

# Use of Machine Learning algorithms for designing efficient cyber security solutions

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**Abstract**—With rapidly increment of internet traffic, the importance of cyber security also increases significantly. Several areas like IP traffic classifications, detection of - intrusion, spam and malware becomes important to be considered. To overcome the cyber security issues traditional techniques are not enough. It is essential to adapt the ongoing changes to keep security always up to date and It can't be denied that the web of Machine Learning keeps increasing in the digital world. The Cyber Security also adopt the Machine Learning to overcome the limitations of algorithms based on traditional rules and to make them more efficient with their integration with Artificial Intelligence. Although complete automation of analysis and detection is enticing goal, but the significant parts of cyber security can be improved. In this paper we will see how several algorithms of Machine Learning can be used to overcome the popular issues faced by cyber security.

**Keywords**—Machine learning, Cyber Security, IP traffic classification, Artificial Intelligence, Security enhancement, Intrusion Detection System, Malware, NetFlow, Packet -Level Data.

## I. INTRODUCTION

With the adoption of Machine Learning, most technologies are getting better with it [1, 2]. Many researches have been done to implement Machine Learning in cyber security issues like IP classification, spam and malware detection [3, 4]. Several platforms like Gmail uses spam detection technique by implementing Machine Learning into their system. In the defense system of a country, it is very important to make their digital system more secure and we can't make it better by adopting the ML techniques [5]. For classification of IP we get variety of algorithms like Bayes Net, Multilayer Perceptron (MLP), C 4.5 Decision Tree, Naïve Bayes Algorithm.

Due to increasing internet traffic, cybersecurity has some challenges: Firstly, the volume of data stream is high, making manual analysis of it impractical. And Secondly, the emerging rate of threats is very high, hence patterns which are short lived and highly adaptive threats become prevalent. Then, detection and prediction of elusive threats becomes hard. Hence tackling of these threats need time and money, also it is expensive and hard to giving employment to domain experts [6, 7].

Data is very important if we talk about Machine Learning. It is because the ML techniques required the data to learn so it is important to have good understanding about the data in order to design a model or apply different algorithms [8, 9]. Machine Learning possess some advantages in the subareas of cybersecurity fields: (a) Behavior modeling can be used to differentiate between normal activities and anomalous ones. (b) New and subtle changes in attacks in signatures-tradecraft could also be discovered dynamically. (c) Machine Learning is more adaptable than tradition method when domains of threat change. Methods of machine learning like balancing bias variance, precision-versus can be used for reducing false alarms [10, 11].

The remainder of the paper is organized as follows. Section II of the paper presents the literature review and highlights the most prominent works in the field. Section III of the paper explores about various cybersecurity applications that use machine learning. Section IV focusses on the cybersecurity data sets for machine learning that includes network flow and packet level data. Various ML techniques related to cyber security are detailed in section V and finally the paper concludes in section VI with several open research challenges.

## II. RELATED WORK

Rafal et al. [12] proposed a novel method to detect cyber-attacks which are targeting web applications. Comparison of this method is done with AdaBoost, Naive Bayes, Part and J48 machine learning algorithms. For assessment of presented model Dataset of CSIC 2010 HTTP is used. The solutions which are using HTTP to make communication of client with server are focused in this study. It is claimed by the author that this model can give higher detection percentage without having higher false positive rate. J48 method is very effective approach for this type of problem having true-positive vale 0.04.

Chowdhury et al. [13] presented a new method for botnet detection which is topological based feature of node in a graph. The method is able to be used for anomaly detection by searching several limited nodes. The proposed model is

generally based on clustering that is (SOM) Self-Organizing Map which comes under the unsupervised system. CTU-13 datasets, the vast dataset which contains the bot labeled nodes. Support Vector Machine (SVM) method is also used to detect the same and compare it with the given method and the results that the proposed method can be able to detect bot with the accuracy which is acceptable by searching few nodes.

