely for SYN flooding attacks, HTTP flooding attacks, and NTP augmentation attacks.

In [20] R. Vishwakarma proposed a compelling strategy in recognizing botnet based Distributed Denial of Service attacks in IoT by utilizing honeypots with ML based approaches. In that they compromised different IoT honey-pots to get gadget malware establishment endeavors and embraced unaided ML methods, for instance, grouping and abnormality recognition to robotize the course of location and expectation of the approaching security dangers by separating highlights from honeypots.

Asad in [21] proposed a detection strategy by depending on ANN to unequivocally distinguish various application-layer DDoS attacks, with the assistance of feed-forward and back-proliferation calculations.

M. Roopak developed a model in [22] that focuses on text acknowledgment at the bundle level and uses RNN (Recurrent Neural Network) techniques with Bidirectional Long Short-Term Memory (LSTM) to identify botnet activities inside consumer IoT networks.

Meidan, Bohadana, and Mathov developed a model in [23], in order to show the model's practicality, nine commercial IoT devices were attacked with the well-known DDoS attacks Mirai and BASHLITE. They distinguished between atypical commercial dealings and corrupted IoT devices using sophisticated autoencoders known as N-BaIoT.

In [24], Doshi and Feamster performed information collection, highlight extraction, and double characterization of organization deals using K-nearest neighbors (KNN), support vector machines (SVM), arbitrary woods, choice trees, and brain organizations. These simulations focus on network Centre boxes (for network switches, firewalls, and switches) and related devices that may be essential for a continuous DDoS attack.

Moreover, in C. She [25], a DDoS attack detection and cautioning structure was created subject to a multi-channel CNN by isolating up highlights considering aspects of time, space, bundle, etc.

R. Doriguzzi-Corin [26], introduced a CNN based DDoS recognition engineering. In which they designated a common sense, lightweight execution with low handling above and attack location time.

Y. Jia in [27], proposed an IoT DDoS guard component named as FlowGuard. In that they planned two parts, specifically Flow-Filter and Flow-Handler. Where Flow-Filter does the filtration of noxious streams on the essential of filtration rules created by Flow Handler. Two created DL models, LSTM (Long Short-Term Memory) and CNN (Convolutional Neural Network), indicate that the handler is responsible for differentiating evidence of and characterizing harmful streams. The application of these techniques is taken into consideration in light of the CICDDoS2019 dataset.

M. Roopak [28] proposed a high-level interruption location framework for DDoS attack recognition in IoT organizations. In this they utilized multi-objective streamlining strategy at their underlying stage for highlight extraction on the chose dataset in view of six basic goals for lessening information and utilized Deep learning models CNN with the mix of LSTM for the classification of attacks.

C. Analysis of various researcher's work with AI Techniques used and Datasets used.

Table 2: DDoS attack detection researches using machine learning and deep learning techniques.

Sr. No.	Paper Title	Year of Publishing	Methods used	Data Set
1	[29]	2019	ML Technique (Random Forest)	Used TFN2K tool conduct local DDoS attacks
2	[30]	2018	LSTM (Long Short-Term Memory)	DDoS attack Software
3	[31]	2019	PCA and RNN	KDD CUP 1999
4	[22]	2019	CNN+LSTM	CICIDS2017
5	[32]	2017	RNN	UNB ISCX
6	[26]	2020	CNN	ISCX2012, CIC 2017, CSECIS 2018
7	[33]	2019	SVM, KNN, ANN	KDDCUP
8	[27]	2020	LSTM, CNN	CICDDoS2019
9	[34]	2020	ANN SMOTE	BOT-IOT
10	[35]	2019	RF with n-estimate	CICIDS 2017
11	[36]	2019	KNN, MLP, SVM	KDD CUP99, NSL KDD
12	[28]	2020	CNN+LSTM	CICIDS2017

IV. RESULT AND DISCUSSION

The assessment index employs the false positive rate(FR), the detection rate(DR), and the overall detection rate to analyze the experimental results because determining if the recognition data is from a DDOS assault is a classification issue. one of them: The normal behavior ratio, or FR=FP/(FP+TP), is used to describe the attack data detection in the false positive rate. The detection rate, or DR=TN/(TN+FN), is the fraction of attack behavior as measured by the attack data detection. The total detection rate, or AR=(TP+TN)/(TP+TN+FP+FN), refers to the detection of normal data as normal data and the detection of attack data as the percentage of attack data. A positive sample that is anticipated to be positive is referred to be TP, and in this instance, normal data is anticipated to behave normally. The attack data in [29] are projected to be violent, while TN refers to a predicted negative sample. The assault data in this study is predicted to behave normally. A negative sample that is expected to be positive is referred to be FP. A positive sample that is projected to be negative is known as a positive sample in this study since normal data are expected to be aggressive.

The remaining set of attack data packets are mixed with the regular traffic as the test set after the random forest model has been trained using the training data set. This allows the model to be detected. To regulate the ratio of normal traffic to attack traffic, cross-sample both attack and normal traffic, determine each sample's categorization behavior, and adjust the sampling flow duration. Simultaneously, the data of the SVM method are detected using the LIBSVM library, and the results of the random forest model detection are compared.

The following tables summarizes the three protocol types' detection results from the DDOS assault data:

Table 3. TCP flood attack detection result [29].

Algorithm model	The specimen period (T)/s	2	4	6	8
Random forest	FR	0.14	0.15	0.15	0.16
	DR	99.15	98.69	98.50	98.10
	AR	99.93	99.67	99.57	99.49
SVM	FR	0.25	0.50	0.43	0.68
	DR	98.15	97.25	96.14	94.48
	AR	98.93	98.5	98.38	98.2

Table 4. UDP flood attack detection result [29].

Algorithm model	The specimen period (T)/s	2	4	6	8
Random forest	FR	0.24	0.30	0.53	0.42
	DR	97.75	96.83	95.23	93.13
	AR	99.93	99.67	99.57	99.49
SVM	FR	0.25	0.48	0.49	0.51
	DR	99.16	98.95	98.43	98.05
	AR	98.93	98.5	98.38	98.2

Table 5. ICMP flood attack detection result [29].

Algorithm model	The specimen period (T)/s	2	4	6	8
Random forest	FR	0.12	0.28	0.75	1.06
	DR	99.14	98.63	98.42	97.91
	AR	99.87	99.67	99.14	98.56
SVM	FR	0.91	1.12	2.75	3.33
	DR	98.22	97.22	96.34	94.41
	AR	98.87	97.79	96.90	95.49

The three tables above show that the detection model presented in [29] outperforms the SVM algorithm model and continues to have a higher detection rate for the outcomes of the three protocols' detection of DDOS attacks as background traffic grows.

V. CONCLUSION

Many analysts are focusing on DDoS attacks and trying to make arrangements in the systems' structure for detecting DDoS attacks in IoT. Many scientists have developed effective defense mechanisms for this, but none of them have provided the ultimate solution, and some of them have left some room for improvement. As a result, an effective DDoS attacks detection component is required to protect IoT organizations.

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