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SYN Flood Attack From TCP/IP Using Statistical Analysis of Machine Learning Techniques

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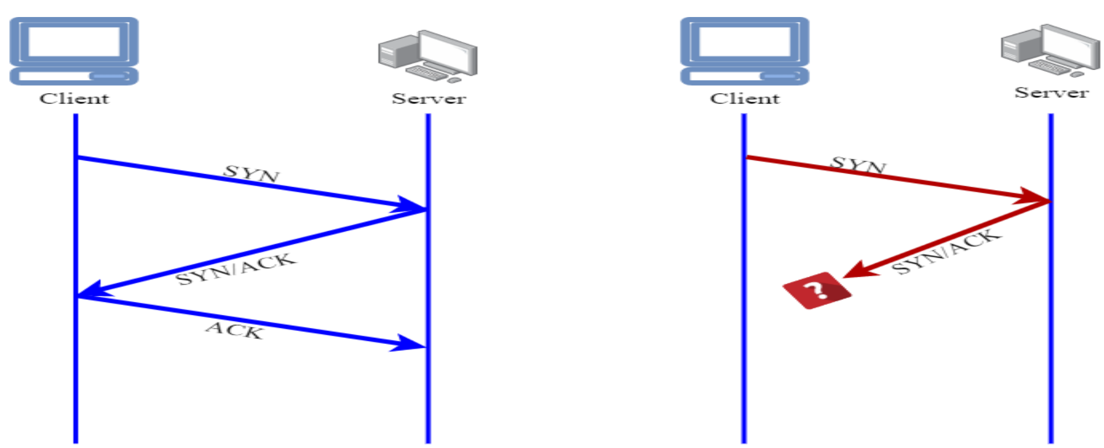
Abstract

Most of the network management affected by SYN flood attack needed to secure the server since being harassed by malevolent attackers. The Transmission control protocol synchronize (SYN) flood malicious attack happens whilst the hacker floods the network system with requests in order to overcome the intention and make it unable to respond to new real connection requests. This makes many of the intention server's communications ports into half-open state. If this kind of attack established in big data analysis, Artificial Intelligence, as well as Internet of Things, then SYN flood has to be found. So we proposed novel model for detecting the attack through statistical analysis in machine learning techniques such as decision tree classifier, ensemble gradient boosting classifier, MLP classifier for enhancing the model performance by evaluating the metrics such as accuracy, F-Score, FNR.

Keywords*: Synchronize (SYN), Machine Learning Techniques, Decision Tree classifier, Ensemble gradient boosting classifier, Multi-Layer Perceptron (MLP) Classifier, Accuracy, False Negative Rate (FNR), F-Score.*

1. Introduction

The working principle of SYN flood attack is to undertake the handshaking (client-server communication) process of Transmission control Protocol (TCP). Initially, the client sends the data by SYN packets to the server, then server respond to the same with acknowledgement as SYN/ACK for improving communication between client and server.



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This kind of malicious attack is simple to secure through placing a trouble-free firewall rule to obstruct packets with the attacker's source IP address that makes the attack shutdown after any attack found. The way of preventing SYN flood attack as follows:

a. Filtering

b. Increase in backlog

c. Half open TCP

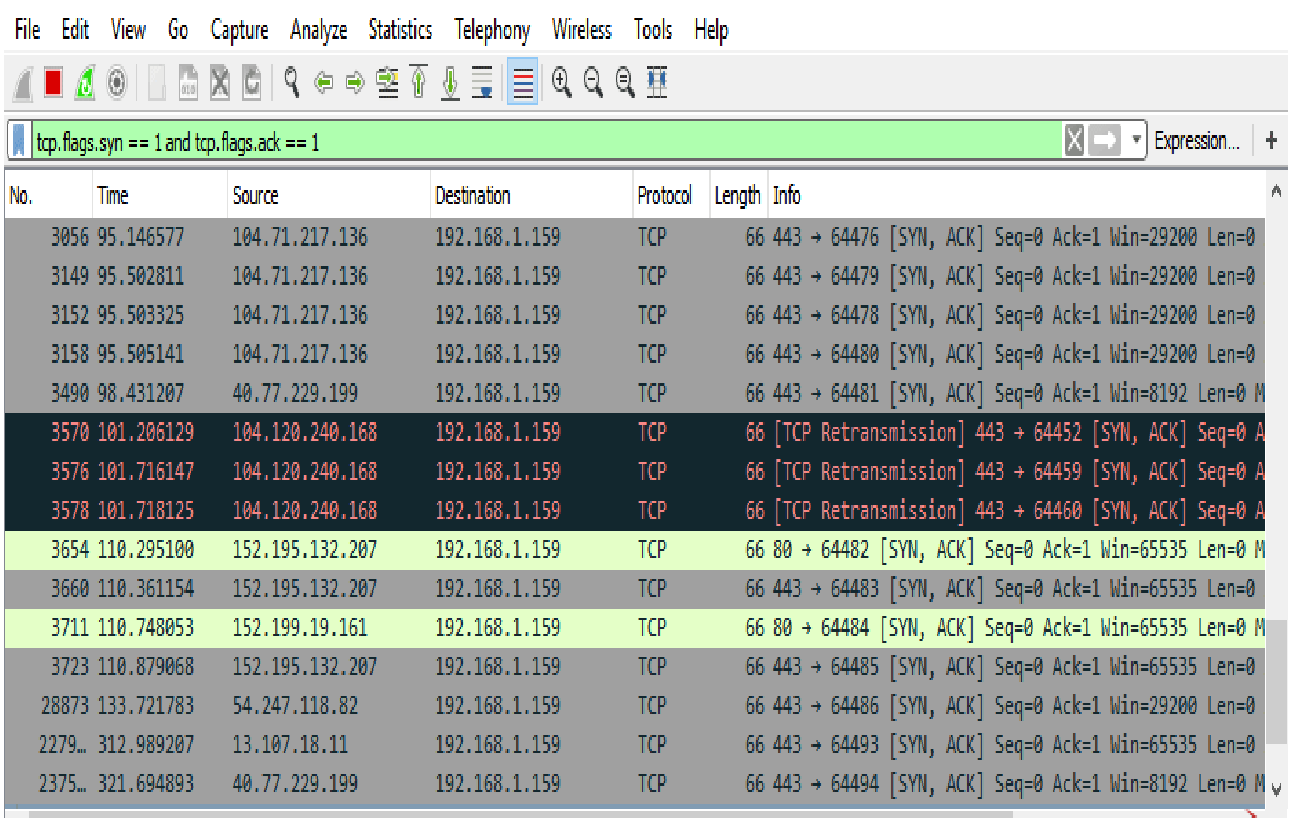
d. Firewalls and Proxies

e. Reducing SYN-Received Timer

f. SYN collection

g. Reprocessing the oldest half-open TCP

[1] Introduced novel method based on Software Defined Network in machine learning algorithm for detecting TCP based SYN flood attack in the network. The final accuracy achieved around 96% deal with the exchange between accuracy and capacity of the device which makes secure for increase and improvement in the performance. Attackers hurriedly send SYN packets exclusive of spoofing their Internet Protocol source address in SYN flood attack.



