Intelligent Cyber Attack Identification Using Machine Learning Techniques: A Review

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***Abstract*—Fast-paced evolution of various technologies like digital communication, cloud computing, IoT, and others brings new cyber risks around the world. Various organizations working in different industries like banking, healthcare, education, defence, e-commerce, and governmental bodies face new cyber risks due to cyber-attacks trying to steal confidential data, damage network infrastructure, and access critical assets. Modern cyber-attacks in the international world cannot in any way be identified using traditional security measures such as firewalls and signature-based intrusion detection systems due to the constantly changing attack styles adopted by attackers as well as the use of zero-day vulnerabilities.**

Machine Learning (ML) has proved to be an intelligent solution that helps detect abnormal behaviour, identify malicious patterns, and detect known and unknown cyber-attacks. In this paper, an approach to classify both benign and malicious activities on a network by using selection tree, random forest, help vector method, and K-nearest neighbour methods with the aid of some datasets from cybersecurity is proposed.

The research will provide detailed information about data preprocessing methods, features selection techniques, attack classification strategies, classifiers training procedures, and performance evaluation. Through experimentation, it will become evident that random forests perform better than other classifiers in terms of accuracy, precision, recall, and F1-scores.

***Index Terms*—Cybersecurity, Machine Learning, Intrusion Detection System, Artificial Intelligence, Cyber Attack Detection, Random Forest, Network Security, Intelligent Systems**

I. INTRODUCTION

The digital age of today has changed human life through rapid technological advancement and global internet connectivity. Companies have become increasingly dependent on cloud computing, online communication tools, wireless networking, and Internet of Things devices for conducting their business activities. While technological advancements have increased productivity and connectivity, they have also presented tremendous cybersecurity challenges. The cyber-attacks have become more intelligent, sophisticated, and harmful targeting businesses, governments, and people around the world.

The cyber attackers are always coming up with more sophisticated attack techniques that allow them to circumvent traditional defence measures. These attacks include ransomware, phishing, malware, botnets, distributed denial of service attacks, advanced persistent threats, and insider attacks. The impacts of such attacks may include economic damages, disruption of operation, violation of privacy, and damage to reputation of the agencies.

Typical Intrusion Detection Systems depend heavily on signature-based detection techniques. These systems check the network traffic by comparing it with known attack signatures saved in their databases. While they are highly effective in detecting any known threats, these IDS cannot identify unknown threats such as 0-day attacks. In addition, these types of IDS are dependent on regular maintenance.

Gadget learning offers clever choice making capability to the security system architecture. Machine gaining knowledge of algorithms are capable of analysing big quantities of network traffic records, identify concealed patterns and accurately classify suspicious behaviours. Unlike classical machine architectures, gadget studying-based totally intrusion

detection systems are able to detect novel attacks via means of behavioural evaluation and anomaly detection.
In this research, a smart attack recognition framework is proposed the use of supervised machine gaining knowledge of algorithms.

II. CYBERSECURITY THREAT LANDSCAPE

Cybersecurity threats have become advanced within the final decade due to evolving internet usage, connectivity of devices, and digitization. Agencies in numerous industries face tens of millions of cyberattack attempts per day. Cyber-attacks target weaknesses in application software, operating systems, database management systems, communication channels, and even human behaviour.

1) Denial of service attacks:
Equations DoS attack seeks to deny beneficial services to valid customers by overwhelming their gadgets or networks with plenty of traffic requests. Attackers consume computing resources i.e., bandwidth, memory & processing capacity leading to denial of service

2) Distributed Denial of service attacks:
DDoS attacks comprise various compromised computers that attack an individual target at once. Such attacks are more complex as they come from diverse sources hence difficult to detect and mitigate.

3) Phishing attacks:
Phishing attacks deceive individuals into revealing their private details that contain their usernames, passwords, bank account details, and identification numbers using false emails and websites.

4) Malware & Ransomware:
Malware is malicious software designed to damage the computer system, steal data, or disrupt the operations of businesses. Ransomware locks down the victim's data and asks for money to decrypt the files.

5) SQL Injection
SQL Injection attacks occur at the same time as attackers insert malicious sq. instructions into internet software enter fields to manipulate databases and advantage unauthorized get right of entry to.