Neethu et al. [14] proposed a framework that is PCA, feature selection is done with Naive Bayes for developing a network intrusion system for detection. KDDCup 1999 dataset for intrusion detection is preferred for this experiment. The results show that the proposed method is very effective having detection rates high, consumes less time and has cost factor lower than decision tree and neural network based approach. This model provides 94% accuracy. Haddadi et al. [15] analyzed various approaches for botnet detection based on types of data employed and model used. Snort and BotHunter are two of approaches based on system which are public rule based. Other approaches are data mining based techniques like traffic flow based and packet payload based. They work on methods like KNN, Bayesian Network, C4.5, SVM (Support Vector Machine) using botnet datasets that are publicly available such as ISOT, CAIDA, etc. The result shows that the system which is traffic flow based is higher and effective or similar to result which are reported in literature. For efficiently detection of network intrusion, an IDS (Intrusion Detection System) which are based on genetic algorithms. Evolution process and parameters of GA were deeply explained. In the work, KDD99 benchmark dataset is used to evaluate the performance. Evolution theory is used for information evolution to filter the data of traffic and complexity get decreased. The study shows that the proposed model achieves effective detection rate [16]. Comparison of various data sets are presented in Table I.

TABLE I. COMPARISON OF VARIOUS DATA SETS

Study	Dataset	Techniques	Problem Domain	Evaluation Method	Feature Selection
[11]	CTU-13	SOM	DDOS Attack Detection	Accuracy	Yes
[14]	KDDC up 1999	Genetic Algorithm	Intrusion Detection	Detection Rate (DR)	Yes
[10]	CSIC 2010 HTTP Dataset	Naive Bayes, Part, J48 and AdaBoost	Web Application Attack	False Positive Rate	Yes

### III. APPLICATIONS OF MACHINE LEARNING IN CYBER SECURITY

Various applications of machine learning in the field of cybersecurity are detailed in the section below.

#### A. Intrusion Detection

It is technology for threat detection, which monitors traffic of network, flows to detect misuses of susceptible traffic. An

(IDS) Intrusion Detection System can execute the process of intrusion detection automatically. On the base of IDS, potential intrusion can be stopped by IPS (Intrusion Detection System). Method of cyber analytics methods are divided into 3 groups that are based on IDSs: anomaly-based, signature-based or misuse-based and hybrid. To categorize IDSs there is another way by identifying where we look for intrusive liked behavior: host- based or network-based. In [17], Anna Buczak presented definitions on aforesaid taxonomy and attached huge number of datasets: Public flow data and NetFlow data Sets, Packet-Level Data Sets. Potentially measurement including (ANN) Artificial Neural Networks, Fuzzy Association Rules and Association Rules Clustering, Ensemble Learning, Bayesian Network, Inductive Learning, Support Vector Machine (SVM), Evolutionary Computation, Decision Tree, Naive Bayes are exhaustively presented in [18]. Table II shows the complexity of ML techniques in intrusion detection system.

TABLE II. COMPLEXITY OF ML TECHNIQUES IN INTRUSION DETECTION SYSTEM

Study	Algorithms	Streaming Capable	Time Complexity
1.	Decision Tree	MEDIUM	$O(mn^2)$
2.	Bayesian Network	HIGH	$\gg O(mn)$
3.	Clustering, Hierarchical	LOW	$O(n^3)$
4.	SVM, Multi-Layer Perceptron	MEDIUM	$O(n)$
5.	Naïve Bayes	HIGH	$O(mn)$

#### B. APT Issues

Advanced Persistent Threat is the well resources and most sophisticated cybercrime which that is aimed to obtain information or data without permissions or authorizations. Life cycle of APT attack contains following steps: (a) Define targets (b) Finding and organizing accomplices (c) Build tools (d) Research target infrastructure (e) Deployment and initial intrusion (f) outbound connection initiated (g) Expand access (h) Obtain credentials and Exfiltrate data (i) Cover Tracks.