No.	Time	Source	Destination	Protocol	Length	Info
3056	95.146577	104.71.217.136	192.168.1.159	TCP	66	443 → 64476 [SYN, ACK] Seq=0 Ack=1 Win=29200 Len=0
3149	95.502811	104.71.217.136	192.168.1.159	TCP	66	443 → 64479 [SYN, ACK] Seq=0 Ack=1 Win=29200 Len=0
3152	95.503325	104.71.217.136	192.168.1.159	TCP	66	443 → 64478 [SYN, ACK] Seq=0 Ack=1 Win=29200 Len=0
3158	95.505141	104.71.217.136	192.168.1.159	TCP	66	443 → 64480 [SYN, ACK] Seq=0 Ack=1 Win=29200 Len=0
3490	98.431207	40.77.229.199	192.168.1.159	TCP	66	443 → 64481 [SYN, ACK] Seq=0 Ack=1 Win=8192 Len=0 M
3570	101.206129	104.120.240.168	192.168.1.159	TCP	66	[TCP Retransmission] 443 → 64452 [SYN, ACK] Seq=0 A
3576	101.716147	104.120.240.168	192.168.1.159	TCP	66	[TCP Retransmission] 443 → 64459 [SYN, ACK] Seq=0 A
3578	101.718125	104.120.240.168	192.168.1.159	TCP	66	[TCP Retransmission] 443 → 64460 [SYN, ACK] Seq=0 A
3654	110.295100	152.195.132.207	192.168.1.159	TCP	66	80 → 64482 [SYN, ACK] Seq=0 Ack=1 Win=65535 Len=0 M
3660	110.361154	152.195.132.207	192.168.1.159	TCP	66	443 → 64483 [SYN, ACK] Seq=0 Ack=1 Win=65535 Len=0
3711	110.748053	152.199.19.161	192.168.1.159	TCP	66	80 → 64484 [SYN, ACK] Seq=0 Ack=1 Win=65535 Len=0 M
3723	110.879068	152.195.132.207	192.168.1.159	TCP	66	443 → 64485 [SYN, ACK] Seq=0 Ack=1 Win=65535 Len=0
28873	133.721783	54.247.118.82	192.168.1.159	TCP	66	443 → 64486 [SYN, ACK] Seq=0 Ack=1 Win=29200 Len=0
2279…	312.989207	13.107.18.11	192.168.1.159	TCP	66	443 → 64493 [SYN, ACK] Seq=0 Ack=1 Win=65535 Len=0
2375…	321.694893	40.77.229.199	192.168.1.159	TCP	66	443 → 64494 [SYN, ACK] Seq=0 Ack=1 Win=8192 Len=0 M

Here, every packet source IP address varies with destination HTTP port 80, length 120, size of the window as 64 (2^5). The protocol used in this attack is Transmission Control Protocol, the value of tcp.flags.syn==tcp.flags.ack==1, and the number of SYN/ACK is moderately very less.

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2. Background

[2] Designed methodology for perceiving LDDoS attacks depends upon the individuality malevolent transmission control protocol (TCP) flows which is a kind of DDoS attack. Here, two different arrangements of datasets one produce from simulated network, the other from publically available CIC DoS dataset. The experimental outcome shows the accuracy around 99.99% with remarkably low false rate, low FNR in detection of LDDoS. [3] Detecting DDoS attack could be found by analyzing flow of packets in the network. The novel method introduced telemetry usage from the cloud through machine learning techniques such as KNN and Decision Tree algorithm (CART) to find DDoS attack. [4] Proposed five rule-based machine learning algorithm namely JRip, decision table, PART, OneR, and ZeroR. Among all algorithms, Slow loris achieves high accuracy of 99.7% using PART classifier for realizing the detection of ICMP attack as well as HTTP flood attack. [5] Suggested the improvement of new defense technologies for differentiating the attack from normal using machine learning method based on DDoS detection system. The investigational outcomes reveals that detection rate accuracy as 96% with high precision, low FAR, through sampling rate with 20% of traffic in the network. [6] Introduced synchronize flood attack in cloud based technology and finding attacks extorted from TCP/IP header based on features in the datasets. The final output has been predicted for model performance by identifying and classifying attacks in the network with reference to some dataset features. [8] Imposes literature survey by comparing various researchers regarding detection of finding attacks in the system through development of protocol, enumeration, selection strategy, and synthesizing using machine learning algorithms. [9] Utilized binary classification and two optimizers for detecting the accuracy of attacks in the system via data pre-processing methods, tuning hyper parameters, and Neural Network architectures. [10] [15] Intended to detect the DDoS system based on C.45 decision based random forest algorithm for classifying the network as normal or attack. The novel introduced algorithm attached with signature based detection techniques produces decision tree to achieve automatic, effective detection of signature attacks for flooding attacks. Machine learning algorithm used for validates the model to enhance the better performance. [12] Recommended the test data calculation based on IRE values evaluated during testing phase via monitoring the incoming and outgoing traffic of the web server for detecting the SYN flood attack in the network device. The auto encoder found the attack with delay of 19.2 seconds after scrutinizing the traffic in the network. [13] exposed the detection of SYN flood attack in the network due to IP header through payload and impractical field which makes the detection faster, and highly effective. Finally the alarming section gives the alert if any abnormal behavior occurs in the network. [14] focused on different security attacks in machine learning algorithms and cloud can be used for identifying attacks in the network. Various machine learning techniques like Naïve Bayes, SVM, Logistic Regression, and ensemble methods can be used for finding attack such as authentication attack, Man-in-the-Middle attack, malware attack, DoS attack. [16] Used DARPA, KDD Cup, and CONFICKER datasets for categorizing attack or normal through evaluating metrics such as accuracy, average delay, cost, loss of packets, overhead, packet delivery ratio as well as throughput. The simulation results shows 99% of high accuracy, less false reduction, less overhead, less packet loss and increase in throughput and packet delivery ratio.

