Project Phase I Report On

Network Intrusion Detection System

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By

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CERTIFICATE

This is to certify that report entitled ***"Network Intrusion Detection System"*** *is a bonafide work done by* ***Thejus PS (RET19CS208)***, ***Tejas Ananthajith (RET19CS206)***, ***Rahul C Karthik (RET19CS173)*** , ***Sleety Kottuviruthil George (RET19CS198)****in partial fulfillment of the requirements for the award of the Degree of Bachelor of Technology in Computer Science and Engineering from APJ Abdul Kalam Technological University, Kerala during the academic year 2022-2023.*

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Thejus PS

ABSTRACT

According to Norton, India faced 18 million cyberattacks within the first quarter of 2022, with an estimate of 200,000 attacks per day. With communication between multiple devices, users and enterprises alike are vulnerable to data breaches. This occurs frequently due to weakly secure networks, lack of updated attack dataset, absence of firewalls and security measures, human error and vulnerable scripting frameworks.

This project develops an Network Intrusion Detection System (NIDS) which is a software to monitor the data packets for malicious or corrupted data within a network and alerts the users of such violations. This project will explore real time network packet sniffing and logging. We will be evaluating various intrusion detection datasets using a deep learning model that aims for more accuracy, more true positives and less false positives. This will enable the user or the enterprise to pinpoint and mitigate the vulnerable network to be more secure against future attacks. For implementation purposes, we will be simulating various attacks to show the efficiency of the Intrusion Detection System.

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Chapter 1

Introduction

1.1 General Background

Currently most devices we see around us are connected to the Internet for convenience and transfer of data. But with this advantage, there is another dark side to the benefits of being connected, the leakage of personal data. Cyber-Terrorists and hackers try to compromise network infrastructure for destruction or monetary gain. Information Systems and Networks are subject to electronic attacks. Attempts to breach information security are rising every day, along with the availability of the Vulnerability Assessment tools that is widely available on the Internet. Tools such as Nmap can be used to scan, identify, probe, and penetrate your systems. Firewalls are put in place to prevent unauthorized access to the Enterprise Networks.

In the 1990's, IDS technology was developed using a method called anomaly detection to address the increasing number and sophistication of network attacks. It relied on identifying unusual behavioural patterns on the network, and provided alerts for any identified abnormality. In the advent of cloud computing and IoT, it resulted in the surge in the IDS market, IDS systems are designed to detect attacks that may occur despite the presence of a firewall in a network.

1.2 Objectives

With growing cyberthreats and intrusions within enterprise networks.This project is aimed at developing a more efficient real time Intrusion detection system to face threat adversaries to the network. With existing updated datasets and growing number of attacks everyday, this project aims to be implemented in the enterprise and personal level with less false positives and better mitigation options. Deep learning is to be implemented to

improve the detection of threats and anomalies, which would have higher true positive rates and lower false positives and false negatives.

1.3 Motivation

Considering that an Intrusion Detection System is one of the top selling security technologies for Enterprise Network Security, the logic and tactics IDS uses are more relevant today than ever before. An Intrusion Detection System is a software within the network that detects the abnormalities or the presence of an unauthorised user within a network. They can be either Detection Based or Range Based. A Detection based can be on the basis of a Signature id or an Anomaly. It also depends on where the IDS is placed within the network.

In the late 1990s, military and enterprise networks were prone to ICMP, TCP, UDP attacks. With the advent of smart devices, IoT, Cloud Computing and Big Data, enterprises were prone to more advanced attacks like DDoS, U2R, and malware attacks. Due to this sophistication, Intrusion Detection Systems have undergone improvements to intercept these attacks.

With deep learning, a network intrusion detection system can be trained on a large dataset of normal and malicious network activity, allowing it to learn the characteristics of each and become more effective at detecting anomalies and potential intrusions. Additionally, because deep learning models are highly flexible, they can be easily adapted to new types of attacks and changing network environments, which would prove to be effective in improving the performance of intrusion detection systems significantly.

1.4 Existing System

SNORT (Simple Network Intrusion Detection System) is an open-source network intrusion detection and prevention system that can be used to detect a wide range of cyber threats. It was developed in the 1990's and currently managed by the Cisco Talos Team and the SNORT Open Source community.

SNORT operates primarily in three modes: sniffer mode, packet logger mode and intrusion prevention system mode. Sniffer mode is a passive operation that enables SNORT to monitor real time network traffic. Secondly, the packet logger mode is also a passive operation that logs all the packet information flowing in a network within a .pcap file under the libpcap library. This file can be later analysed using network monitoring tools like Wireshark and tcpdump, and often used by incident engineers during the forensic phase in the aftermath of a attack.

Finally, the intrusion prevention system mode is the active operation and often known as offensive SNORT, it relies on a configuration file that contains the ruleset that defines a controlled environment within the network. If these rulesets are violated, the SNORT proceeds to alarm the administrator and isolate the infected system from the network or a particular network switch from the main enterprise network to prevent compromising the entire network.

Through this, SNORT is configured to detect malicious packet , unauthorised scanning, illegal access and malware in the network ensuring data security and preventing further exploit and compromise to the network.

Chapter 2

Proposed Method

2.1 Problem Definition

To develop a Network Intrusion Detection System that logs all malicious, corrupted packets and illegal user activity within a network and reports it to the user in real time. This enables users and enterprise authorities to strengthen their network framework to prevent unauthorised user breaches and malicious packets within the network.

2.2 Purpose and Need

- Privacy of data and sensitive information is a high priority in this day and age.
- Numerous issues like malicious packets, man in the middle attack, flooding attacks arise as a result of poor network security infrastructure.
- The development of a Network Intrusion Detection System will enforce user and enterprises against a potential vulnerability in a feeble network.

2.3 Project Scope

With growing cyberthreats and intrusions within enterprise networks.This project is aimed at developing a more efficient real time Intrusion detection system to face threat adversaries to the network. With existing updated datasets and growing number of attacks everyday, this project aims to be implemented in the enterprise and personal level with less false positives and better mitigation options.

2.4 Target Group

The target group of a network intrusion detection system are sysadmins, cybersecurity personnel namely technical staff, security operations centre admins, cybersecurity engineers and incident ananlysts or any individual that require real time monitoring and detection for malicious events in their network.

2.5 Proposed System

For the Intrusion Detection System, we use Deep Convolutional Neural Networks, Long Short Term Memory as the deep learning algorithms.

- Train the model with the CIC IDS 2017 and KDD Cup 99' dataset for the detection of bot, bruteforce, SQL injection and Denial of Service attacks.
- For the IDS, and rule-set formulation, we will use the libpcap library for SNORT, an Intrusion Prevention System and analyse traffic with the aid of Wireshark.

Chapter 3

Literature Survey

3.1 Increasing the Performance of Machine Learning-Based IDSs on an Imbalanced and Up-to-Date Dataset

In recent years, due to the extensive use of the Internet, the number of networked computers has been increasing in our daily lives. Weaknesses of the servers enable hackers to intrude on computers by using not only known but also new attack-types, which are more sophisticated and harder to detect. To protect the computers from them, Intrusion Detection System (IDS), which is trained with some machine learning techniques by using a pre-collected dataset. If the dataset is imbalanced and a specific category composes the most significant part of the dataset, then the use of accuracy as a single metric is not much acceptable. If there is a large gap between the data size within the majority and minority categories, sophisticated attackers can focus on minority attack types to increase their efficiency.

Unlike the NSL-KDD, the number of duplicate data in the CIC IDS 2018 dataset is very low, uncertain data is nearly absent,and the dataset is in a CSV format, so it ready to use without preprocessing. This paper has been a preliminary study to examine the success of deep learning algorithms in detecting small sample attacks in up to date datasets. Therefore, deep learning algorithms should be used in future work.

Six different machine learning models (Decision Tree, Random Forest, K Nearest Neighbor, Adaboost, Gradient Boosting, and Linear Discriminant Analysis) were implemented using a recent dataset (CSE-CIC-IDS2018). To decrease the imbalance-ratio, a data sampling model was used by increasing the data size of the minority groups. The experimental results showed that the implemented models have a very good accuracy level when com-

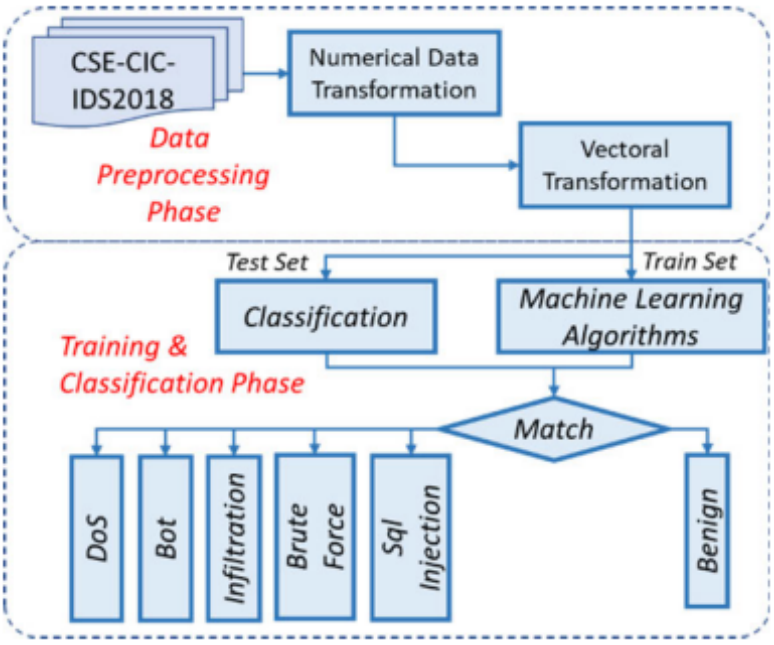

Figure 3.1: **Flow Chart of the IDS using CIC IDS 2018**

pared with recent literature. The use of a sampled dataset caused the average accuracy of the models to increase between 4.01% and 30.59%. The use of sampled data leads to, a considerable increase in the accuracy of the system, as 99.34% accuracy rate is measured using the Random Forest machine learning algorithm.

This paper clearly states the advantages of using the CIC IDS 2018 dataset to detect variety of attacks while maintaining high accuracy, high True positive Rate and low False Positive Rate due to low unbalanced and up to date data using a machine learning technique and additionally recommends using deep learning algoithms will enable better results.

3.2 A Deep Learning-Based Intrusion Detection and Preventation System for Detecting and Preventing Denial-of-Service Attacks

In the field of computer security, intrusion detection is the ability to detect unauthorized access to a computer network. Such unauthorized access seriously threatens the confidentiality, integrity, and availability of the computer system and the data it stores. Generally, experts in this field use different tools and techniques that analyze network traffic to detect unusual behaviors, thus, protect data, and avoid harmful consequences.

The model uses deep learning algorithms which satisfies four conditions namely; the algorithm available in the java deep learning library, the model's training configuration with the deep learning should be available, the dataset used to train the model containing DOS attack packets and the accuracy of the model trained with deep learning algorithm should be more than 90. Three deep learning algorithms were found to satisfy these conditions; they were Deep feed Forward Neural Network,Recurrent Neural network and Long Short Term Memory.

The algorithm used in the paper was deep feed forward neural network, this is explained by the fact that the DL4J library required the dataset to be already organized and need no preprocessing as such RNN and LSTM could not be used. The model was trained in a Debian environment as it consumes less resources.The dataset used was CICDDoS2019 which was split in the ratio 7:3. The 70% was used for training the model while the 30% was used for the testing of the model.The trained model gave an accuracy value of .9994. The project adopts the concepts of DDoS attack detection using Intrusion Detection Systems in real time considering the

3.3 AI-IDS: Application of Deep Learning to Real-Time Web Intrusion Detection

Deep Learning has been widely applied to problems in detecting various network attacks. However, no cases on network security have shown applications of various deep learning algorithms in real-time services beyond experimental conditions. Moreover, owing to the integration of high-performance computing, it is necessary to apply systems that can handle large-scale traffic. Given the rapid evolution of web-attacks, they implemented and applied thier Artificial Intelligence-based Intrusion Detection System (AI-IDS).

They propose an optimal convolutional neural network and long short-term memory network (CNN-LSTM) model, normalized UTF-8 character encoding for Spatial Feature Learning (SFL) to adequately extract the characteristics of real-time HTTP traffic without encryption, calculating entropy, and compression. They demonstrated its excellence through repeated experiments on two public datasets (CSIC-2010,CICIDS2017) and fixed

real-time data. By training payloads that analyzed true or false positives with a labeling tool, AI-IDS distinguishes sophisticated attacks, such as unknown patterns, encoded or obfuscated attacks from benign traffic. It is a flexible and scalable system that is implemented based on Docker images,

For all experiments for each dataset, the model parameters were modified to obtain the results above and to optimize the performance on different datasets. Considering that their model has 14,000 trainable parameters, the CSIC-2010 and CICIDS- 2017 are relatively small, which leads to overfitting and low performance which is lower than the experimental results of the previous real-time data. Experimental results showed that the performance of the model is affected by the number of samples and the diversity of the training data. Considering the CSIC-2010 and the CIC-IDS 2017, accuracy obtained was 93% and 91.54%, precision is 98.54% and 86.47%, recall of 68.26% and 76.83%, F score of 80.65% and 81.36% respectively.It was difficult to cross-validate the model with two published datasets owing to small samples. If they had a large amount of non-repeated HTTP data, the experimental performance would improve and would return more reliable results. Considering the above results, their model is more suitable for a large amount of data, and they demonstrated the excellence of their model by training with various datasets of more than 6 million HTTP traffic data.