6) Insider Threats:
Insider threats arise from personnel or authorized users who deliberately or by chance misuse organizational sources and privileges.

7) 0-day attacks:
This attack takes advantage of vulnerabilities that are not known by the software developers or security organizations. It is quite challenging to detect using traditional signature-based systems.
The growing variety and sophistication of cyber threats require sensible and adaptive defence mechanisms capable of real-time intrusion detection and class.

III. LITERATURE REVIEW

Many researchers around the world have focused on learning methods for cybersecurity and IDS. Different studies have proven that machine learning algorithms are more effective than traditional security systems in detecting unusual behaviour in the network.
Different researchers have applied the Decision Tree classifier for detecting intrusions as it is interpretable and fast in processing. Decision Tree classifies the data on the basis of entropy and information gain.
Random Forest algorithms have gained popularity in recent years because they use an ensemble of decision trees to classify data more accurately. Ensemble methods are more generalized compared to individual algorithms.
SVM algorithms are widely used for anomaly detection and binary classification tasks. SVM classifiers are useful for analysing high dimensional network traffic data and provide accurate results in IDS.
Moreover, deep learning methods such as CNN, RNN, and Long Short-Term Memory have been used for studying cybersecurity problems. These methods can automatically extract features from the network traffic data and increase intrusion detection effectiveness.

The majority of studies employ datasets that consist of KDD Cup 99, NSL-KDD, CICIDS2017, and united states of america-NB15 in order to study different intrusion detection mechanisms. Modern datasets include real-life visitor behaviours and up-to-date attack types.

According to the current research, intrusion detection mechanisms based on device learning prove to be more efficient, flexible, and scalable in comparison to the conventional security techniques.
There are several serious challenges that are encountered by the traditional cybersecurity systems to detect modern cyber threats. Traditional intrusion detection models are based on signature-based intrusion detection models, which need predefined attack signatures and thus are unable to identify new attacks. Since modern cyber-attacks constantly evolve, traditional detection mechanisms become inefficient.

The major challenges in the context of traditional intrusion detection systems are the following:

- High rate of false positives
- Lack of ability to detect zero-day attacks
- Lack of flexibility
- Lack of scalability
- Difficulties in dealing with high traffic volumes
- Inefficiency in real-time detection

Therefore, there is an urgent need for advanced intrusion detection systems based on device learning.

IV. RESEARCH OBJECTIVES

The different objectives of this research are as follows:

1) To build an intelligent detection model for cyber attacks:

In other words, through this objective, an efficient and intelligent model of cybersecurity will be developed for identifying cyber attacks. This model should be able to analyze the activities of the network and identify any abnormalities that might show the presence of cyber threats.

2) To use machine learning algorithms in intrusion detection:

Intrusion detection involves the identification of any malicious or unauthorised actions by an entity that tries to compromise the security of the network. By employing machine learning algorithms, this study aims at learning from network activities to better identify any possible cyber threat.

3) To analyze various classifiers used in machine learning algorithms:

Machine learning algorithms differ from one another based on different factors, especially the types of cybersecurity data. By analyzing various algorithms such as Decision tree classifier, random forest classifier, support vector machine and k-nearest neighbor classifier, a comparative performance of each algorithm will be carried out.

4) For accurate detection of cyber attacks:

Accuracy is the most crucial factor for any kind of intrusion detection system. The main aim is to make the system able to detect attacks accurately and without any mistakes. With the help of improved accuracy, we can protect our systems in a much more efficient way.

5) For lowering false positive and false negatives:

It is always preferable to have less waste of time on false detections or alerts. False positives and false negatives are not good for an efficient system because the former will result in loss of unnecessary time and the latter can cause loss of security itself.

6) For detecting malicious activities in real-time:

As the cyber attacks spread very fast and they can do much harm in just a few seconds, so there should be a system that can detect the malicious activity in real time and stop the attack.

7) Minimize rate of false positives and false negatives:

The most reliable system will be that which reduces unnecessary alarm calls and does not fail to alert whenever there is a breach of security. False positives may lead to wastage of time, whereas false negatives mean that a dangerous attack is left unnoticed. Hence, this goal centers on reducing the aforementioned problems.