Sana et al. [19] through the TCP/IP processing obtained feature vector and it is used to construct an anomalous traffic patterns model for classification based on APT with high reliability and high accuracy, comparison to K-NN is done to validate this model. Ibrahim et al. [20] shows a (MSSLD) Malicious SSL certificate detection module for detecting APT C and C data communication which is based on Blacklist of MSSLD.

#### C. Malware Detection

Malicious Software a.k.a Malware, are the software that harms the computer system or accessing of data without authorizations or user permission [21]. Malware classification can be seen in Worms, Viruses, Spyware and Trojans. Blacklist is the traditional for defending malware detection.

However, Blacklist method have several limitations which makes it unreliable enough, e.g., lack of ability to detect freshly generated malware. Doyen Sahoo mentioned utilized machine learning techniques in detection of Malware URLs and categorizing feature representation and also learning development of algorithms in this domain [22]. Tahan et al. [23] proposed a new analysis methodology Mal-ID. Mal-ID uses analysis of common segment instead of whole file for detection of malware files. After doing various measurements and comparison with other traditional method, this method is found to be effective. A method is developed for classifying byte sequences which is based on Lempel Ziv Jaccard Distance called SHWeL and it is developed by Edward Raff [24].

#### D. Phishing Detection

Phishing is a form of fraud in which the sensitive information such as account information or login credentials are stolen by attacker. Phishing cycle consists of three main phases: (a) Selection of target internet community and creating phishing website. (b) Sending spam emails to oriented or random users (c) After clicking on these links user is sent to the phishing sites. Effective machine learning techniques are summarized by Ammar Almoman in [25] to tackle phishing emails. In the paper a work on comparative survey about propose approaches for filtering phishing emails, e.g., authentication, network level protection, user education, client side tool, server side classifiers and filters, etc.

### IV. CYBERSECURITY DATASETS FOR ML

. The types of data which are used by the algorithms are briefly described in this subsection:

#### A. NetFlow Data

Originally, Cisco introduced NetFlow as a feature of router. The task of collecting the incoming and outgoing IP network traffic is done by switch or router. Network Flow is defined (by 5<sup>th</sup> version of Cisco's NetFlow) as a unidirectional order of packets which shares the seven packet attributes exactly same: source IP address, ingress interface, destination IP address, source port, IP protocol, destination port and type of IP service. There are three components of the logical architecture of NetFlow: NetFlow Exporter, Analysis Console and NetFlow Collector. Currently NetFlow has total 10 versions in which 1 to 8 versions are similar but NetFlow differs significantly from the version 9.

#### B. Packet-level Data

(IETF) Internet Engineering Task Force lists 144 IPs which includes commonly used protocol like (UDP) User Datagram Protocol, (TCP) Transmission Control Protocol, (IGMP) Internet Gateway Management Protocol, etc. Packet of internet network traffic is generated by these protocols when these are used by User's program. An API called PCAP can be used for capturing the network packet transmitted or received at the computer physical interface (e.g., Ethernet Port). For network tools likes packet sniffers, protocol analyzer, network IDSs, network monitors, traffic generators etc., WinPCap and

LibPCap software libraries for packet capturing. Table III presents the packet headers of the cyber security datasets.

TABLE III. PACKET HEADERS OF THE CYBER SECURITY DATASETS

S. No.	Packet headers	Description
<b>IP Header (IPv4)</b>		
1.	Protocol	The protocol used in the data portion of the IP datagram
2.	Source Address	This field is IPv4 address of the sender of the datagram
3.	Destination Address	This field is IPv4 address of the receiver of the datagram
4.	Time to Live	This field limits a diagram's lifetime, in hops (or time)
5.	Total Length	The entire packet size, including header and data, in bytes
6.	Internet Header Length	The number of 32-bit words in the header
<b>UDP packet</b>		
7.	Length	The length in bytes of the UDP header and UDP data
8.	Source Port	Identifies the sending port
9.	Destination Port	Identifies the receiving port
<b>TCP packet</b>		
10.	Source Port	Identifies the sending port
11.	Destination Port	Identifies the receiving port
12.	Acknowledgement Number	The next sequence number that the receiver is expecting
13.	Flags	ECE, CWR, ACK, URG, SYN, FIN, PSH
14.	Sequence Number	Initial or accumulated sequence number
15.	Data Offset	Specifies the size of the TCP header in 32-bit words
<b>ICMP packet</b>		
16.	Type	Control (E.g., destination unreachable, ping, trace route)
17.	Code	Details with the type
18.	Rest of Header	More details