3.4 Wireless Network Intrusion Detection Based on Improved Convolutional Neural Network

The diversification of wireless network traffic attack characteristics has led to the problems what traditional intrusion detection technology with high false positive rate, low detection efficiency, and poor generalization ability.

This paper proposes a model based on ICNN (Improved Convoluted Neural Networks), called the ICNN Based Wireless Network Intrusion Detection Model (IBWNIDM). The low-level intrusion traffic data is abstractly represented as advanced features by CNN, which extracted autonomously the sample features, and optimizing network parameters by stochastic gradient descent algorithm to converge the model.

ICNN consists of 5 convolutional layers, 2 pooling layers, 4 fully connected layers and 1 SoftMax layer, where Conv1, Conv2, and Conv3 those 3 convolutional layers use the relu activation function to increase network sparsity. The module includes two processes of forward propagation feature extraction and back propagation iterative optimization. Classifiers are trained for classification tags based on five sample categories: Probe, DOS, U2R, R2L, and Normal, and the pre-processed test data set is put into the trained classifier as test data. The classifier performs classification detection on the detected samples, and outputs a five-dimensional confusion matrix, which is the detection result.

Compared with Intrusion Detection Algorithm Based on Convolutional Neural Network (IDABCNN) and Network Intrusion Detection Model Based on Convolutional Neural Network (NIDMBCNN), the detection accuracy and true positive rate of IBWNIDM are higher than the other two models, but the false positive rate is slightly higher than the latter two, so IBWNIDM has further room for improvement.

IBWNIDM got an accuracy of 95.36% with 95.55% TPR and 0.76% FPR on the NSL-KDD test set. The experimental results show that the accuracy and true positive rate of intrusion detection of IBWNIDM are higher and the false positive rate is lower.

Chapter 4

Detailed System Design

4.1 Functional Requirements

- The Network Intrusion Detection System should have a up to date dataset to detect variety of attacks in real time.
- It should have a low false positive and false negative rates to improve anomaly detection.
- An NIDS should be configured based on a enterprise network traffic trend and architecture.

4.2 Architecture Diagram

In this chapter, we will outline the system architecture along with the basic functioning of the system. Figure 4.2 represents the architecture of the system.

The Architecture mainly has the following components :

1. Real time Intrusion Detection System
2. Dataset Cleaning and Feature Extraction module
3. Training Module
4. Evaluation Module

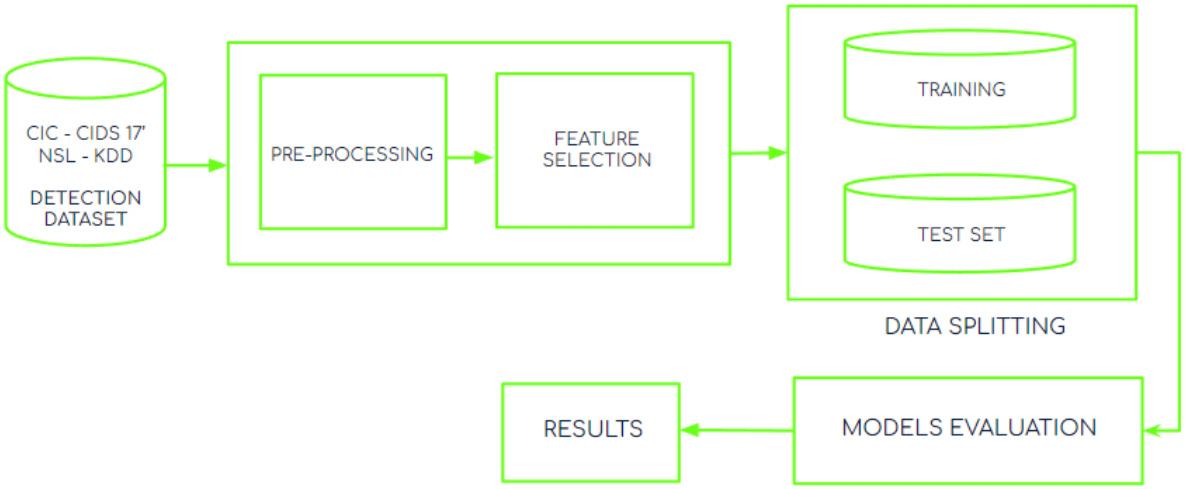

Figure 4.1: **Project Architecture:Deep learning model**

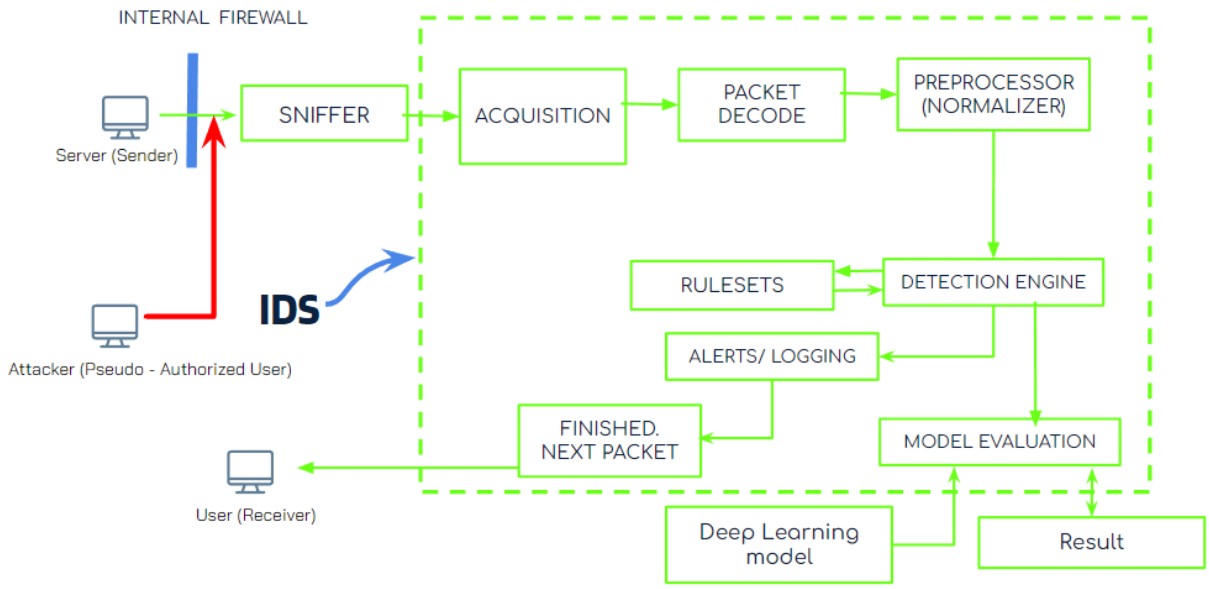

Figure 4.2: **Project Architecture: NIDS**

The Project Architecture includes the deep learning model architecture and the Intrusion Detection system itself. Firstly, we need to evaluate the 2 datasets namely the NSL KDD 99 and the CIC IDS 2018 datasets using deep learning. This is done by preprocessing the data and feature extracting the required information of a attack packet. After this is done, the dataset is divided into a testing and training set; and further evaluated to obtain the deep learning model accuracy, F score, recall , True positive rate, False Positive rate.

Secondly, the Intrusion Detection System monitors the entire network packets flowing within an enterprise network at a given instant of time. An individual packet is acquired and decoded, after further processing the packet information is forwarded to the detection engine that checks whether the information may or may not match the intrusion detection dataset. If not, then it proceeds to the next packet and in the event of a match, the intrusion detection engine alarms the administrator.

4.3 Sequence Diagram

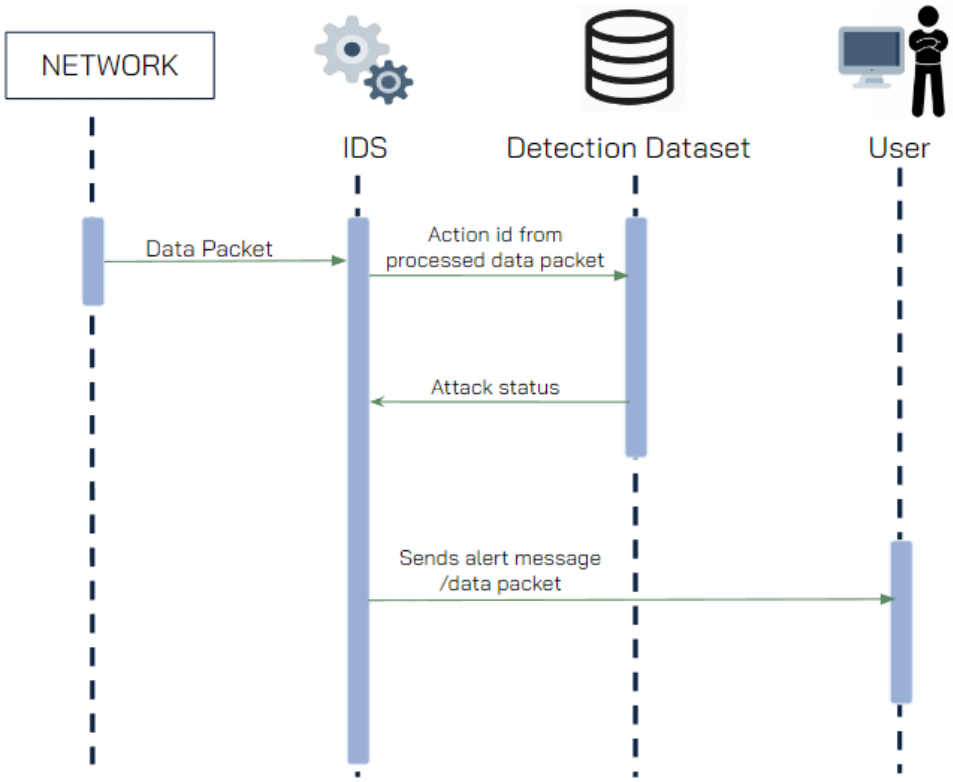

Figure 4.3: **Sequence Diagram of a Network Intrusion Detection System**

A sequence diagram is a Unified Modeling Language (UML) diagram that illustrates the sequence of messages between objects in an interaction.

In the case of a Network Intrusion Detection System, it consists of 4 objects, and the steps include:

- Firstly, data packets from the network are monitored by the Intrusion Detection System.
- The IDS pre-processes and feature extracts individual packets from the network and checks if the packet data matches with the data within the IDS detection dataset.
- If its a match, the IDS proceeds to the next packet, otherwise, the IDS sents an alarm to the system administrator.

4.4 Module Wise Split-up

The application developed so far has the following modules

- Packet Sniffing - Monitors the real time traffic packets within the network
- Packet Acquisition - Selects a single packet from the traffic for further analysis
- Pre-processing and Feature Extraction - The dataset used contains NaN values and duplicate values which require cleaning to obtain better accuracy and optimal TPR and FPR. To classify packets to their respective protocol and services, the data packet undergoes feature extraction to obtain the required information to distinguish one packet from another.
- Detection Engine - Detection Engine is a application that will monitor the traffic and compare it with the rulesets configured by the system administrator and alerts them incase a violation is detected.
- Model Evaluation - This module involves the determination of accuracy, F score , Recall, FPR and TPR of the deep learning model used.

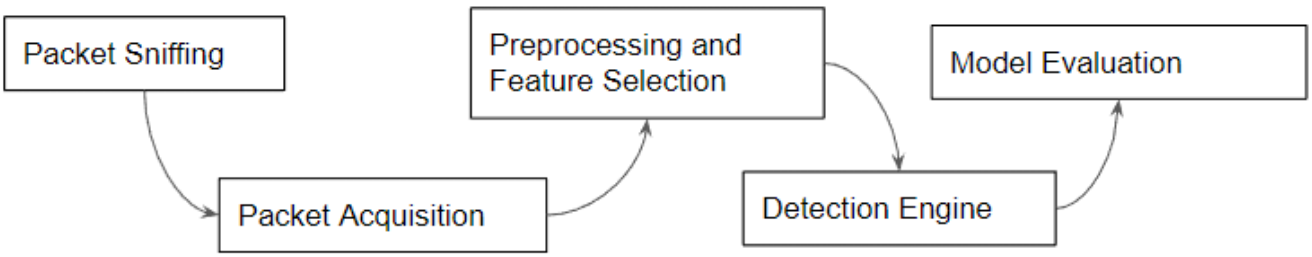

Figure 4.4: **Module Wise Diagram**

4.5 System Requirements

4.5.1 Software Requirements

Jupyter Notebook

Project Jupyter is a non-profit, open-source project, born out of the IPython Project in 2014 as it evolved to support interactive data science and scientific computing across all programming languages. Jupyter will always be 100 % open-source software, free for all to use and released under the liberal terms of the modified BSD license.
Jupyter is developed in the open on GitHub, through the consensus of the Jupyter community. For more information on our governance approach, please see our Governance Document. All online and in-person interactions and communications directly related to the project are covered by the Jupyter Code of Conduct. This Code of Conduct sets expectations to enable a diverse community of users and contributors to participate in the project with respect and safety.