3. Proposed work

3.1 Workflow for proposed model

The flow of work includes organizing and repetitive prototype of any action facilitate by some association resources into processes which converts the resources, services or any information about process.

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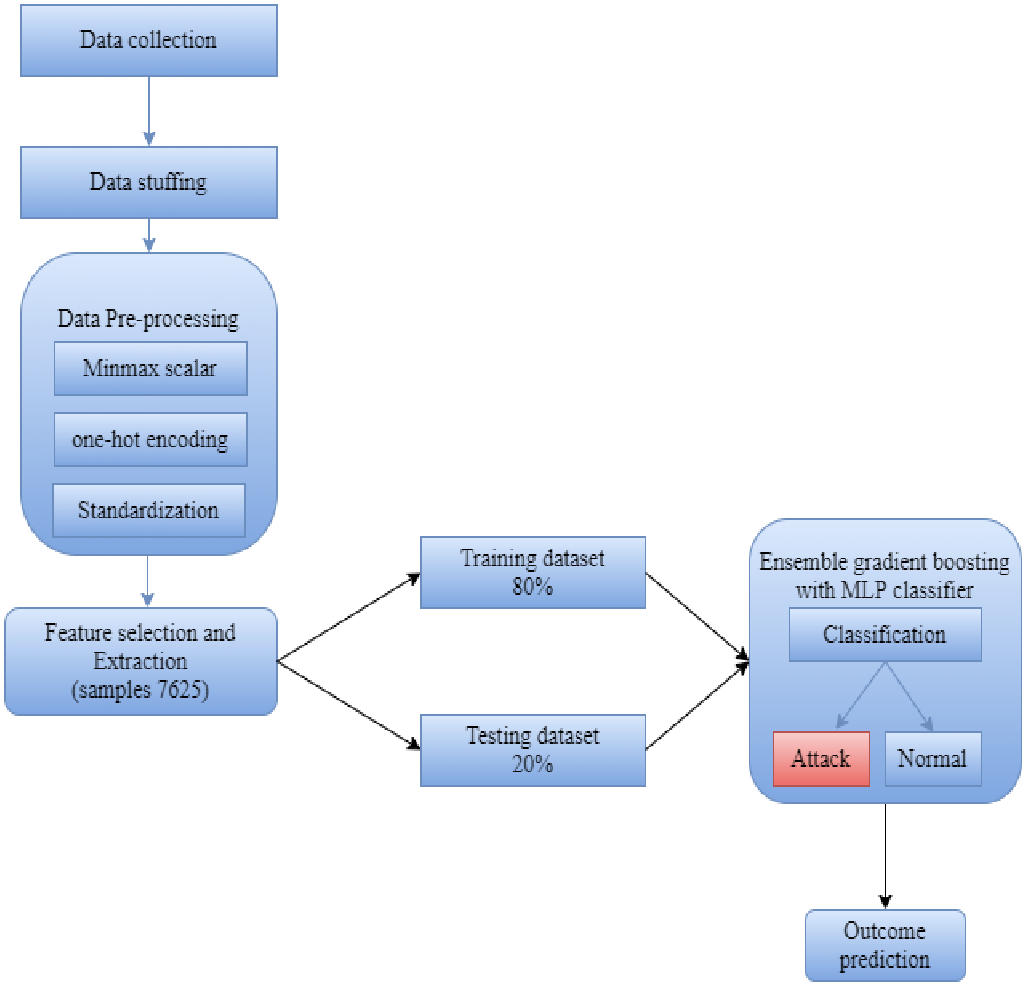

The first step is to collect the data from corresponding repository, then loading the data for further processing leads to data pre-processing in which min-max scalar initialized, then apply it to the features for further transformation, thus scaling applied features can be shown including percentage of attacks. Hence, calculate the feature-wise distribution for every feature with training and testing ratio as 80:20 as well as choosing classifiers such as ensemble gradient boosting along with MLP classifier for categorizing the network as malicious or normal. Thus the overall performance model can be predicted through the final outcome prediction via classifier algorithms in machine learning techniques.

3.2 Proposed work algorithm

In the proposed method, finding SYN flood attack through machine learning techniques such as decision tree classifier, ensemble gradient boosting classifier, Multi Layer Perceptron classifier.

A. Decision tree classifier: Decision tree classifier comes under supervised machine learning for categorizing the SYN flood based on Transmission Control Protocol into either malware or benign. The figure shows that if IP range specified as xxxx-yyyy, then the class found to be malware otherwise IP address is executable. If IP address is executable, then class is specified as malware or else referring some port address. If it is mentioned as port then the class is malware or found the class to be benign.

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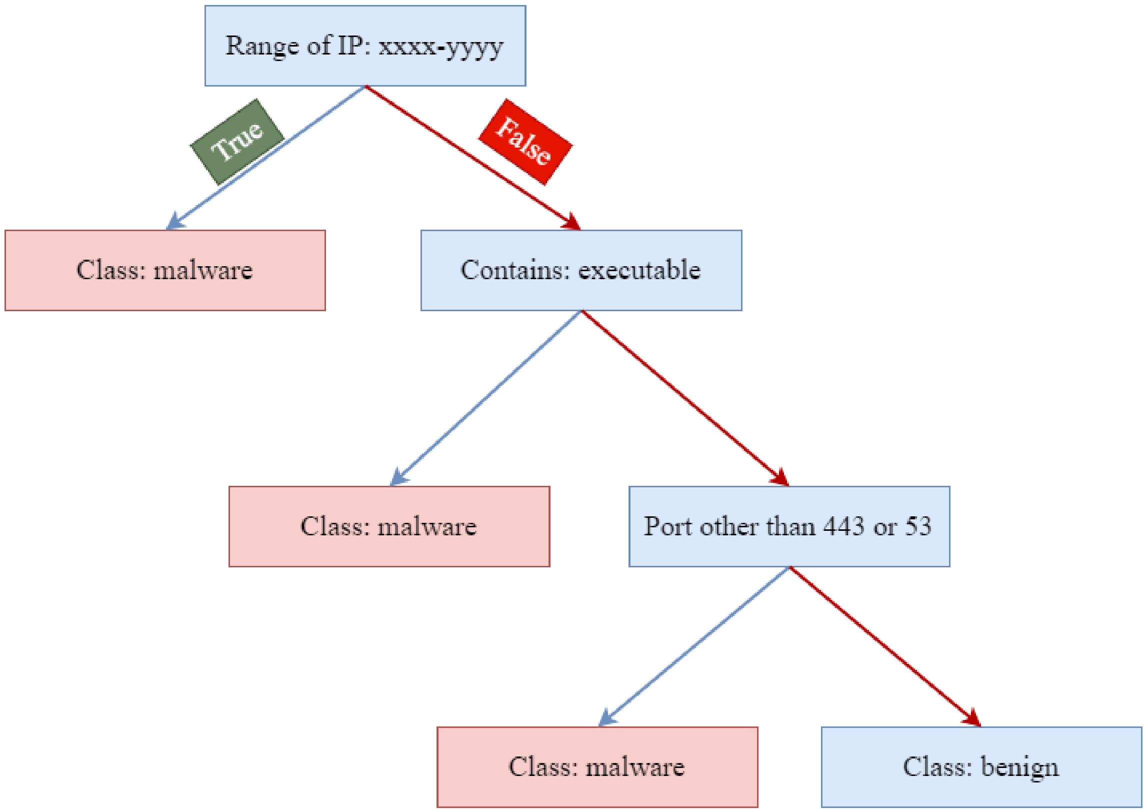