8) Real time detection of malicious activities:

Attacks in the online space may pose a lot of danger to any computer or network within a very short period. Hence, the system should be able to monitor network activity and detect any malicious activity in real time.

9) Boosting the cybersecurity *defense using intelligence systems:*

Last but not least, it is worth noting that the primary purpose of this project is to boost the security of networks using machine learning approaches.

V. PROPOSED METHOD

The proposed methodology includes many ranges such as statistics sequences, pre-processing, feature selection, classifier training, testing, and evaluation.

Data acquisition: The study uses benchmark cybersecurity datasets which include:

- NSL-KDD dataset
- USA-NB15 dataset

These datasets include network site visitors' statistics labeled as ordinary or malicious.

Statistics Pre-processing*:*
Raw statistics usually incorporate replica records, missing values, inconsistent codecs, and noisy records. Statistics preprocessing enhances the standard of the dataset and version efficiency.

The steps of statistics preprocessing encompass:
1) Duplicated Data Handling:
There might be cases when the collected data contains the same data points. The duplication of data causes a failure of learning on the part of the algorithm and can result in inaccuracies. For that reason, duplicates are removed from the data set in order to improve the quality of the data and enhance the effectiveness of intrusion detection system.

2) Missing Values Handling:
At times, there may be values that are missing from the data accumulated. The lack of these values makes problems arise during education and affects the precision of the predictions. In order to solve this problem, missing values can either be replaced by other values or omitted altogether.

3) Data Normalization:
Variables of network data sets are often characterized by different scales. This means that the values of one variable may range from 1 to 100, while another one may have values ranging from thousands. Data normalization is necessary to scale the data and prevent any variable from dominating others.

4) Feature Transformation:
Raw data from the network might have some irrelevant or complicated features that are hard for the machine learning model to comprehend. In feature transformation, we manipulate the available data into a better form that makes it easy for machine learning algorithms to learn the required patterns.

5) Data Balancing:
Cyber attacks can spread rapidly and cause serious damage within a short period. Therefore, the proposed system aims to monitor network traffic continuously and detect suspicious activities instantly. Real-time detection enables faster response and helps prevent data breaches or system failures.

6) To strengthen cybersecurity defence using intelligent systems:
In a cybersecurity dataset, there will be many instances of normal activities while the instances of attacks will be few. This imbalance in the dataset leads to bias in the machine learning model towards normal activities, thereby compromising on the detection ability of attacks. Hence, techniques such as data balancing are applied.

Feature choice*:*
Feature choice decreases computational complexity and increases detection performance.
Important characteristics encompass:

- Protocol form
- Source bytes
- Destination bytes
- Packet period
- Service type
- Connection quality
- Packet fee

Feature choice enhances the speed of model training and classification accuracy.

VI. MACHINE LEARNING ALGORITHMS

Machine Learning (M.L.) algorithms are useful in modern cybersecurity applications since they help computers recognize suspicious activities and cyber-attacks automatically. They learn certain patterns based on network traffic data and classify the data based on learned knowledge as normal or suspicious activities. Traditional approaches to cybersecurity are based on predefined rules or signatures which cannot cope with novel attack patterns.
Various Machine Learning (ML) algorithms are applied in cybersecurity based on the type of data and

particular demands in terms of performance. While some algorithms are best at achieving accuracy, others perform well when it comes to fast processing and working with complex datasets. For example, algorithms including Decision Tree, Random Forest, SVM, and K-Nearest Neighbour are used in cybersecurity to classify network traffic data.
The training depends entirely on cybersecurity data sets that contain information regarding the number of attacks made each day. The learning model has to undergo evaluation once trained to ascertain if it would detect the intrusion accurately. Efficiency testing of such models can take into consideration accuracy, precision, recall, and the F1-score among others. Evaluation of different algorithms would determine which algorithm should be selected to conduct intrusion detection.

a) Decision Tree (DT):
Choice bushes use hierarchical schemes to categorize information based on entropy and benefit of records. those classifiers are straightforward to apprehend and implement.