Python version (3.10)

Python is a high-level programming language with a simple, readable syntax, which makes it relatively easy to learn and use. This can be particularly helpful for developers who are new to programming or who are working on a complex project such as an AI chess game.Python has a large and active community, and as a result, there are many libraries and frameworks available for a wide range of tasks. For example, Python has libraries for machine learning, data manipulation, and visualization that can be useful for evaluating deep learning models.

Python is a general-purpose programming language that can be used for a wide range of tasks, including web development, data analysis, and scientific computing. This makes it a good choice for projects that may require a diverse set of capabilities. It is a high-level language, but it is also reasonably fast, making it suitable for performance-critical tasks such as game development.Python is cross-platform, meaning that it can be used on different operating systems, such as Windows and Linux. This can be helpful when developing an Network Intrusion Detection System that needs to run on multiple platforms.

Kali Linux

Kali Linux is a free and open-source operating system that is widely used for security testing and penetration testing. It is based on the Debian Linux distribution and is developed and maintained by Offensive Security, a cybersecurity training and certification company.

Kali Linux is designed to be a comprehensive platform for conducting penetration tests, forensic analysis, and security assessments. It includes a wide range of tools for these purposes, including network scanning, vulnerability assessment, password cracking, wireless analysis, and exploit development.

One of the key features of Kali Linux is its extensive collection of pre-installed security-related tools. These tools are organized into categories such as information gathering, vulnerability assessment, exploitation tools, and forensic tools.

4.5.2 Hardware Requirements

- **Processor:** Training of the deep learning algorithm requires the sufficient processing power to train models faster.
  - Intel Core i5
- **Memory:** The project requires a large amount of RAM for deploying multiple virtual machines simultaneously to simulate and detect the attack in real time. Storage space is also required to store datasets and intermediate processing outputs while evaluating the deep learning model.
  - 6GB DDR4 RAM or greater
- **Storage:** Storage space is required to store intrusion detection datasets namely the NSL - KDD and the CIC IDS 2018 dataset; and intermediate processing outputs while evaluating the deep learning model.
- 25GB HDD or more (SSD Recommended)

- **Graphics:** As training using the normal processor will take a lot of time having a graphical processor can increase the speed at which the training is done.

4.6 Assumptions

There are several assumptions that should be considered when developing a real-time signature-based network intrusion detection system:

- The system should be able to operate in real-time, meaning it should be able to process and analyze network traffic as it is received, without any significant delays.
- The system should be able to accurately identify known malicious patterns or signatures in network traffic. This requires the use of a comprehensive and up-to-date set of signatures that are known to be associated with different types of attacks.
- The system should be able to handle a high volume of network traffic without experiencing any performance degradation.
- The system should be able to operate on multiple network environments and protocols, including both wired and wireless networks.
- The system should be able to operate on multiple network environments and protocols, including both wired and wireless networks.
- The system should be able to adapt to new or evolving threats by continuously updating its signature database and adapting its detection algorithms.

4.7 Risks and Challenges

1. **False negatives:** Signature-based IDS rely on a database of known attack patterns, or signatures, to detect malicious activity. If a new, unknown attack is launched, the IDS may not be able to detect it, leading to a false negative.
2. **False positives:** Signature-based IDS may sometimes generate false positives, or false alarms, when they identify normal network traffic as malicious. This can lead to unnecessary investigation and wasted resources.

3. **Signature evasion:** Attackers may try to evade detection by modifying their attack patterns to avoid matching known signatures.

4. **Limited coverage and context:** Signature-based IDS can only detect known attacks, so they may not be effective against zero-day vulnerabilities or other unknown threats. Signature-based IDS do not typically provide much context about the nature or scope of an attack, which can make it difficult to understand the full extent of the threat and formulate an appropriate response.

5. **Data storage and management:** The NIDS may generate a large volume of data, including logs, alerts, and reports. This data must be stored and managed in a way that is secure, scalable, and easy to access as needed.

6. **Threat intelligence and analysis:** The NIDS must be able to stay up-to-date with the latest threats and vulnerabilities, and must be able to analyze incoming traffic in real-time to identify and classify potential threats. This may require implementing advanced analytics and machine learning techniques, as well as continuously gathering and analyzing threat intelligence from a variety of sources.

Chapter 5

Project Workflow and Specifications

5.1 Module Wise Scheduling

Module	Topics	Content division
1	Obtaining the datasets	Tejas Ananthajith, Rahul
2	Coding the neural network	Thejus PS, Sleety
3	Training the neural network	Thejus PS, Rahul
4	Evaluation of neural network	Tejas Ananthajith, Thejus PS
5	Setting Up IDS rulesets	Sleety, Rahul
6	Integration of IDS with deep learning model	Sleety, Thejus

Figure 5.1: **Module Wise Scheduling**

In the above figure :

- Module 1 is Obtaining the datasets
- Module 2 is Coding the neural network
- Module 3 is Training the neural network
- Module 4 is Evaluation of neural network
- Module 5 is Setting UP IDS rulesets
- Module 6 is Integration of IDS with deep learning model

The Module Wise Diagram is shown in Figure 4.3

5.2 Gantt Chart

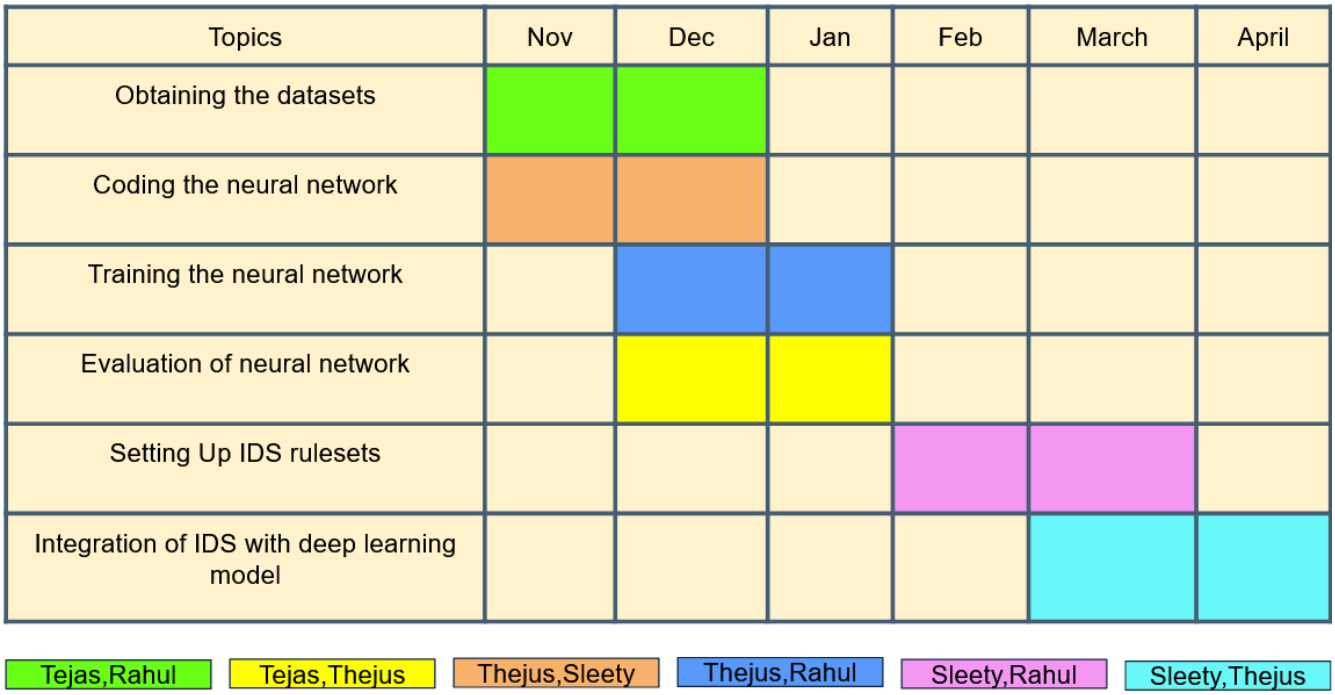

Figure 5.2: **Gantt Chart**

5.3 Budgetting

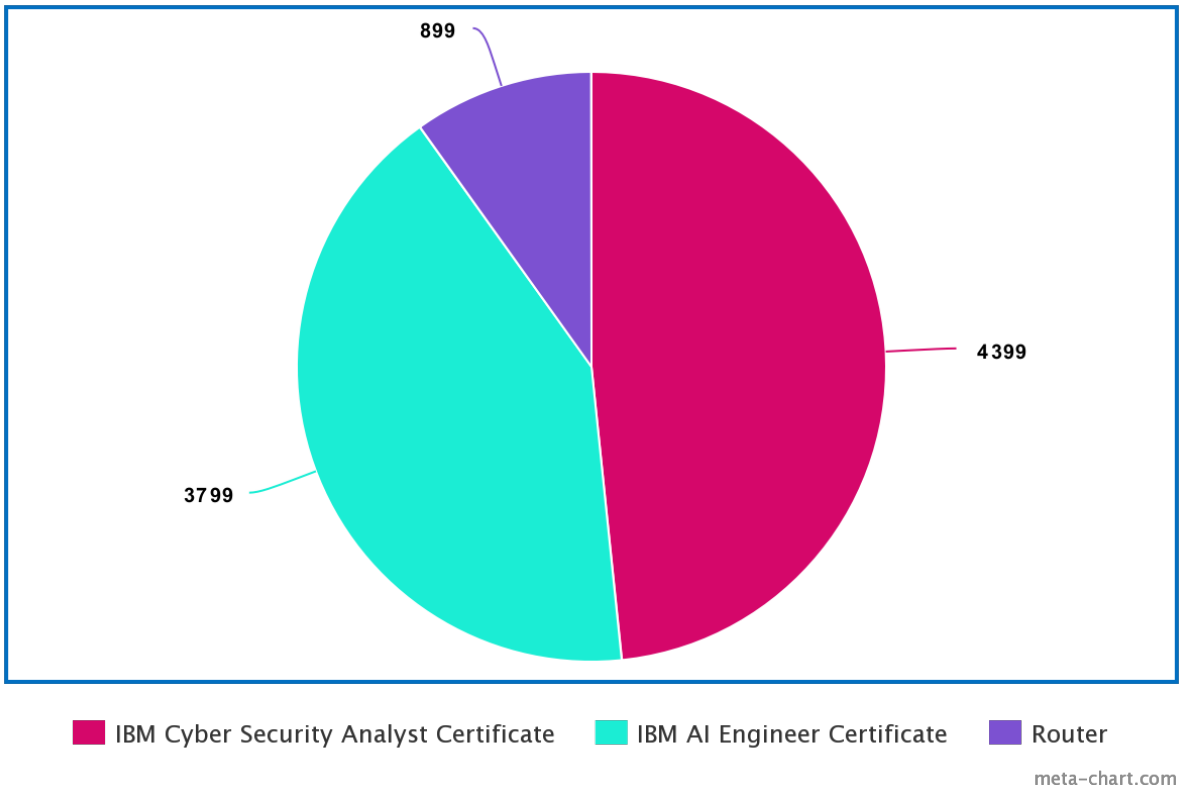

Figure 5.3: **Pie Chart for expenses**

The piechart(Figure 5.3) shows the prices of all the necessities that are required for the development and implementation of the project.

Chapter 6

Concluding remarks

6.1 Conclusion

Our architecture and activity diagrams were created after doing a literature review that included summaries of five separate research journals. Additionally, we've seen how the work is divided among the team and the many kinds of assumptions that are made. To give the project a clear scope, the needs for software and hardware as well as the risks and difficulties involved are examined.

We aim to develop a Real Time Network Intrusion Detection System that will detect malicious packets and anomaly traffic within a enterprise private network using both Signature and Rule based architecture. Evaluation of both NSL KDD and CIC IDS 2018 datasets are done using deep learning models to obtain the accuracy, F Score, Recall, TPR and FPR. To showcase the efficiency of the IDS, the bad agent attack is simulated in real time and the compromised traffic is alerted to the network administrator.