B. Ensemble Gradient Boosting Classifier: An ensemble gradient boosting classifier is one of the machine learning methods which can be utilized in case of both classification as well as regression problems that generates a prophecy model in the form of an ensemble of weak model normally decision trees. [11] Proposed support vector machine for categorizing the datasets as normal or attack in the network processed under four phases namely attack simulation, data collection, feature selection and classification. Finally, the process generates the classification accuracy as 100% and True Positive Rate as 100% reveals dazzling performance which supply as valuable asset in the field of network security. In our proposed model, the detection accuracy achieved as 100% which outstands the performance of the model through ensemble gradient boosting algorithm along with decision tree.

C. Multi-Layer Perceptron: Mainly MLP relies on intrinsic neural network to complete the undertaking of classification problems. Importing and initializing MLP classifier using Python code.

```
#importing MLP classifier
From sklearn. neural network import MLPClassifier
# initializing the MLPClassifier
Clf_C= MLPClassifier (solver='lbfgs', alpha=1e-5, hidden_layer_sizes = (5, 2), random_state=1)
```

Now, the solver = lbfgs or gradient descent parameter in neural network optimizes the log loss function, alpha= 1e-5 parameter for regularization that assist in evade over fitting by chastising weights with huge scale, hidden layer size parameter permit the number of nodes and layers in neural network classifier, random_state parameter allocate to set seed for generating the output.

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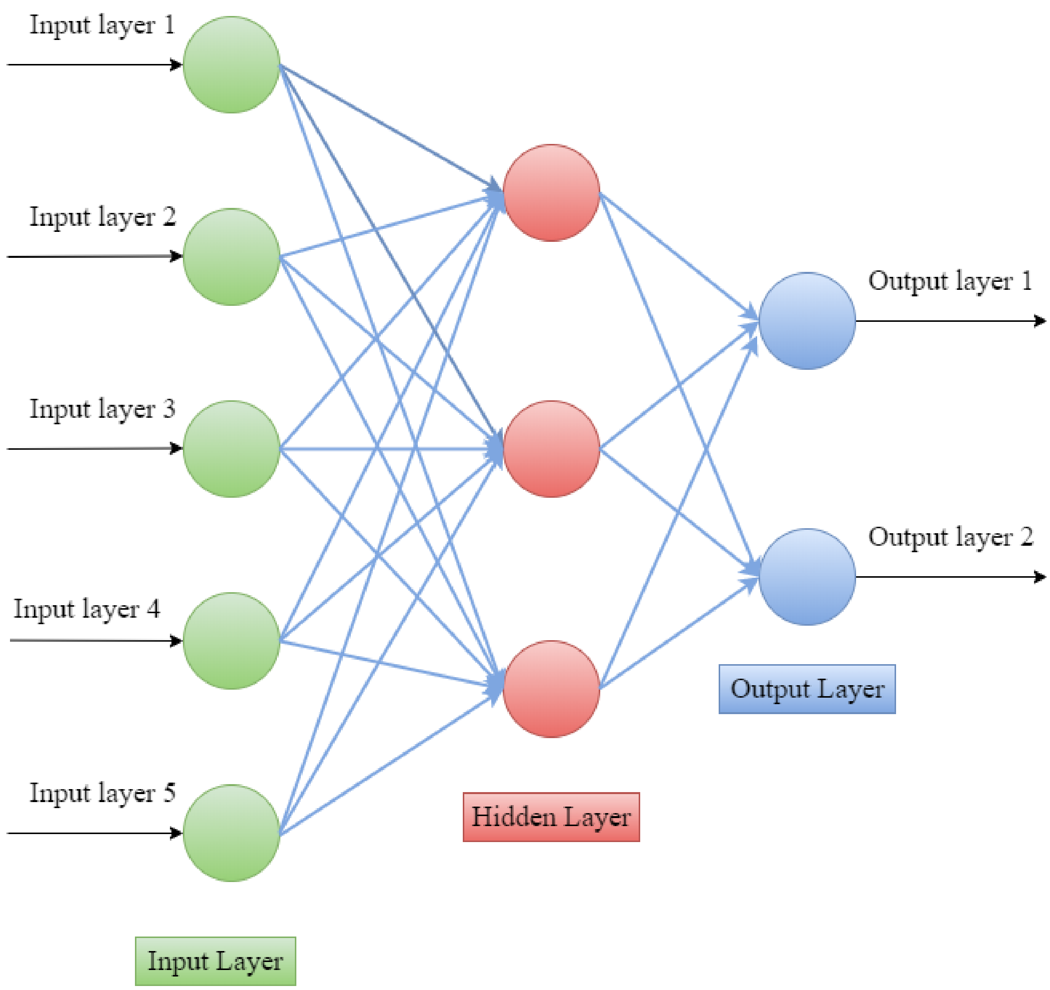

The above diagram shows the input layer as 5 and the output layer as 2 with hidden layers (i.e) hidden_layers_size= (5, 2)

4. Dataset description

The dataset is collected from Kaggle resource datasets which has 7167 samples with 82 features that performs splitting phase which has 5733 samples for training sets with 80 percent and the remaining 1434 samples allotted for testing sets with 20 percent as well. Herein, the number of normal records is 2166, the number of attacks refer 5001 attacks, the percentage of attacks in SYN flood found to be 69.78%. This kind of attack has to be found via statistical analysis of some techniques in machine learning.