### V. ML TECHNIQUES AND ALGORITHMS

Various ML techniques related to cyber security are detailed in the section below. Decision Tree model is predictive model, mapping between object value and object class is represented by this model. Bayesian Network (Bayes Net) popularly called as Belief Network, is a graphical model (probabilistic) in which a set of some random variables and their dependencies (conditional) is represented by using (DAG) Directed Acyclic Graph. For representing the uncertain domain knowledge, this model is used.

#### A. Decision Tree

Like a tree, the decision tree has internal leaves structure where each leaf or represents the various classifications or a category and each branch represent output of test or we can say the features or links that provide the path which directs the classification. C4.5, ID and CART are some commonly used for generating the decision tree.

Having the numerous amounts of signatures, the SNORT rules comparison process with incoming network traffic is slow. Various SNORT rules around 150 is replaced by ID3 algorithm variant by Kruegel and Toth et al [26]. They have

done this replacement in order to implement Decision Tree Model, so that the speed of processing gets faster. Snort rules was replaced by Rule clustering. The comparison procedure gets speed up because this allows parallel evaluation. For clustered rule, DARPA 1999 dataset is used. After comparing this model with Snort, it was found that the maximum speed of around 105% was reached and minimum speed up around 5%. For making further experiments on this, number of rules changes or replaced was increased from 150 to around 1580. Although any quantitative figure is not provided, a profound speeding was observed using the decision tree model and the time of processing was reduced.

### B. Bayesian Networks

In this graphical model, a random variable is represented as node and the edges between nodes are used to represent the probabilistic dependencies among corresponding random variables. These conditional dependencies are determined by using known computational and statistical methods. Learning of Bayes Net occurs in two phases: (a) learning the structure of network (b) learning the probability tables.

Bayes Net can be applied for anomaly detection and also the comparison of known attack pattern and signatures is with the streaming data for the attacks which are known. An intrusion detection system is developed by Jemili et. al. [27] with the help of Bayesian Network. The KDD 1999 dataset with 9 of its attributes was used for modelling the system. About 88% and 89% of performance was achieved in attack and normal scenarios. This model provided detection rate of 21%, 99%, 7%, 89% for scan, probe, R2L and DOS. The accuracy of model in case of R2L suffered substantially because of smaller number of instances for training. For IP classification, Bayesian Network along with K2 search algorithm and simple estimator has been used. Figure 1 shows the sample Bayesian network model.

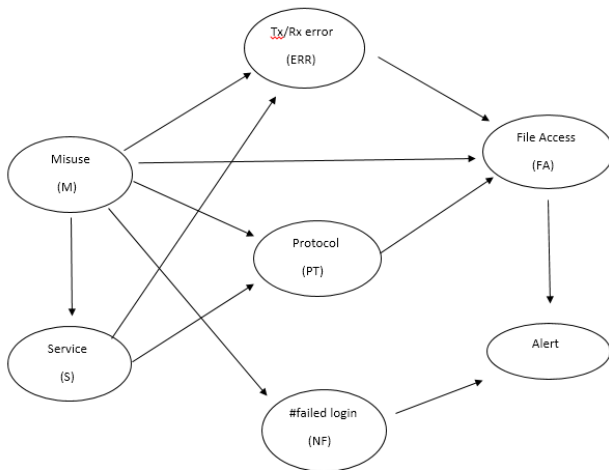


Fig 2. Sample of Bayesian Network Model.