6.2 Future Scope

As of now it is difficult to predict the exact future of signature-based network intrusion detection systems (NIDS), as technology and cybersecurity threats are constantly evolving. One potential future direction for signature-based NIDS is its conjunction with other types of intrusion detection systems, such as behavior-based or anomaly-based systems, to provide a more comprehensive view of network activity or by incorporating Artificial Intelligence and Deep Learning to understand, learn and detect new attacks with attack patterns similar to pre-existing ones.

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Appendix A

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Machine Learning and Deep Learning Approaches for CyberSecurity: A Review

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ABSTRACT The rapid evolution and growth of the internet through the last decades led to more concern about cyber-attacks that are continuously increasing and changing. As a result, an effective intrusion detection system was required to protect data, and the discovery of artificial intelligence's sub-fields, machine learning, and deep learning, was one of the most successful ways to address this problem. This paper reviewed intrusion detection systems and discussed what types of learning algorithms machine learning and deep learning are using to protect data from malicious behavior. It discusses recent machine learning and deep learning work with various network implementations, applications, algorithms, learning approaches, and datasets to develop an operational intrusion detection system.

INDEX TERMS Cybersecurity, machine learning, deep learning, intrusion detection system.

I. INTRODUCTION

The internet is transforming people's jobs, learning, and lifestyles, and today, allowing to the integration of social life and the internet, which increases security threats in various ways. What counts now is learning how to identify network threats and cyberattacks, particularly those previously seen. Cybersecurity is defined as the process of implementing cyber protective measures and policies to protect data, programs, servers, and network infrastructures from unauthorized access or modification. The internet connects the majority of our computer systems and network infrastructure. As a result, cybersecurity emerged as the backbone for practically all types of corporations, governments, and even people to secure data, grow their businesses, and maintain privacy.

People send and receive data across network infrastructure, such as a router, that can be hacked and manipulated by outsiders. The increased use of the internet has increased the amount and complexity of data, resulting in the emergence of big data. The constant rise of the internet and extensive data necessitated the creation of a reliable intrusion detection system. Network security is a subset of cybersecurity that safeguards systems connected to a network against malicious activity. The goal is to provide networked computers to ensure data security, integrity, and accessibility. Current cybersecurity research focuses on creating an effective intrusion detection system that can identify both known and new attacks and threats with high accuracy and a low false alarm rate [1].

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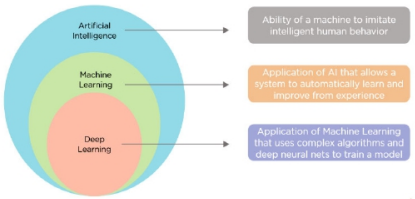

FIGURE 1. Relation between Artificial Intelligence, Machine Learning, and Deep Learning.

As shown in Figure 1, the terms Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) are frequently used interchangeably to describe the same

principles in software development. These names all indicate the same thing: a machine programmed to learn and find the best solution to a problem. DL is a subfield of machine learning, whereas machine learning is a subfield of AI. As a result, ML and DL are employed to create an efficient and effective intrusion detection system. This paper provides an overview of machine learning and deep learning applications and approaches in intrusion detection systems by concentrating on network security technologies, methodologies, and implementation.

Alan Turing stated that general use computers could learn and qualify originality, which has paved the way to whether computers should look at data to develop rules rather than allow humans to do it. Machine learning algorithms are algorithms that can learn and adapt based on data. Machine learning algorithms are designed to generate output based on what is learned from data and examples. For example, such algorithms will allow a computer to choose and perform a particular task on novel traffic detection without explicit information [2].

Automatic analyses of attacks and security events, such as spam mail, user identification, social media analytics, and attack detection may be performed efficiently using machine learning [1]. As indicated in Figure 2, there are three main techniques to machine learning: supervised, unsupervised, semi-supervised, and reinforcement learning. Supervised learning is based on labeled data, unsupervised learning is based on unlabelled data, and semi-supervised learning is based on both.

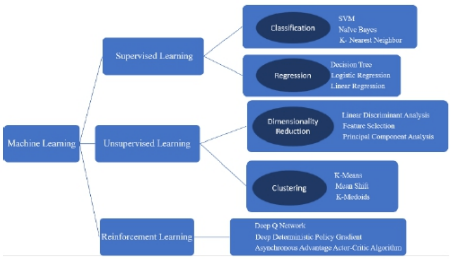

FIGURE 2. Machine learning approaches and algorithms.

Deep learning (DL) is a new subfield of machine learning, which is itself a subfield of Artificial Intelligence (AI). Traditional machine learning techniques are limited to processing natural raw data that rely on adequate feature extraction, and in order to classify or find patterns by a classifier, the raw data must be transformed into the appropriate format, which is where deep learning comes in. Deep learning is a machine learning approach that can learn from unstructured or unlabeled data and representation based on human brain knowledge [3].

Deep learning is motivated by neural networks (NN), which can mimic the human brain and perform analytical learning by analyzing data like text, images, and audio [4]. In contrast to deep learning models, which feature multiple connected layers, shallow learning models are built up of a few hidden layers. By stacking layers on top of layers, DL will be able to express increasing complexity functions more effectively. DL is used to learn representations with many abstraction levels [5]. Deep neural networks are capable of finding and learning representations from raw data and performing feature learning and classification [6]. Machine learning methodologies are also utilized in deep learning. However, other ways are employed in deep learning, such as Transfer Learning, as shown in Figure 3.

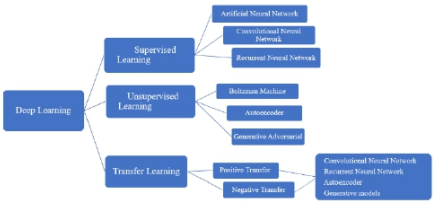

FIGURE 3. Deep learning approaches.

The remainder of the paper is organized as follows: Section 2 discusses the intrusion detection system concept. Section 3 summarises the most frequently utilized datasets for the intrusion detection system. Section 4 discusses recent advances in machine learning and deep learning-based intrusion detection systems, while Section 5 concludes this paper.

II. INTRUSION DETECTION SYSTEMS

Intrusion Detection is the process of monitoring network traffic and events in computers in order to detect unexpected events, and it is called Intrusion Detection System (IDS) when a software application is used to do so [7]. IDS is a type of network security that can identify and sense risks before services are lost, illegal access is granted, or data is lost [6]. IDS can also provide a graphical user interface through which users can interact by having access to various features when doing the IDS testing and training process [4]. Figure 4 depicts the deployment of two IDS methods depending on activities: a Network-Based Intrusion Detection System (NIDS) and a Host-Based Intrusion Detection System (HIDS). NIDS, for example, examines packets gathered by network devices such as routers, while HIDS examines events on a host computer. Hybrid detection is a system that combines the best of both worlds [1], [8].

A. INTRUSION DETECTION SYSTEM APPROACH

Intrusion detection techniques are classified into Anomaly Detection Methods and Misuse Detection Methods [8], as shown in Table 1.

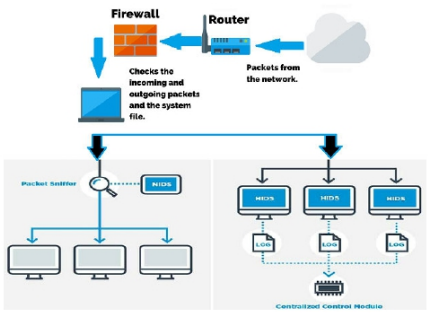

FIGURE 4. NIDS versus HIDS.

1) ANOMALY DETECTION

This model assumes that specific abnormal traffic has a low probability and can be distinguished from regular traffic with a high probability [9]. Unsupervised learning and statistical learning-based anomaly detection algorithms can detect unique and undiscovered assaults.

2) MISUSE DETECTION

This approach is a signature-based technique. While monitoring threats in an IDS, detection can occur based on known attack signatures [1]. This strategy is based on supervised learning and can detect illegal or suspicious behaviors that can be used to defend against similar assault behaviors.

TABLE 1. Differences between intrusion detection system approaches.

	Anomaly Detection	Misuse Detection
Detection of attacks	Known and unknown attacks	Only known attacks
Detection performance	High false alarm	Low false alarm
Attack background data required	No, depend on knowledge for part of the feature design	Yes, depend on knowledge for all detections
Detection efficiency	Depend on the complexity of the model	High, inverse relation with a signature database
Update required	No need for updates	Yes, requires updates

B. ATTACK CLASSIFICATION

As the network's diversity increased, attacks and threats evolved, becoming more sophisticated and non-repetitive. As a result, numerous attack types have been identified, including DoS, Probe, U2R, Worm, Backdoor, R2L, and Trojan [9]. Denial of service (DoS) attacks are among the most common network resource attacks, as they render network services unavailable to all users. They employ a variety of different behaviors and methods to consume network resources. For Probe, the intruder marks open ports after scanning all devices connected to the network to exploit them and gain network access. Then there is Remote to User (R2U), in which an attacker sends packets to various devices across a network to gain access as a local user [10]. For this definition, a worm is defined as a malicious application capable of self-replication from one device to another [9]. Finally, User to Root (U2R) is used, in which the intruder attempts to access network resources to use them as a local user after numerous trials [11].

C. EVALUATION METRICS

Some indications are used to assess an intrusion detection system's performance, either machine learning or deep learning-based. These indicators are based on the confusion matrix component that contains four metrics: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), and the assessment indicators are as follows [1]:

- *Accuracy* - The ratio of correct predictions to records; a higher accuracy indicates a more accurate prediction by the learning model.
- *Recall* - The model's capacity to locate all positive records is the detection rate, as it quantifies the correctly predicted records.
- *Precision* - The capacity to avoid mislabeling negative records as positive; a high precision rate equates to a low rate of false positives.
- *F1-Score (F1)* - The sum of Precision and Recall; a higher F1 indicates a more effective learning model.
- *False Positive Rate (FPR)* - To compute the False Alarm Rate, divide the total number of normal records identified as attacks by the total number of normal records.

TABLE 2. Confusion matrix.

	Predicted as Positive	Predicted as Negative
Labeled as Positive	True Positive (TP)	False Negative (FN)
Labeled as Negative	False Positive (FP)	True Negative (TN)

For decades, scientists and researchers have been attempting to develop and build an intrusion detection system that is both effective and efficient. With the advent of artificial intelligence, all IDS models utilized machine learning methodologies and approaches. However, after years of research, deep learning began to perform better for IDS, as seen by assessment indicator outcomes. Section IV will explore machine learning and deep learning in IDS.

III. DATASETS

When it comes to intrusion detection systems, one should consider the dataset employed to ensure the system's accuracy. Nowadays, applications and networks are growing exponentially, necessitating resilient network security. It can be accomplished by selecting the proper datasets for training and testing. Following that, a summary of the most often used dataset in intrusion detection systems will be discussed.

A. KDD CUP 1999

This dataset is the most widely used dataset for intrusion detection, based on the DARPA dataset. This dataset includes basic and high-level TCP connection information such as the connection window but no IP addresses. In addition, this dataset contains over 20 different types of attacks and a record for the test subset [10].

B. UNSW-IDS15

Founded in 2015 by Australian Centre for Cyber Security (ACCS). Samples in this dataset contain normal and malicious traffic [12], and it has been collected from three real-world websites; BID (Symantec Corporation), CVE (Common Vulnerabilities and Exposures), and MSD (Microsoft Security Bulletin) and then to generate the dataset, it emulated in a laboratory environment. This dataset has nine attack families, such as worms, DoS, and fuzzers [9].

TABLE 3. Attack types in UNSW-IDS15.

Attack Class	No. of records	Description
Normal	93,000	Natural traffic data
DoS	16,353	Attack to make resources inaccessible for legitimate users
Analysis	2,677	Port-based intrusion attacks, HTML penetrations, and spam
Fuzzers	24,246	Scan-based intrusion attacks. Using software testing to discover flaws in the operating system or network.
Reconnaissance	13,987	Attack aims to collect information about flaws in system security
Backdoors	2,329	Penetration remote attacks to access the computer by avoiding background security
Generic	58,871	Penetration attack for block cipher attacks

C. CIC-IDS2017

The dataset was generated in 2017 by the Canadian Institute for Cybersecurity. This dataset contains normal and attack scenarios and includes an abstract behavior for 25 users based on SSH, HTTPS, HTTP, FTP, and email protocols [8], [13].

D. NSL-KDD

It is the improved KDD dataset, where a large amount of redundancy has been removed, and an advanced sub-dataset has been created [10]. This dataset utilizes the same KDD99 attributes and belongs to four attack categories: DoS, U2R, R2L, and Probe [8].

E. PU-IDS

A derivative dataset from NSL-KDD is generated to extract a statistic from an input data and then utilized to create new synthetic instances. The traffic generator of this dataset obtained the same format and attributes as the NSL-KDD dataset [8].