Total number of records	Number of attacks	Number of normal records	Percentage of attacks
7167	5001	2166	69.78%

Some of the features namely source IP, source port, destination port, destination IP, protocol, timestamp, flow duration, total forward packets, total backward packets, active std, active min max, idle mean, idle std, similar HTTP, inbound, and type of the attack. The features used in detecting SYN flood attack with its description are summarized.

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Features	Description
Source IP	The IP address of the device sending IP packet
Source port	The subsequent offered data assigned to the user by TCP/IP
Destination IP	The machine to which the packet is being used
Destination port	Well-known ports (Server application)
Protocol	Data transmission between dissimilar devices in similar net
Timestamp	Current time of an incident saved by a system
Flow duration	Time duration for flow of packets
Total forward packets	Number of received packets from interface which is linked to a particular system
Total backward packets	Reverse of forward packets
Active standard	Node performs certain operation in the network
Active minimum	Minimum flow of packets
Active Maximum	Maximum flow of packets
Idle mean	Finding mean value
Idle Standard	Finding standard value in the network
HTTP	Hypertext Transfer Protocol
Inbound	Inbound firewall defend the system beside referral traffic from internet
Attack type	Finding type of the attack

Metrics	Description	Formula

4.1 Metrics Evaluation in proposed model

The overall model performance can be evaluated through metrics such as accuracy, prediction time, F-Score, False Negative Rate (FNR), for both training and testing samples. The number of incorrect and correct predictions are summarized with count values and broken down by every class. Confusion matrix frequently used to illustrate classification model performance.

	Class 1 Predicted value	**Class 2 Actual value**
Class 1 Actual value	TP	FN
Class 2 Predicted value	FP	TN

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Accuracy	Correctly classified percentage	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$
F-Score	Harmonic mean of precision and recall	$F - score = \frac{2 * recall * precision}{recall + precision}$
FNR	Miss rate	$FNR = \frac{FN}{FN + TP}$
Precision	Measure of result relevancy	$\Pr ecision = \frac{TP}{TP + FP}$
Recall	Measure of success prediction when classes are imbalanced.	$\mathrm{Re}\,call = \frac{TP}{TP + FN}$
Prediction time	Time to predict the future value	-

Based on the metrics evaluation such as accuracy, F-score, FNR, Precision, Recall, prediction time, the overall model performance can be calculated through statistical analysis of metrics.

4.2 Feature calculation for mean, median, mode

The below table reveals that finding mean, median, mode for both attack or normal mentioned some features of synchronize attack based on Transmission control protocol.

Features	**Mode attack**	**Median attack**	**Mean attack**	**Mode normal**	**Median normal**	**Mean attack**
Source port	35363.5	35461.000000	3.545055e+04	443.0	56221.500000	4.566191e+04
Destination port	19951.0	32793.000000	3.305446e+04	53.0	443.000000	1.017277e+04
Protocol	6.0	6.000000	6.000000e+00	6.0	6.000000	9.847645e+00
Total Fwd Packets	2.0	2.000000	4.188562e+00	2.0	2.000000	9.573869e+00
Total Backward Packets	0.0	2.000000	1.708458e+00	2.0	2.000000	1.040859e+01
Total Length of Fwd Packets	12.0	12.000000	2.514897e+01	6.0	64.000000	8.994307e+02
Total Length of Bwd Packets	0.0	12.000000	1.024115e+01	0.0	82.000000	8.007978e+03
Fwd Packet Length Max	6.0	6.000000	6.008798e+00	6.0	32.000000	1.426385e+02
Fwd Packet Length Min	6.0	6.000000	6.004399e+00	6.0	6.000000	1.687073e+01
Fwd Packet Length Mean	6.0	6.000000	6.005279e+00	6.0	31.000000	3.884630e+01
Fwd Packet Length Std	0.0	0.000000	1.854832e-03	0.0	0.000000	3.865311e+01
Bwd Packet Length Max	6.0	6.000000	3.212158e+00	0.0	41.000000	2.445300e+02
Bwd Packet Length Min	6.0	6.000000	3.212158e+00	0.0	6.000000	3.311450e+01
Bwd Packet Length Mean	6.0	6.000000	3.212158e+00	0.0	32.666667	8.485964e+01
Flow IAT Mean	1.0	35.333333	1.472787e+06	1.0	6963.166666	3.987781e+05