### C. Clustering

Clustering and classification are very similar but the main difference between them is that clustering is unsupervised

method where the data is grouped on the basis of similar measurement, or we can say data about the information or knowledge about the class for which the data is classified is unknown. This algorithm can learn things from audit data, explicit description of classes of attacks is not necessary. Supposedly, forensic analysis is very good task for clustering. To differentiate anomalies among the all the activities, clustering can be used. In malware detection it can also be used. Real time detection of signatures and their applications using clustering algorithm is demonstrated by Hendry et. al. [28]. (SLC) Simple Logfile Clustering is based on a scheme that is density-based clustering for creating anomalous and normal traffic. Two clustering schemes: (a) for detection of attack and normal scenarios, (b) for determining normal internet traffic in supervised manner, are used. KDD dataset for validation of generated model was used. Cluster integrity as performance metrics was taken for improving the accuracy of the generated model. Accuracy of about 70% to 80% for unknown attacks was achieved and it is quite impressive accuracy.

### D. Naïve Bayes

Naive Bayes is a profoundly simplified model of Bayesian probability model. It is operated on strong individuality assumptions means that one attribute's probability should not affect that of other. The naïve base classifier makes  $2^n$  assumptions for  $n$  number of attributes. Naïve Bayes classifier can easily be constructed because a priori is provided in its structure and hence any procedure of structure learning is not required. It requires less time for training or modeling a model for classification. The naïve bayes formula is given below.

$$P(C|x) = P(x|C) \cdot \frac{P(C)}{P(x)} \quad (1)$$

where  $P(C|x)$  represents the posterior probability,  $P(x|C)$  represents the likelihood,  $P(C)$  presents the class prior probability and  $P(x)$  represents predictor prior probability. Shubhangi et. al. [29] proposed a model for intrusion detection system based on real time data with the help of naïve bayes model. This model has several phases: scanning of packet from network traffic, capturing of real time packets and assigning of labels to create a dataset for training. It gives several experimental results 92%, 96%, 90.46% and 87.58% for TCP data flood, normal data flood, SYN data flood, UDP data flood.

### E. MultiLayer Perceptron

Multilayer Perceptron (MLP) commonly known as Back Propagation Neural Network is multilayer feed forward ANN (Artificial Neural Network). In this network, the error signal between actual output and desired output is propagated in the backward direction from the output to hidden layer and after hidden it is propagated to input layer for training the weights of network. The multilayer perception model is shown in figure 2.

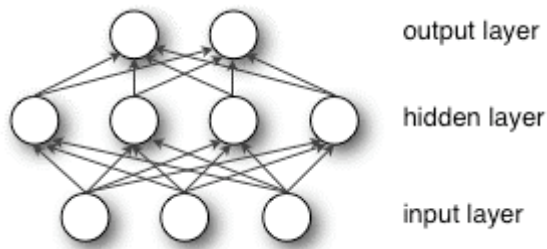


Fig 2. Multilayer Perceptron Model.

Ahmed Saleh et. al. [30] Proposed a method based on MLP for intrusion detection and compare it with eight other classifiers or methodology, this detection of true positive attacks using MLP classifier is 99.63%. Only 0.47% false positive result which means it is good methodology for intrusion detection system. Easy to use and its ability to approximate any input or output map.

## VI. CONCLUSION

In this paper we have described about the applications of integrating machine learning in cyber security system to provide more security. Nowadays various datasets and techniques being analyzed to integrate ML in security system and we have discussed some of type of data, some popular datasets and several algorithms which gives very good results like for intrusion detection Naive Bayes and MLP gives very good result. Bayes Net is used for IP classification, anomaly detection and also for intrusion detection system it means by doing several modifications how the method is applied, we can overcome more than one issues. Clustering techniques is good in malware detection as well as real time detection of signatures and attacks. Various improvements are being done to get above results better in the future by improving way in which these algorithms are applied and by getting more well-structured datasets

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