TABLE 4. Attack types in CIC-IDS2017.

Attack Class		No. of records	Description
Benign		2,358,036	Natural traffic data
DoS	DDoS	41,835	Multiple users operate simultaneously to attack one service
	Heartbleed	11	Unauthorized access gained by inserting malicious data into OpenSSL memory
	DoS Hulk	231,073	Unique and obfuscated traffic produced by Hulk tool to perform DoS
	DoS slowloris	5796	Slow lorries tool implemented to perform DoS
PortScan		158,930	Collecting data such as services and type of operating system through sending packets with different destination port
Web Attack	XSS	652	Injects malicious data through web applications into normal websites
	Brute Force	1507	
	SQL Injection	21	Method to attack application that involves inserting malicious SQL statements into the entry field for execution
Brute-Force	FTP Patator	7938	Attacks to guess the password of FTP login
	SSH-Patator	5897	Attacks to guess the password of SSH login
Bot		1966	Trojan used to breach the security of many devices to gain control and organize all devices in Bot network so it can be operated remotely by the attacker
Infiltration		36	Infiltration techniques and tools used to gain unauthorized access to networked system data

TABLE 5. Attack types in NSL-KDD.

Attack Class	No. of records		Attack Types
	Training	Testing	
Normal	67,343	9,711	Natural traffic data
DoS	5,927	7,456	Worm, Land, Smurf, Udpstorm, Teardrop, Pod, Mailbomb, Neptune, Process table, Apache2, Back
Probe	11,656	2,421	Ipsweep, Nmap, Satan, Portsweep, Mscan, Saint
R2L	995	2,756	WarezClient, Worm, SnmpGetAttack, WarezMaster, Imap, SnmpGuess, Named, MultiHop, Phf, Spy, Sendmail, Ftp_Write, Xsnoop, Xlock, Guess_Password
U2R	2	200	Buffer_Overflow, SQLattack, Rootkit, Perl, Xterm, LoadModule, Ps, Httptuneel

Table 6 shows a comparison of several deep learning methods, the year the dataset was created, whether it was publicly available, the number of characteristics that were utilized for analysis, and lastly, how much traffic the data handled.

TABLE 6. Comparison between datasets.

Data Set	Year	Availability	No. of features	Kind of traffic
KDD Cup99	1998	Public	41	Emulated
NSL-KDD	1998	Public	41	Emulated
ISOT	2010	Public	49	Emulated
ISCX 2012	2012	Public	8	Emulated
UNSW-NB15	2015	Public	42	Emulated
KYOTO	2015	Public	24	Real traffic
CIC-IDS2017	2017	Public	84	Emulated

IV. INTRUSION DETECTION SYSTEMS IN RECENT WORKS USING MACHINE LEARNING AND DEEP LEARNING

Methodologies and algorithms have undergone significant change and evolution to produce the most acceptable intrusion detection system in many applications that attempt to identify constantly changing threats and attacks. Initially, classification was based on machine learning, but as performance needed to be further improved, deep learning was utilized to produce higher accuracy and a lower false alarm rate.

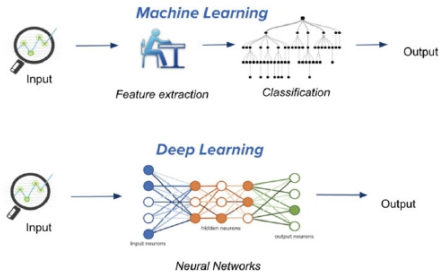

FIGURE 5. Machine learning Vs. deep learning.

The primary distinction between machine learning and deep learning is illustrated in Figure 5, and it is based on the method by which the system gets input. It depends on how the data is trained by machine learning, but it depends on the connections between artificial neural networks in deep learning to train data without requiring many human interactions. Additional differences between machine learning and deep learning are summarised here and in Table 7.

- *Data dependencies* – This metric indicates the volume of data. In traditional machine learning, based on rules, performance is improved when the data set is limited. In comparison, deep learning performs better with a vast number of data since a significant amount is required for accurate interpretation and understanding.
- *Feature processing* – This is a method of extracting features to generate patterns that contribute to the implementation of learning algorithms and reduce the complexity of the data. In other words, the feature process is used to do categorization and feature detection on raw data. While in machine learning, the expert must determine the necessary representations, in deep learning, the representations are identified automatically through the use of deep learning algorithms.
- *Interpretability* – This is described as a model's capacity to comprehend human language. An interpretable model can be understood without extra tools or procedures. On the other hand, it is difficult to specify how neurons should be modeled and how the layers should interact in deep learning, making it difficult to explain how the result was obtained.
- *Problem-solving* – In conventional machine learning, the problem is divided into sub-problems, each of which is solved independently, and then the final answer is obtained. On the other hand, deep learning will resolve the issue completely [4].

The following subsections describe how researchers employed machine learning and deep learning to create an intrusion detection system.

A. MACHINE LEARNING IDS ALGORITHM

This subsection discusses recent research into IDS implementations that utilize a variety of machine learning algorithms. Machine learning algorithms, such as support vector machine (SVM) and random forest (RF), have been used to investigate the binary categorization of IDS using a supervised learning approach [14]. SVM outperformed RF throughout the training process, whereas RF outperformed SVM during the test procedure. Additionally, they concluded that a classifier's performance would vary based on the dataset and attributes.

An IDS model based on a decision tree, naïve Bayes, and the random forest was proposed by [15] to classify Probe, R2L, and U2R on the NSL-KDD dataset. It is discovered that the highest accuracy was achieved in detecting DOS attacks using the RF algorithm. Additionally, when they compared their hybrid model with its 14 features to other hybrid models with varying features, the hybrid model had a greater accuracy for DOS, Probe, and U2R and a nearly identical accuracy for R2L.

In order to increase the performance of the attack detection model, an intrusion detection strategy utilizing SVM ensemble with the feature was presented in [16]. They examined validated training data and discovered that it might be used to improve the detection process resulting in the fast training time, high accuracy, and low false alarm rate. However, because this strategy trains classifiers independently of feature spaces and then combines judgments via an ensemble, some correlations across feature spaces will be missed during classifier learning, lowering the model's accuracy.

Three datasets comprising high-level network features were explicitly created for non-payload-based network intrusion detection systems in [17] by enabling machine learning classifiers to use Advanced Security Network Metrics (ASNM) features. It was the first dataset to include

TABLE 7. Comparison between machine learning and deep learning.

	Machine Learning	Deep learning
Input	Thousands of data	Millions of data (Big data)
Output	Numerical values	Numerical values, text, sounds
Hardware requirements	Low-end machines like CPU	Machines with GPU
How it works	Different algorithms are used to learn and predict future data from past data	Neural networks are used to pass the data through processing layers to interpret relations and features
Human Intervention	Require human intervention a lot	Does need much human intervention
How its managed	Data analysts direct the algorithms to examine specific variables in the dataset	Once the process starts, the algorithms will be self-directed to analyze the dataset
Dataset size	Works well with the small-medium dataset	Works well with a big dataset
No. of layers	A shallow network that consists of input, output, and one hidden layer	A deep network that consists of input, output, and at least three hidden layers
Features	Manual identification of the features	Automatic identifications of the important features
Processing Time	Few seconds or hours	Few hours or weeks
Training Time	Long time	Short time
Decision	The machine takes a decision based on the past data	With the help of an artificial neural network, machines take the decision
Hyperparameter tuning	The capability of tuning is limited	It can be tuned in many ways
Implementations	Prediction and simple applications	Complex applications
Problem-solving	Problem is divided into sub-problem	Solve the whole problem, end to end
Interpretability	Easy to understand the result in some algorithms like DT, and some hard to understand like SVM	Difficult to understand
Power	Low processing power	Requires high processing power
Algorithms no.	Many	Few
Accuracy	Less accuracy than DL	Higher accuracy than ML

adversarial obfuscation techniques and benign traffic samples that were applied to the malicious traffic execution of TCP network connections. While such classifiers can detect a sizable percentage of unknown threats, some unknown attacks may be undetectable, as illustrated in Figure 6.

The requirement for a horizontal platform for IoT applications/M2M resulted in creating the worldwide standard OneM2M [18], which aims to address the requirement for an M2M service layer that enables communication across heterogeneous apps and devices seen in Figure 7. Additionally, the authors investigated the second line of defense for oneM2M IoT networks that can identify and prevent threats and intrusions, dubbed Machine Learning-based Intrusion

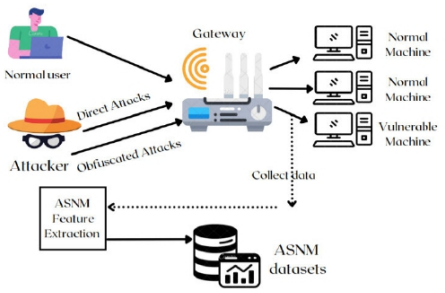

FIGURE 6. An overview of constructing ASNM datasets.

Detection and Prevention System, which can detect and prevent not only known but also unexpected attacks.

They developed their dataset from real-world IoT networks and implemented a detection model with three machine learning levels to identify and detect assaults and threats. They obtained 99.93 % accuracy for the second detection level when using a decision tree-based machine learning algorithm and 99.34 % accuracy when using an encoder-based machine learning strategy. However, this model obtained a high degree of accuracy and can detect and respond to risks associated with the oneM2M service layer.

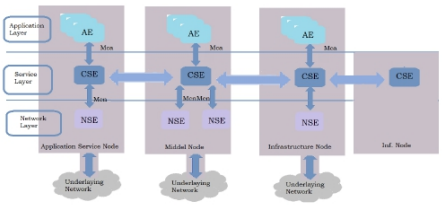

FIGURE 7. OneM2M architecture.

The use of Artificial Neural Networks (ANNs) was proposed by [18] to detect malicious traffic by training them on a large variety of benign and malicious traffic data. ANNs create weights that are adaptively tuned during the training phase by a learning rule. Their methodology outperformed signature-based detection, with an accuracy of 98 %. Table 8 analyses the learning method, performance metric, dataset, attack type, strengths, and limits of machine learning techniques based on intrusion detection systems.

B. DEEP LEARNING IDS ALGORITHM

This subsection discusses recent implementations of DL-IDS using a variety of deep learning methods. A model was introduced by [24] to collect and label real network traffic using their dataset in order to investigate mobile application identification and connect it to a cloud server.

TABLE 8. Machine learning algorithms for IDS.

Author	Learning algorithm	Performance metric	Dataset	Attack targeted	Strengths	Limitation
Farnaaz & Jabbar, 2016 [19]	RF	Accuracy, detection rate, false alarm rate, and Mathews correlation coefficient	NSL-KDD	DoS, Probe, R2L, and U2R,	The model provides a low false alarm rate and high detection rate	The increasing number of trees will slow the real-time prediction process
Rao & Swathi, 2017 [20]	KNN	Accuracy, detection rate	NSL-KDD	DoS, Probe, R2L, U2R, and normal	The model was able to increase the accuracy and faster classification time	The authors did not consider the precision and recall rate.
Khammassi & Krichen, 2017 [21]	Logistic Regression with Genetic Algorithm	Accuracy, detection rate, and false alarm rate	UNSW-NB15 KDD Cup99	DoS, U2R, and R2L	The model provides high accuracy with only 20 features of UNSW-NB15 and 18 features of KDDCup99	Depending on KDDCup99 may lead to misleading the evaluation as this dataset is outdated and contains redundant data
Verma & Ranga, 2018 [22]	KNN and K-means	Accuracy, detection rate, and false-positive rate	CIDDS-001	Network traffic attacks	The model provides the best performance of TP rate and low false alarm rate	The authors did not implement cross-validation to measure the robustness of their model
Hamed et al., 2018 [12]	SVM with Recursive Feature Addition (RFA)	Accuracy, detection rate, and false alarm rate	ISCX 2012	Network traffic attacks	Dealing with a large number of features and a small number of samples to avoid overfitting	The model ignores class distribution as it only works for binary classification.
Belouch et al., 2018 [23]	SVM RF DT NB	Accuracy, sensitivity, specificity, and execution time	UNSW-NB15	Network traffic attacks	DT has the best performance of all other ML algorithms	No feature selection is implemented, and that cause increase in detection and training time

The classification was learned using deep learning methods such as AE, CNN, and RNN, with the greatest performance, obtained when utilizing CNN and LSTM, with an accuracy of 91.8 % for 1D CNN classifiers and 90.1 % for F-measure. However, their analysis was limited to a particular application, and because all features are equally essential, CNN and RNN lack a crucial evaluation function while still extracting features adequately.

An intelligent intrusion detection system was developed by [25] that combines deep learning algorithms with network virtualization to detect malicious behavior on IoT networks. Their technique enables efficient anomaly detection in IoT networks regarding scalability and interoperability by simulating and tracing five different attacks. Their model achieved a precision rate of 95% and a recall rate of 97% for various threat scenarios. However, as with many other IDS models, they emphasize detection rather than prevention techniques. Figure 8 illustrates the implementation of the deep learning model for IDS.