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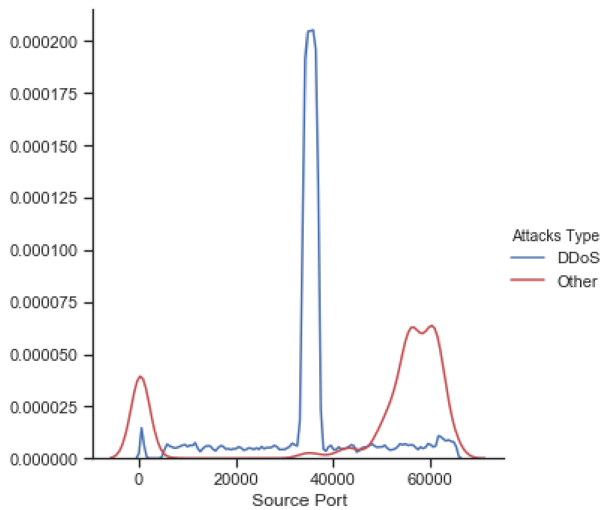
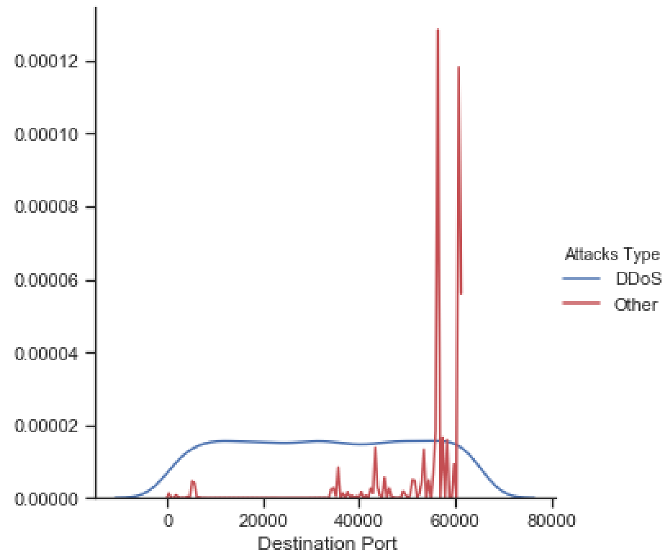
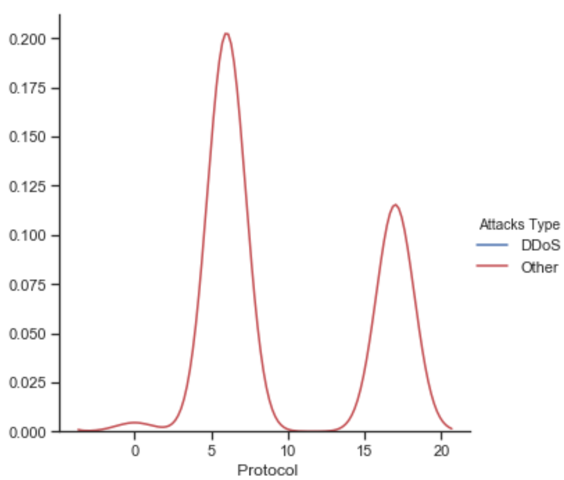
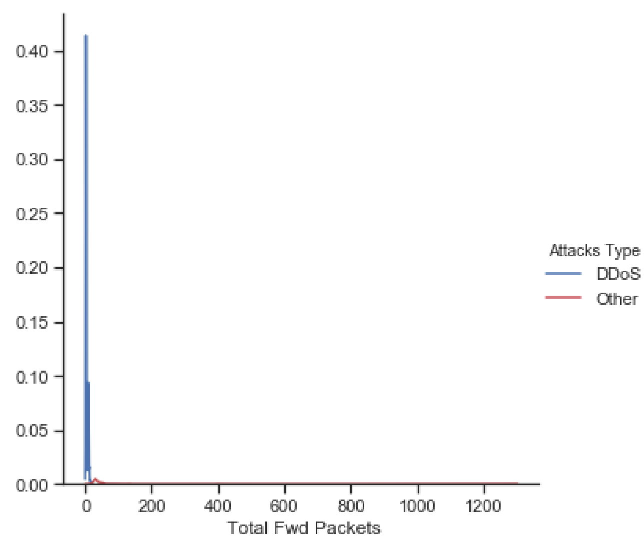
5. Statistical Analysis

Suppose if we wish to concern in some other techniques such as big data analytics, Artificial Intelligence, Internet of Things which causes major issues to the network of recognize attacks. Thus identifying and classifying the network as malicious or standard is necessary in recent technology trends. So, the novel proposed method expose to do favor to the network by implementing statistical analysis of such classifiers in machine learning models for categorizing malicious or normal. [7] Anticipated machine learning methods based on cloud which is on source side for detecting the attack namely Denial of Service in the network. This paper illustrates the model performance through statistical analysis from user as a virtual machine and cloud server to check both inward and outward packets in the network. Hence, the accuracy achieved as 99.7% in detecting DoS attack via experimental results.









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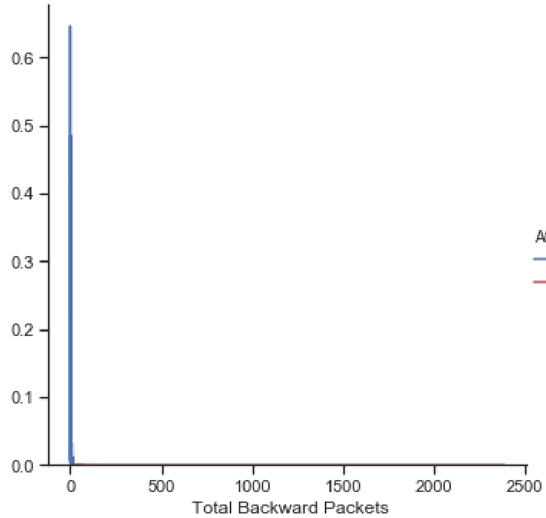