b) Random Forested Area (RF):
Random Forest applies greater than one selecting timber to gain extra stability and lower down overfitting. It yields very excessive precision for cyber security applications.

c) Support Vector Machines (SVM):
SVM identifies the most effective hyperplanes that can separate harmful from harmless traffic classes.

d) k-Nearest Neighbours (KNN):
KNN operates by means of applying similarity comparison of the nearest neighbours.

e) Training & Testing:
The knowledge set is break up right into training & trying out sets. device gaining knowledge of fashions are skilled the use of education knowledge and evaluated the use of checking out knowledge.
Architecture of Device:

The smart cyber-attack detection device proposed consists of the following components:

1. Data Acquisition Layer: Captures network site visitor data through communication channels.
2. Pre-processing Layer: Cleansing, normalizing, and transforming data.
3. Feature engineering module: Identification of appropriate feature set for model training.
4. ML Engine: Implements ML algorithms for attack detection and classification.
5. Intrusion Detection Layer: Categorizes site visitors as regular or malicious.
6. Alert Generation Module: Provides security alerts and notifications on detected assaults.

VII. EXPERIMENTAL SETUP

The experiments are conducted using the Python programming language and machine learning packages.
Software requirements:

1. Python
2. Jupyter Notebook
3. Scikit-learn
4. Pandas
5. NumPy
6. Matplotlib

Hardware requirements:

1. Intel Core i5/i7 processor
2. 8 GB RAM or more
3. SSD storage

The environment provides support for green training and evaluation of system learning classifiers.

VIII. EXPERIMENTAL SETUP

The performance of system studying models is evaluated using numerous metrics.
Accuracy

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision

$$Precision = \frac{TP}{TP+FP}$$

Recall

$$Recall = \frac{TP}{TP+FN}$$

F1-Score

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision+Recall}$$

Where:

- TP: True Positive
- TN: True Negative
- FP: False Positive
- FN: False Negative

IX. EXPERIMENTAL RESULTS AND ANALYSIS

From experimental analysis, it is clear that Random Woodland provides the best classification results compared to all other analysed methods.

Algorithm	Accuracy	Precision	Recall	F1-Score
Decision Tree	94.1%	93.6%	92.9 %	93.2 %
KNN	92.4%	91.8%	90.7 %	91.2 %
SVM	95.7%	95.1%	94.5 %	94.8 %
Random Forest	98.3%	97.9%	97.6 %	97.8 %

RANDOM FOREST

- Best Classification Accuracy
- Best Stability
- Minimum Over-Fitting
- Minimal False Positives

DECISION TREE

- Best Interpretability
- Fast Execution
- Good Performance for Large Data Sets

SVM

- Best Precision
- Best for High Dimensional Data
- More Complex Computations

KNN

- Simple Algorithm
- Works well for Small Data Sets
- Slow Prediction Speed

The findings confirm that mastering techniques significantly enhance intrusion detection results.

X. VARIOUS ADVANTAGES OF THE PROPOSED SYSTEM

- IDS systems based on Deep Learning techniques
- Hybrid AI cybersecurity architectures
- Explainable Artificial Intelligence (XAI)
- Federated learning security approaches
- Blockchain-based intrusion detection systems
- Cloud-native cybersecurity analysis
- Real-time threat intelligence systems using advanced AI

Similarly, advanced AI techniques can also contribute to enhancing cybersecurity defence capabilities against evolving attack techniques.

XI. CONCLUSION

Cybersecurity threats keep on evolving unpredictably, posing significant challenges for modern-day organizations. Traditional security approaches cannot recognize sophisticated cyber threats that they have never seen before. For this study, an innovative approach to cyber threat detection using intelligent machine learning techniques has been suggested.

Decision Tree, Random Forest, SVM, and k-Nearest Neighbour algorithms were suggested to be employed as classifiers to detect malicious behavior within networks. According to the experiments, it was seen that the Random Forest algorithm is the best classifier among them because it provides high accuracy and few false positives.

Cybersecurity solutions based on machine learning are efficient, intelligent, scalable, and adaptable approaches that can secure today's digital environments. The future integration of deep learning and XAI will strengthen cybersecurity solutions even more.

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