A deep learning classification model using NSL-KDD and KDD CUP99 was proposed in [26] to address increased human engagement and decreasing accuracy. The model was constructed using an unsupervised learning technique known as Non-symmetric Deep Autoencoder (NDAE). Their model required less training time than DBN and improved accuracy

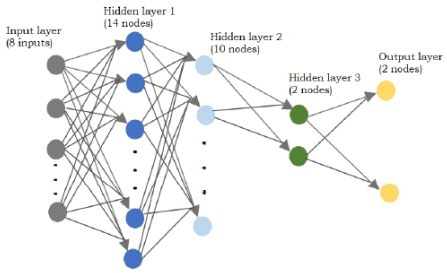

FIGURE 8. Sample of IDS deep learning model.

by 5% compared to pure Autoencoder, and is depicted in Figure 9. It consists of two NDADs with three hidden layers each, and the two NDAEs are joined using an RF method. Their methodology, however, is ineffective in detecting complex attacks due to its high false alarm rate.

Convolutional neural networks with the NSL-KDD dataset were investigated in [28] and are depicted in Figure 10. In addition, the authors investigated a method for detecting threats in a vast real-time network by converting the raw

data to an image data format, which aids in resolving the unbalanced dataset issue by computing the cost function for each class from the training sample. As a result, they were able to reduce the number of computing parameters in their model, but their model's accuracy was low compared to other machine learning and neural network models. Table 9 summarizes various deep learning algorithms for IDS.

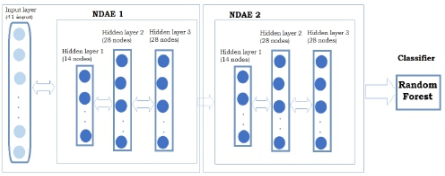

FIGURE 9. Stacked NDAE classification model.

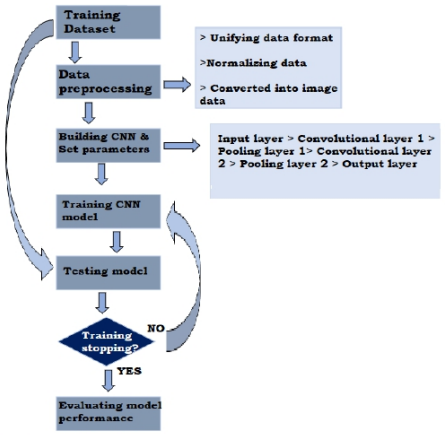

FIGURE 10. IDS based on CNN.

In [27], a combination of CIC-IDS 2017, NSL-KDD, Kyoto, UNSW-NB15, and WSN-DS datasets was proposed to categorize and detect unplanned and unexpected cyberattacks using a deep neural network. The performance of this model was evaluated by comparing it to other machine learning classifiers, and their model outperformed the others. Similarly, in [2], the author suggested a deep neural network approach for classifying network data as harmful or benign. He supplemented his analysis with two more datasets: UNB-ISCX 2012 and CIC-IDS 2017. First, a feedforward Deep Neural Network was utilized for training the model, and then an Autoencoder was employed to categorize assaults and threats in the absence of tagged harmful data. Their model was 99.96% accurate for UNB-ISCX 2012 and 99.96% accurate for CIC-IDS 2017. Additionally, their research established the critical nature of the datasets needed to construct an IDS and the efficacy of Autoencoder for anomaly detection.

To enhance detection accuracy in IDS, the author incorporated big data, deep learning approaches, and natural language processing in [28]. They worked with KDD CUP99 and achieved an accuracy of 94.32 % with their model. In addition, another deep neural network method was introduced in [29] to detect risks and attacks in the cloud environment. Their approach used Simulated Annealing and Improved Genetic Algorithms to create the hybrid optimization framework IGASAA using the datasets NSL-KDD2015, CIC-IDS2017, and CIDDS-001. Compared to the Simulated Annealing Algorithm (SAA), their model demonstrated a higher detection rate, increased accuracy, and a lower false alarm rate.

Web application security is highly reliant on detecting malicious HTTP traffic, which needs a significant investment in training data gathering and a large dataset. To detect malicious HTTP traffic, the authors in [29] introduced the DeepPTSD method based on a deep transfer semi-supervised learning methodology. The construction of their model is given in Figure 11. They used two raw public datasets from FSecurify and another from their lab via a honeypot server. When a little training dataset is available, their model exceeds other existing baselines, with a precision of 93.33% compared to 86.67 % and 86.61 % for CNN and RNN, respectively.

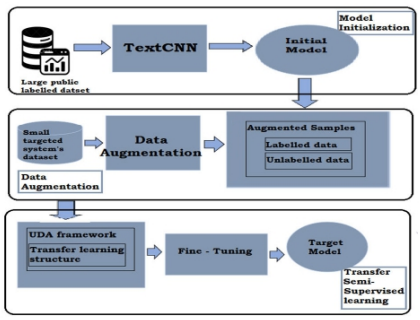

FIGURE 11. DeepPTSD architecture.

An intrusion detection model based on a convolutional neural network was presented in [30] to extract structural information. The authors performed multiclassification on NIDS using the NSL-KDD and KDD-CUP99 datasets. Their model's accuracy increased compared to other classifiers, resulting in enhanced detection of unknown threats and a decrease in false alert rates. A feedforward deep neural network was proposed by [1] for an intrusion detection system to perform binary classification on the NSL-KDD dataset. Due to the dense structure of this model, it beat the usual machine-learning technique in terms of scalability with big datasets and time for training data. As a result, there was

TABLE 9. Deep learning algorithms for IDS.

Author	Learning algorithm	Performance metrics	Dataset	Attack targeted	Strengths	Limitation
Xiao et al., 2019 [33]	CNN	Accuracy, detection rate, and false alarm rate	KDD CUP99	DoS, Probe, R2L, U2R, and normal	The model provides a short classification time for real-time traffic and high accuracy	R2L and U2R have a low detection rate compared to other attacks
Papamartzivanos et al., 2019 [34]	Autoencoder	Accuracy, precision, recall, F1-score	KDD CUP99 NSL-KDD	DoS, Probe, R2L, U2R, and normal	The model provides autonomous misuse detection for large scale networks	Low detection accuracy for U2R and R2L attacks
Mayuranathan et al., 2019 [35]	RBM	Accuracy, detection rate, precision, and recall	KDD CUP99	DoS and DDoS in the cloud environment	By using feature selection, the model improved the performance of detecting attacks	High computational resources for IoT devices
Jiang et al., 2020 [36]	LSTM-RNN	Accuracy, detection rate, and false alarm rate	NSL-KDD	Network traffic attacks	The model outperformed the accuracy of other machine learning algorithms	The model does not detect new types of attacks
Tian et al., 2020 [37]	DBN	Accuracy, F1-score, precision, recall, and false-positive rate	NSL-KDD UNSW-NB15	Network traffic attacks	The model is robust and provides a low false alarm rate	The accuracy of the model may be affected due to the uncertainty of selecting parameters
Zhang et al., 2020 [38]	CNN MLP C-LSTM	Accuracy, F1-score, precision, and recall	CSE-CIC-IDS2018	NES Boundary HopSkipJu Pointwise Opt-Attack	The model provides a high detection rate	The model was vulnerable against adversarial instances

a high proportion of true positives and accurate categorization records, with this model achieving an accuracy of 89%. In [31], an RNN-based IDS binary and multiclass classification technique were investigated. This model outperformed convolutional machine learning algorithms and demonstrated that it is suited for classification with high accuracy. The authors trained and tested their model on the NSL-KDD dataset. Figure 12 illustrates the RNN structure and the proposed RNN-IDS model.

Deep neural networks were used in [32] to investigate the applicability of anomaly-based intrusion detection systems. Based on the NSL-KDD dataset, the authors studied a variety of machine learning and deep learning frameworks. According to the comparison, deep learning outperformed machine learning in the accuracy test. The best performance was first achieved by the RNN, then by the CNN, and finally by the Autoencoder. A comparison of deep learning methods based on intrusion detection systems is presented in Table 9, which compares the learning algorithm, performance metric, dataset, attack targeted, strengths, and limits of the algorithms.

C. HYBRID LEARNING IDS ALGORITHM

This section discusses works that combine machine learning and deep learning or use many algorithms of the same learning type. First, a deep learning-based intrusion detection system for an IoT network was developed in [39]. By providing a model based on Gated Recurrent Neural Networks (GRU and LSTM), their detection dataset was KDD99 cup.

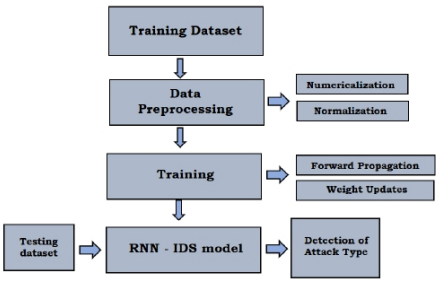

FIGURE 12. RNN and RNN-IDS architecture.

They proposed adding deep learning classifiers to each TCP/IP architecture layer to increase its complexity. The model's accuracy was 98.91 %, and the false alarm rate was 0.76 %. However, one may argue that the model's robustness was low.

Hierarchical Intrusion Detection System (HAST-IDS) was developed in [40] to improve anomaly detection. As illustrated in Figure 13, they began by extracting spatial features using CNN and then temporal characteristics using LSTM. Finally, they evaluated the performance of their proposed model using the ISCX2012 and DARPA datasets. Although the hierarchical CNN-LSTM model beats pure CNN or LSTM models and gives higher accuracy for IDS, it is computationally expensive because of its complicated architecture.

TABLE 10. Hybrid learning algorithms for IDS.

Author	Learning algorithm	Performance metrics	Dataset	Attack targeted	Strengths	Limitation
Yang et al., 2017 [48]	SVM and RBM	F1-score and precision	Real online network traffic	Network traffic attacks	The model increased training speed and improved traffic detection	F1-score for some training sizes had a high false-negative rate
Yang et al., 2019 [49]	DBN with density peak clustering algorithm	Accuracy, recall, precision and F1-score	UNSW-NB15 NSL-KDD	Network traffic attacks	The model outperformed other algorithms in accuracy and detection rate	The performance may be affected because the model was not able to learn low-level feature representations
Zhang et al., 2019 [50]	Genetic algorithm and DBN	Accuracy, detection rate, precision, recall and false alarm rate	NSL-KDD	IoT network layer	The model was able to select the optimal parameters to be trained	The model needs more time for training the dataset
Rajagopal et al., 2020 [51]	SVM, RF, LR, and KNN	Accuracy, precision, recall, false alarm rate	UNSW-NB15 UGR'16	Blacklist Spam Scan SSHscan UDPscan DOS DDOS	The combined algorithms increased the accuracy and detection rate	Evaluate a new dataset that contains recent attacks, and their work only focuses on the classifiers, not metadata.

D2H-IDS [41] is an intrusion detection system that was developed to ensure the security of connections between connected smart vehicles. This model is built on a framework for continuous automated secure service availability and utilises a decision tree and deep belief network to classify attacks and reduce their dimensionality.

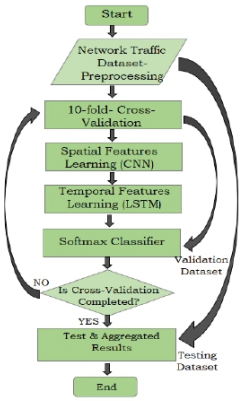

FIGURE 13. Hierarchy of HAST-IDS.

Security attacks in smart connected vehicles an intrusion detection system based on continuous automated secure service availability framework was proposed in [41]. The model classifies attacks and reduces their dimensionality using a decision tree and deep belief machine learning. A model for enhancing IDS performance was provided by [42] by integrating three classifiers with big data. The methods utilized were a combination of machine learning and deep learning techniques, including Random Forest (RF), Deep Neural Network (DNN), and Gradient Boosting Tree (GBT). The authors evaluated their strategy using the CIC-IDS2017 and UNSW-NB15 datasets. DNN has the highest accuracy at 99.19 % based on UNSW-NB15 and 99.99 % based on CIC-IDS2017. Although all three classifiers achieved good accuracy, training the model was difficult due to the features' wide variety of numerical data.

In wireless sensor networks, IDS was performed using a combination of machine learning and deep learning [43]. The authors proposed the Restricted Boltzmann machine-based clustered RBC-IDS approach as a deep learning technique. They used the KDD Cup99 dataset and Network Simulator-3 to compare their model against adaptive machine learning-based IDS (NS-3). While RBC-IDS has high accuracy, the detection time was comparable to that of the adaptive machine learning model, resulting in overhead expenses. A hybrid network IDS was utilized in [6] using the UNSW-15 dataset that utilized the CNN-LSTM algorithm. When applied to real-world devices, they employed a transfer learning approach to optimise the IDS model's efficiency. Their model was 98.43 % accurate.