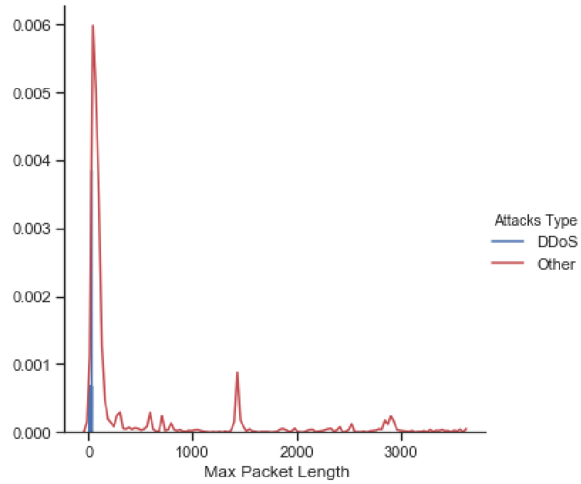

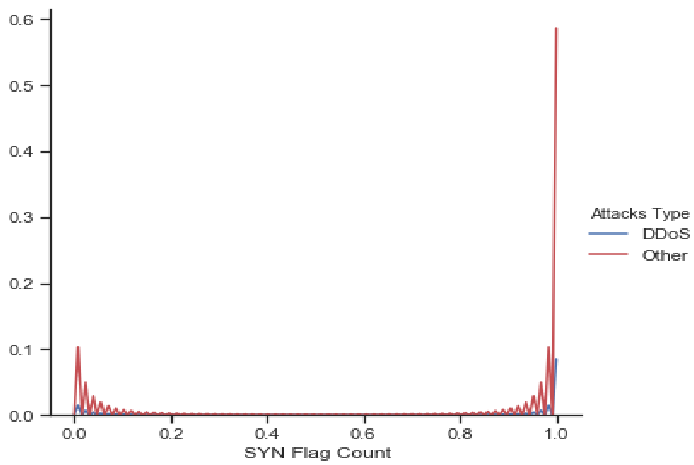

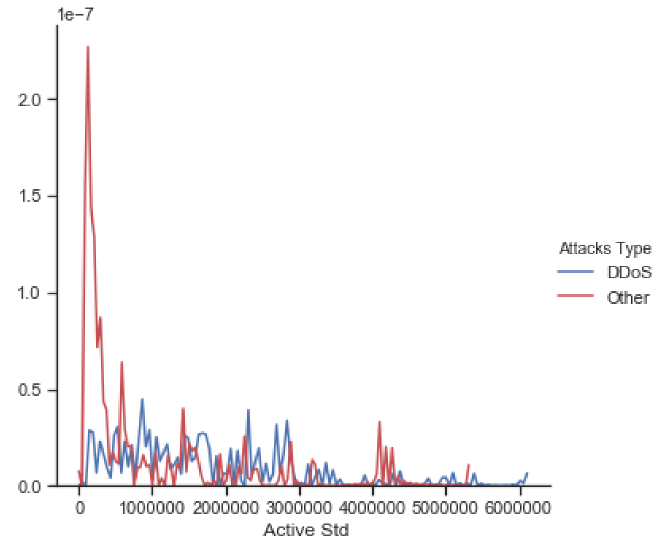

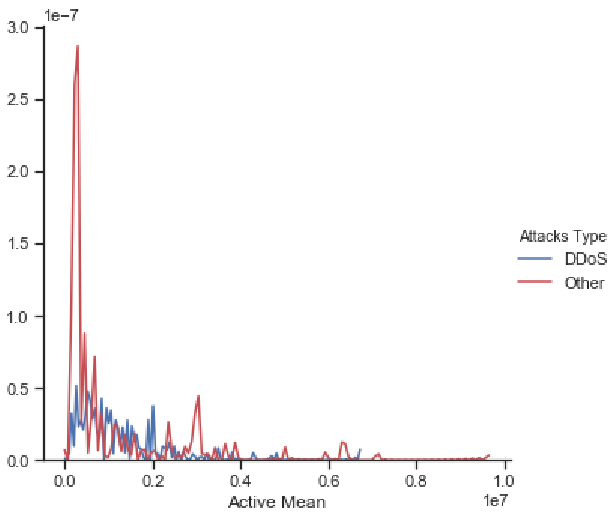

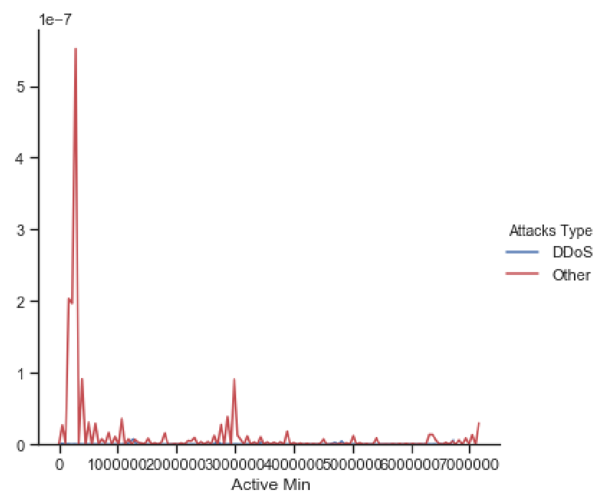

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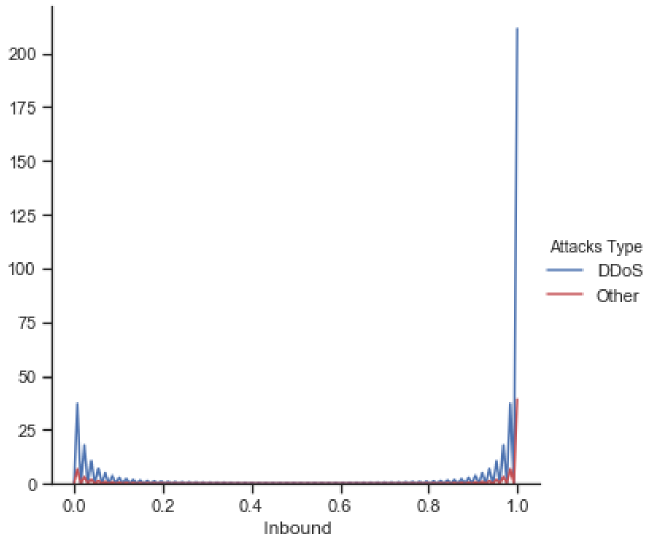

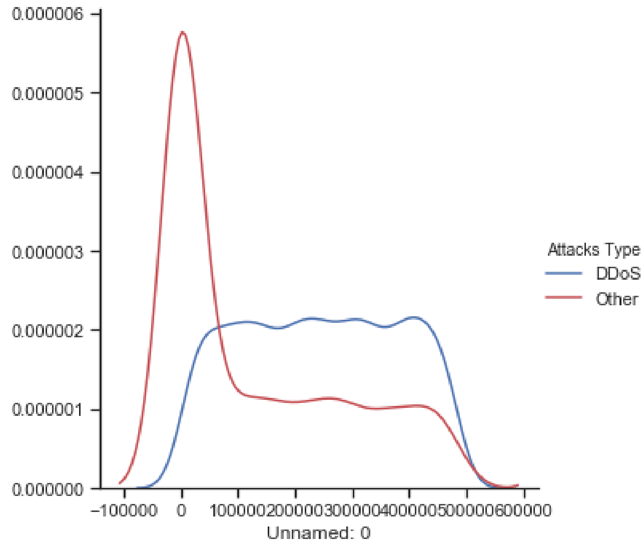

6. Results and Discussion

6.1 Algorithm evaluation with full feature set

	1% training samples			10% training samples			100% training samples		
	GB	DT	MLP	GB	DT	MLP	GB	DT	MLP
Train_time (s)	0.031404	0.003999	0.015275	0.140637	0.005999	0.028002	1.264150	0.056145	0.102025
Prediction_time	0.000000	0.006002	0.007003	0.000000	0.005007	0.007006	0.008994	0.000000	0.004998
Accuracy_train	0.976667	0.973333	0.596667	1.000000	1.000000	0.590000	1.000000	1.000000	0.590000
Accuracy_test	0.987448	0.982566	0.598326	0.996513	0.997211	0.597629	1.000000	1.000000	0.597629
F_train	0.983683	0.981395	0.699752	1.000000	1.000000	0.693267	1.000000	1.000000	0.693267
F_test	0.991045	0.987605	0.685590	0.997484	0.997996	0.684182	1.000000	1.000000	0.684182
FNR_train	0.000000	0.000000	0.331754	0.000000	0.000000	0.341232	0.000000	0.000000	0.341232
FNR_test	0.000000	0.000000	0.369478	0.005020	0.000000	0.372490	0.000000	0.000000	0.372490

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6.2 Algorithm evaluation with statistical feature set

	1% training samples			10% training samples			100% training samples		
	GB	DT	MLP	GB	DT	MLP	GB	DT	MLP
Train_time (s)	0.059633	0.009479	0.011116	0.152682	0.152682	0.018001	1.189550	0.052131	0.049473
Prediction_time	0.011002	0.004001	0.005886	0.015635	0.015635	0.007006	0.015626	0.004996	0.002510
Accuracy_train	0.976667	0.970000	0.296667	1.000000	1.000000	0.296667	1.000000	1.000000	0.296667
Accuracy_test	0.987448	0.978382	0.305439	0.993724	0.993724	0.305439	1.000000	1.000000	0.305439
F_train	0.983683	0.979118	0.000000	1.000000	1.000000	0.000000	1.000000	1.000000	0.000000
F_test	0.991045	0.984676	0.000000	0.995461	0.995461	0.000000	1.000000	1.000000	0.000000
FNR_train	0.000000	0.000000	1.000000	0.000000	0.000000	1.000000	0.000000	0.000000	1.000000
FNR_test	0.000000	0.000000	1.000000	0.009036	0.009036	1.000000	0.000000	0.000000	1.000000

The table specifies the algorithm evaluation for full feature set as well as statistical feature set with 1%, 10%, 100% training samples for all classifiers in the sequence of 57, 573, 5733 samples on training datasets.

6.3 Feature importance determined by t-test

The t-test score value can be calculated for determining the importance of features in synchronizes dataset for classifying the attack as break up.

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	ACK Flag Count	Inbound	URG Flag Count	Protocol	Destination Port	Bwd Packet Length Min	CWE Flag Count	Average Packet Size	Avg Fwd Segment Size	Fwd Packet Length Mean	Subflow Bwd Bytes	Idle Min	Active Mean	Flow IAT Min	Fwd IAT Min	SYN Flag Count	Active Std	Bwd IAT Std
t-Score (squared)	22960.54668	21861.03077	4078.03611	2558.23402	2035.87731	1638.49086	1325.82968	1268.59244	1209.33493	1209.33493	26.79566	25.63777	23.95676	17.27751	10.06518	7.62092	7.11081	4.77502
P-Value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00003	0.00152	0.00578	0.00768	0.02891

From analyzing the algorithm evaluation statistically with three different classifiers, the outcomes could be predicted for finding the model performance. In this proposed model, among three classifiers in MLT, ensemble gradient boosting and decision tree classifier shows better accuracy as 100 %. Hence, by referring the percentage of accuracy in validation stage this novel proposed model is best for categorizing the net as attack or normal in SYN flood attack based upon TCP.

6.4 Comparative Analysis

Comparative Analysis for accuracy detection determined by various authors is shown below:

Authors	Techniques used	Detection of attack	Accuracy detection
[1]	MLP	TCP-SYN	96%
[2]	DT, KNN	LDDoS	99.99%
[3]	KNN	DoS	99.3%
	CART		91.07%
[4]	PART	HTTP flood attack	99.7%
[5]	ML	DoS	96%
[6]	NN	TCP/ IP syn flood	99.9%
	NB		99.1%
	KNN		98.2%
	DT		99.9%

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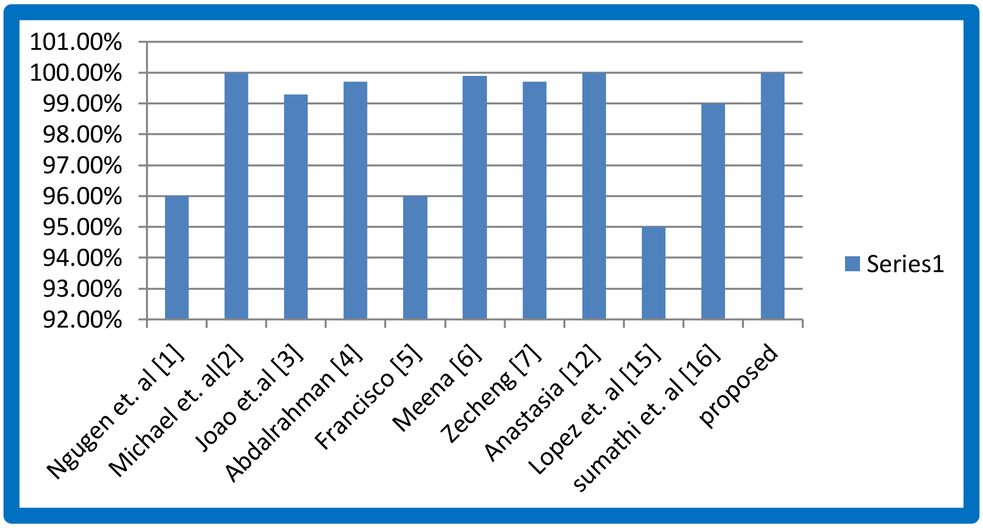
[7]	Cloud based ML	DoS	99.7%
[8]	ML and DL	DDoS	
[9]	BNN LSTM RNN	DDoS	
[10]	C4.5 Decision Tree	DDoS	
[11]	SVM	DoS	100%
[12]	Auto encoder	DoS, Code injection	
[13]	Packet filtering algorithm	TCP SYN flood	
[14]	SVM, NB,DT, ensemble methods		✓
[15]	Decision Tree based RF KNN	DDoS	 95%
[16]	Deep Learning NN classifier	DoS	99%
Proposed	Machine Learning classifier	SYN flood attack	100%



The above chart shows the classification accuracy detection for all authors classifies attack or normal with 100% accuracy using decision tree classifier. Thus our proposed work shows better outcome among various authors.

7. Conclusion

In this novel proposed method, the SYN flood attack could be recognized and categorizing the datasets as attack or normal using statistical analysis in machine learning techniques like Decision Tree, ensemble gradient boosting classifier, as well as Multi-Layer Perceptron classifier by extracting features acquired from TCP/IP header protocol. Hence, the efficiency of IDS in distinguishing SYN flood attack depends on extracting specific features using MLT. The investigational outcomes demonstrate that ensemble gradient boosting and decision tree algorithm generates 100% accuracy with least prediction time as 0.01 seconds in detection of SYN flood attack. Based on accuracy prediction evaluated through various classifiers, the performance of the model can be acknowledged. The future scope is to assess the feature extraction implemented in machine learning techniques that concerned it in real world application through indispensable alteration which may improve the performance of the model.

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