CBR-CNN (Channel Boosted and Residual Learning) was created in [44], employing deep Convolutional Neural Networks for intrusion detection using the NSL-KDD dataset. Training is carried out using an unsupervised learning approach, and normal traffic is modeled using stacked autoencoders (SAE). Their model had an accuracy of 89.41 % for KDD-Test+ and 80.36 % for KDD-Test-21, respectively. Table 10 analyses the learning method, performance metric, dataset, attack type, strengths, and limits of hybrid learning algorithms based on intrusion detection systems.

D. DISCUSSION AND OPEN CHALLENGES

Intrusion detection systems are now considered a necessary component of our daily lives. However, developing an intrusion detection system capable of detecting and

TABLE 11. Comparison of machine learning and deep learning algorithms.

Algorithm	Learning approach	Ease of implementation	Advantages	Disadvantages	Overfitting
Decision Tree (DT)	Supervised learning	Easiest algorithm to implement	Does not require normalization of data. During pre-processing less effort is required to prepare data	Require more time to train the model, and some calculations will go far more complex. Due to higher time and complexity; training will be comparatively expensive	Common to occur
Support Vector Machine (SVM)	Supervised learning	Moderate	In high dimensional spaces is efficient. Can model non-linear data	Difficult to understand the structure of the algorithm. Training is slow	Unlikely to occur
Naïve Bayes (NB)	Supervised learning	Simple and easy	Very effective to solve complex problems. Does not require much training data	Better performance with categorical than numerical. Less accurate than complicated algorithms	Less likely for overfitting
Logistic Regression (LR)	Supervised learning	Easy	Easy to interpret. No assumptions are required for feature space.	Used to predict only discrete functions. Unable to solve a non-linear problem	Tend to overfit
k-Nearest Neighbors (KNN)	Supervised learning	Easy	New data can be added seamlessly as no training is required for predictions.	The performance will be affected by a large dataset. Affected by missing values and noise.	Common to occur
Convolutional Neural Network (CNN)	Supervised learning	Hard	Automatic detection of the most important features	Not capable to detect spatial data	Common to occur
MultiLayer perceptron (MLP)	Supervised learning	Easy	Capable of learning based on initial experience	A very high number of parameters lead to insufficiency and redundancy	Common to occur
Autoencoder (AE)	Unsupervised learning	Moderate	Capable of providing for each layer a representation & can learn non-linear transformations	May remove important information from the input data & add complication to the final result more than a value	Tend for overfitting
Restricted Boltzmann Machines (RBM)	Unsupervised learning	Easy	Capable of producing samples similar to the original data	The training process is difficult	Common to occur
Recurrent Neural Network (RNN)	Supervised learning	The training process is hard but the model is simple	Capable of processing arbitrary length of input and output	The computation time is slow and training is complicated	Prone to overfitting

responding to a wide range of attacks and threats is a difficult task. As a result, hundreds of studies in the field of intrusion detection systems have been carried out for various applications by academic researchers. Some academics believe that deep learning, through a neural network, will enable greater flexibility in IDS, allowing it to detect and classify harmful threats more effectively. This flexibility is because its algorithms have hidden layers with a high-dimensional feature representation of the data.

A comprehensive assessment of network-based intrusion detection systems was offered in [10], in which they stressed the need for labeling data when doing evaluation and training on anomaly-based intrusion detection systems. Moreover, in [45], the author investigated the possibility of improving model optimization, and they concluded that the supervised learning approach is more successful than the unsupervised learning approach. After all, it can achieve higher performance in terms of the algorithms used because it uses labeled data to train the models. NADS implementation with various applications, data centers, fog, cloud computing, and the Internet of Things (IoT) was a priority [13]. The authors asserted that datasets not based on reality might result in mistaken studies in their conclusions. Employing ESR-NID computation approaches, they provided in [45] a model for searching for a solution to automatically generate rulesets for network intrusion detection by using computation techniques (Evolving Statistical Rulesets for Network Intrusion Detection). The model outperforms other existing models and is capable of dealing with a variety of various types of attacks.

To summarize, some researchers were concentrating on whatever algorithm would provide the best performance, such as [14], [15], [21]–[23], [33], [39]. A comparison between different types of algorithms used for IDS is presented in Table 11, in terms of the learning approach, advantages, and disadvantages.

As a means of increasing accuracy and improving model implementation, some researchers investigated combining algorithms in order to achieve higher accuracy or a lower false alarm rate, as in [40], [41], while others combined methods in machine learning and deep learning, as in [43], [44], [46]. Some researchers experimented to see which dataset could provide a more stable model,

as in [15], [21], [25], [35], [38], [43], while others created their dataset to use in IDS development, as in [17], [24], [47]. Each dataset contains a different range of threats and attacks, so some researchers experimented to see which dataset could provide a more stable model.

The intrusion detection system field has many challenges, represented by:

1) UNAVAILABILITY OF UP-TO-DATE DATASET

A highly effective IDS must be trained and tested against a dataset of new and old threats and attacks. When more patterns and types of attacks are discovered in a dataset, the model becomes more resistant to various attack types. Thus, one of the challenges for IDS is to maintain an up-to-date dataset with sufficient records to cover the majority of attack types.

2) HYPERPARAMETER TUNING

The deep structure of an IDS model requires that the hyperparameters be specified. The activation function and optimization method, the number of nodes per layer, and the total number of layers in a network are all hyperparameters. Hyperparameters affect training and model building, with the ability to increase or decrease the IDS model's accuracy and detection rate. Hyperparameters can be tuned manually, which will take a significant amount of time, or automated to improve the performance of the IDS model.

3) IMBALANCED DATASET

Existing datasets contain varying numbers of records for various types of attacks. These differences will affect the accuracy and detection rate of various types of attacks. A low-record attack will have a lower detection rate than a high-record attack. This issue can be resolved by either balancing the dataset or by increasing the number of minority attack records.

4) PERFORMANCE IN REAL-WORLD

When researchers attempt to develop an intrusion detection system, they train and test the model in laboratories, with the majority of the data coming from public sources. Thus, an IDS model faces a challenge when it is implemented in a real-world environment, as the model developed in the lab should be validated in a real-world environment to ensure its efficiency.

V. CONCLUSION

One of the essential subjects in the cybersecurity area was intrusion detection systems. Many researchers are developing a system that will secure data against malicious conduct. However, research into other applications of learning algorithms, such as establishing a new dataset or merging algorithms, is currently ongoing. As a result, we explain the concept of an intrusion detection system, types of attacks, and how to determine whether or not we have an effective system in this work.

Selecting a good dataset to train and test an intrusion detection system is a crucial parameter, and it was clear that datasets have an impact on research in this sector, as some deem it out of date or contains redundant information. As a result, the most frequent datasets used to detect threats over the last decade are compared in the research.

The final step in this project was to look into what other people did to save their data. Recent research has revealed that there are numerous data protection implementations. They employed machine learning for several purposes at first, and many studies were conducted to determine which algorithm would provide higher accuracy or which datasets would produce a lower false alarm rate. Finally, they arrived at deep learning after extensive investigation and testing. Many studies and experiments have shown that deep learning is superior to machine learning because it can handle more complicated problems with greater accuracy and lower false alarm rates. Previous work has been used in a variety of applications. They employed various datasets, architectures, learning methodologies, and learning algorithms to secure data from attacks and dangers each time.

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He was the Head of the Department of Electrical and Computer Engineering, from 2015 to 2016, and the Head of Programme Accreditation and Quality Assurance with the Faculty of Engineering, International Islamic University Malaysia, from 2017 to 2018. He has been a Chartered Engineer at IET, U.K., since 2016, an Insinyur Profesional Utama at PII, Indonesia, since 2021, and a Registered ASEAN Engineer, since 2018. He has been a Professor, since 2019, and has been an ASEAN Chartered Professional Engineer, since 2020. His research interests include speech and audio processing, biomedical signal processing and instrumentation, image and video processing, and parallel computing. He was awarded the Best Researcher Award at IIUM, in 2018. He was the Chairperson of IEEE Instrumentation and Measurement Society—Malaysia Section, in 2013, 2014, 2021, and 2022.

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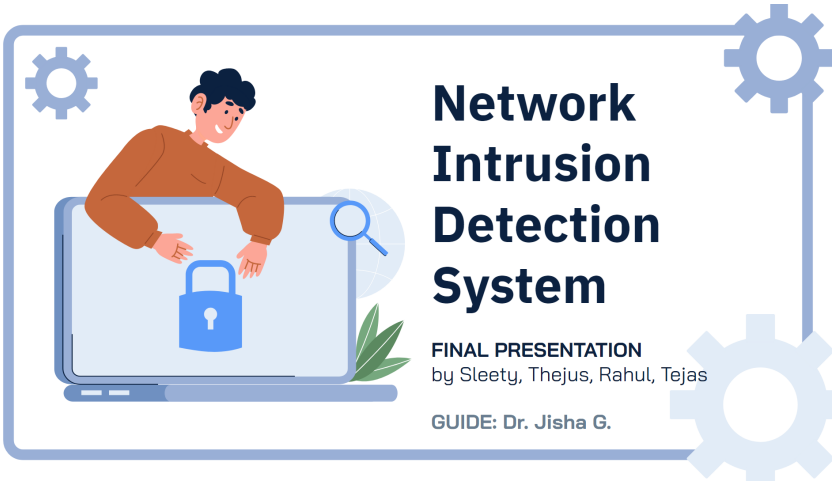
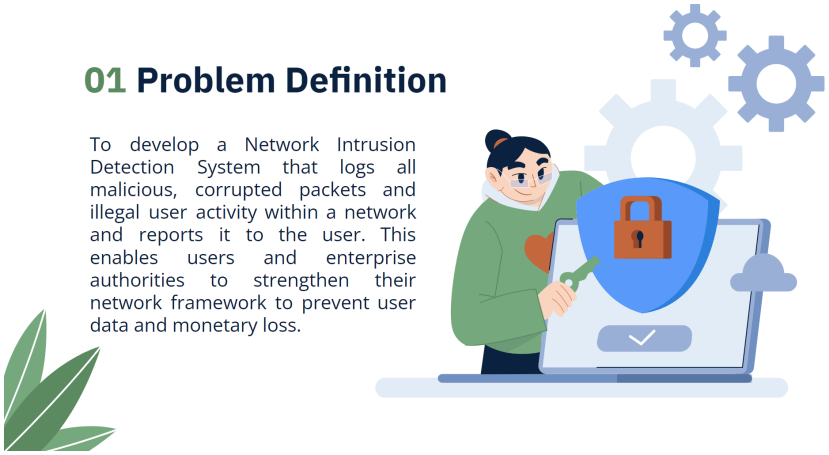
Appendix B


Network
Intrusion
Detection
System
FINAL PRESENTATION
by Sleety, Thejus, Rahul, Tejas
GUIDE: Dr. Jisha G.


01 Problem Definition
To develop a Network Intrusion Detection System that logs all malicious, corrupted packets and illegal user activity within a network and reports it to the user. This enables users and enterprise authorities to strengthen their network framework to prevent user data and monetary loss.

02 Purpose and Need

- Privacy of data and sensitive information is a high priority in this day and age.
- Numerous issues like malicious packets, man in the middle attack, flooding attacks arise as a result of poor network security infrastructure.

- The development of a Network Intrusion Detection System will enforce user and enterprises against a potential vulnerability in a feeble network.

03 Project Objectives

- To study accuracy, F1 scores obtained by different machine learning and deep learning models against NSL-KDD and CIC-CIDS datasets
- Create a Intrusion Detection system that stores potential vulnerability attack ids in a separate log file.

- Integrate packet sniffing and network monitoring abilities of SNORT, an Intrusion Detection and Prevention System.
- Detects DDoS, flooding, identity manipulation attacks and potential weaknesses within the network.
- To simulate a real time attack environment to demonstrate the abilities of an IDS.
- Notify the authorities in case of any violations.

04 LITERATURE SURVEYS

1 Asmaa Halbouni, Teddy Surya Gunawan, Mohamed Hadi Habaebi, Murad Halbouni, Mira Kartiwi, And Robiah Ahmad: "Machine Learning and Deep Learning Approaches for CyberSecurity: A Review" [Feb 24th, 2022]

- This paper cover the concepts of Intrusion Detection Systems, its different types and compares machine learning models with Deep Learning and Hybrid Learning models on different IDS datasets.
- A network intrusion detection system is a software device that detects bad packets or abnormal behaviour or unauthorised users within a network and alerts the administrators.
- The best results obtained were when a deep neural network was implemented against the CIC-IDS 2017 dataset with the least false positives and a accuracy of 99.96%, the same model is implemented against the NSL-KDD 2015 and it obtains a accuracy of 94.37%.

1 **Asmaa Halbouni, Teddy Surya Gunawan, Mohamed Hadi Habaebi, Murad Halbouni, Mira Kartiwi, And Robiah Ahmad: "Machine Learning and Deep Learning Approaches for CyberSecurity: A Review" [Feb 24th, 2022]**

- As a means to obtain more accuracy, better implementation of model, low false alarms, more stability and wider range of attack recognition, wide range of datasets, mono or poly deep learning models are implemented.

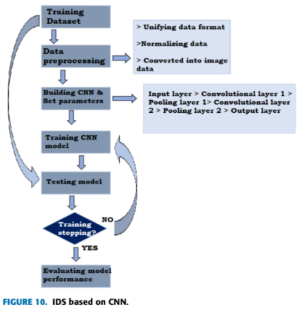


FIGURE 10. IDS based on CNN.

1 **Asmaa Halbouni, Teddy Surya Gunawan, Mohamed Hadi Habaebi, Murad Halbouni, Mira Kartiwi, And Robiah Ahmad: "Machine Learning and Deep Learning Approaches for CyberSecurity: A Review" [Feb 24th, 2022]**

TABLE 9. Deep learning algorithms for IDS.

Author	Learning algorithm	Performance metrics	Dataset	Attack targeted	Strengths	Limitation
Xiao et al., 2019 [33]	CNN	Accuracy, detection rate, and false alarm rate	KDD CUP99	DoS, Probe, R2L, U2R, and normal	The model provides a short classification time for real-time traffic and high accuracy	R2L and U2R have a low detection rate compared to other attacks
Papamartziva nos et al., 2019 [34]	Autoencoder	Accuracy, precision, recall, F1-score	KDD CUP99 NSL-KDD	DoS, Probe, R2L, U2R, and normal	The model provides autonomous misuse detection for large scale networks	Low detection accuracy for U2R and R2L attacks

2 **Gozde Karatas, Önder Demir And Ozgur Koray Sahingoz: "Increasing the Performance of Machine Learning-Based IDSs on an Imbalanced and Up-to-Date Dataset" [Feb 24th, 2020]**

- An IDS is used to detect malicious activity and analyse network traffic.
- They are of two detection types: Anomaly and Signature based.
- Anomaly based IDS detects anomalies within the network by the means of a administrator formulated ruleset, any violations will be reported.
- Signature based IDS will map packets id to a attack database, if the id matches, the packet is deemed malicious, otherwise benign.
- The KDD dataset consists of imbalanced and outdated data and thus cause a high rate of false positives, this is avoided in the CIC- IDS 2018 dataset.
- The best results were obtained using the random forest machine learning model against the CIC- CIDS 2018 with 99.34% accuracy and low false alarm rate.

2 **Gozde Karatas, Önder Demir And Ozgur Koray Sahingoz: "Increasing the Performance of Machine Learning-Based IDSs on an Imbalanced and Up-to-Date Dataset" [Feb 24th, 2020]**

TABLE 6. CSE-CIC-IDS2018 labels.

Label	Value
Benign	0
Bot	1
Brute Force	2
DoS	3
Infiltration	4
SQL injection	5

TABLE 2. CSE-CIC-IDS2018 data distribution.

Class Label	Number	Volume (%)
Benign	2,856,035	63.111
Bot	286,191	6.324
Brute Force	513	0.011
DoS	1,289,544	28.497
Infiltration	93,063	2.056
SQL injection	53	0.001
Total	4,525,399	100

2 **Gozde Karatas, Önder Demir And Ozgur Koray Sahingoz: "Increasing the Performance of Machine Learning-Based IDSs on an Imbalanced and Up-to-Date Dataset" [Feb 24th, 2020]**

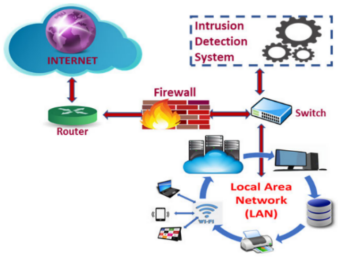


FIGURE 1. Intrusion detection systems and local area networks.

3 **Juan Fernando Cañola Garcia, Gabriel Enrique Taborda Blandona: "Deep Learning-Based Intrusion Detection and Prevention System for Detecting and Preventing Denial-of-Service Attacks" [Aug 5th,2022]**

- This paper covers the shallow learning and deep learning approaches that can be taken while developing an effective NIDS system and compares them to identify the better approach.
- It identifies deep learning model as a better choice due to the several advantages it has over shallow learning such as proportional increase in accuracy with increase in datasets,automatic feature recognition and time consumption etc.
- The data set used to train the chosen algorithm was CIC-DDoS 2019.
- The main type of attack this paper focuses on is Denial Of Service attacks,as such the various deep learning models are trained to identify said attacks and their accuracy values are compared to find the best deep learning model.

3 Juan Fernando Cañola Garcia, Gabriel Enrique Taborda Blandona: "Deep Learning-Based Intrusion Detection and Prevention System for Detecting and Preventing Denial-of-Service Attacks" [Aug 5th,2022]

- The deep learning algorithms taken were LSTM, RNN ,Deep Feedforward Neural Networks which satisfied the four criterias given in Table 8.
- Among the three deep learning algorithms Deep Feedforward Neural Network was taken because all data preprocessing could be easily done using java code and the model using DFNN displayed an accuracy of 99.94 which is the highest among all other algorithms cited in the paper.

TABLE 8. Selection criteria.

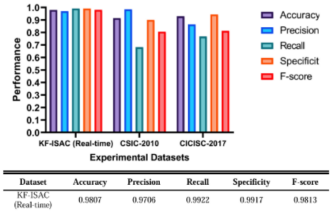
No.	Selection criteria
1	The algorithm is available in the Java Deep Learning library.
2	The model's training configuration used with the DL algorithm is available.
3	The dataset employed with the DL algorithm to train the model contains DoS attack packets.
4	The accuracy of the model trained with the DL algorithm is above 90%.

4 Aechan Kim, Mohyun Park, And Dong Hoon Lee : "AI-IDS: Application of Deep Learning to Real-Time Web Intrusion Detection " [April 10th,2020]

- This paper propose an optimal convolutional neural network and long short-term memory network (CNN-LSTM) model, normalized UTF-8 character encoding for Spatial Feature Learning (SFL) to adequately extract the characteristics of real-time HTTP traffic without encryption, calculating entropy, and compression.
- It is a flexible and scalable system that is implemented based on Docker images, separating user-defined functions by independent images.
- It also helps to write and improve Snort rules for signature-based IDS based on newly identified patterns.
- As the model calculates the malicious probability by continuous training, it could accurately analyze unknown web-attacks.

4 Aechan Kim, Mohyun Park, And Dong Hoon Lee : "AI-IDS: Application of Deep Learning to Real-Time Web Intrusion Detection " [April 10th,2020]

- Repeated experiments are performed on two public datasets (CSIC-2010, CICIDS2017) and fixed real-time data.
- Previous works have mainly considered accuracy (ACC) in terms of performance measures, but scalability and precision are also important indicators for applying deep learning in the real-world. In real time the best accuracy obtained was 98.54



Dataset	Accuracy	Precision	Recall	Specificity	F-score
KF-ISAC (Real-time)	0.9807	0.9706	0.9922	0.9917	0.9813
CSIC-2010	0.9154	0.9854	0.6826	0.9002	0.8065
CICISC-2017	0.9300	0.8647	0.7683	0.9440	0.8136

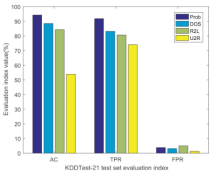
FIGURE 6. Experimental results on public datasets.

5 H. Yang and F. Wang, "Wireless Network Intrusion Detection Based on Improved Convolutional Neural Network" [17 May 2019]

- This paper proposes a wireless network intrusion detection method based on Improved Convoluted Neural Networks (ICNN)
- The low-level traffic data is represented as advanced features by CNN where the sample features are extracted and stochastic gradient descent algorithm is applied to optimize the network parameters
- The dataset used to train this model was the NSL-KDD CUP which includes Probe, DOS, U2R, R2L attack data

5 H. Yang and F. Wang, "Wireless Network Intrusion Detection Based on Improved Convolutional Neural Network" [17 May 2019]

- Tests were conducted on KDDTEST+ test set shown detection rate that is 8.82% and 0.51% than of LeNet-5 and DBN
- It also shown the recall rate being 4.24% and 1.16% higher than LeNet-5 and RNN
- This model has shown higher accuracy and true positive rates and the false positive rate is lower with the highest accuracy being 95.36%



Data set	Model	AC(%)	TPR(%)	FPR(%)
KDDTest+	IBWNIDM	95.36	95.55	0.76
	LeNet-5	86.54	91.31	2.03
	DBN	92.45	95.68	0.85
	RNN	93.08	94.39	0.92
KDDTest-21	IBWNIDM	90.91	92.42	3.96
	LeNet-5	82.36	87.93	3.24
	DBN	88.69	89.48	4.46
	RNN	79.47	80.58	1.75

Paper	Model Used	Dataset	Result
Title: Machine Learning and Deep Learning Approaches for CyberSecurity: A Review **Author:** Asmaa Halbouni, Teddy Surya Gunawan, Mohamed Hadi Habaebi, Murad Halbouni, Mira Kartiwi, And Robiah Ahmad **Year:** 2022	• FeedForward Deep Neural Network	• CIC- IDS 2017 • NSL - KDD	Less false positives with short classification time for real time traffic and high accuracy. The model shows an accuracy of 99.96% and 94.32% for CIC-CIDS 2017 and NSL - KDD 99' respectively.

Paper	Model Used	Dataset	Result
Title: Increasing the Performance of Machine Learning-Based IDSs on an Imbalanced and Up-to-Date Dataset **Author:** Gozde Karatas, Önder Demir And Ozgur Koray Sahingoz **Year:** 2020	• Random Forest	• CIC- IDS 2017 • NSL - KDD	Due to imbalance and outdated data, the model gives 99.9% accuracy for NSL - KDD. Low false positive rate and a accuracy of 99.34% for CIC - CIDS.

Paper	Model Used	Dataset	Result
Title: Deep Learning-Based Intrusion Detection and Prevention System for Detecting and Preventing Denial-of-Service Attacks **Author:** Juan Fernando Cañola Garcia, Gabriel Enrique Taborda Blandona **Year:** 2022	• Feed forward Deep Neural Network	• CIC- DDoS 2019	Deep Feedforward Neural Network can easily preprocess data using java code and the model using DFNN obtained an accuracy of 99.94%.

Paper	Model Used	Dataset	Result
Title: AI-IDS: Application of Deep Learning to Real-Time Web Intrusion Detection **Author:** Aechan Kim, Mohyun Park, And Dong Hoon Lee **Year:** 2020	• CNN - LSTM	• CSIC - 2010 • CIC - IDS 2017 • Real time data	It is a flexible and scalable system that is implemented based on Docker images. The LSTM - CNN model performed the best in real time data with an accuracy of 98.54%.

Paper	Model Used	Dataset	Result
Title: Wireless Network Intrusion Detection Based on Improved Convolutional Neural Network **Author:** H. Yang and F. Wang **Year:** 2019	• Improved convolutional neural networks (ICNN)	• NSL KDD CUP	This model has shown higher accuracy and true positive rates and the false positive rate is lower with the highest accuracy being 95.36%

5 Existing Method

- The most widely used enterprise Intrusion Detection/ Prevention System is SNORT (Simple Network Over Real Traffic).
- SNORT is Rule-set based; the admin places a set of rules, when violated, the admin is notified.

5 Existing Method

S.N.O.R.T Methodology

- SNORT uses a configuration file which includes a set of rules.
- The ruleset follows a basic general syntax

<operation> <protocol> <source ip> <source port> -> <destination ip> <destination port> {msg: " Attack Type",sid:100001}

alert icmp any any -> <server/target ip> any {msg:"ICMP Attack",sid:100001}

- Run SNORT in the terminal with the following command:

sudo snort -A console -q -c /etc/snort/snort.conf

06 Proposed Method

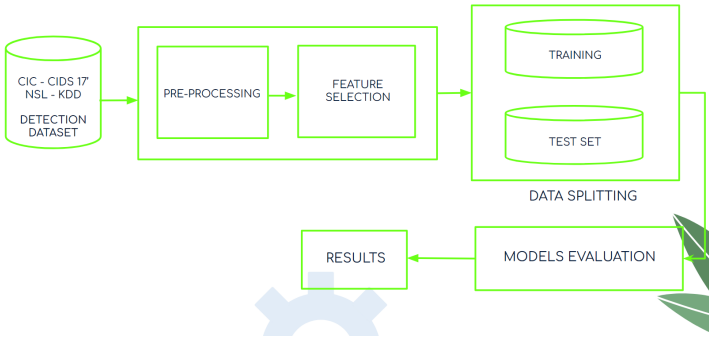
For the Intrusion Detection System, we use Deep Convolutional Neural Networks, Long Short Term Memory as the deep learning algorithms.

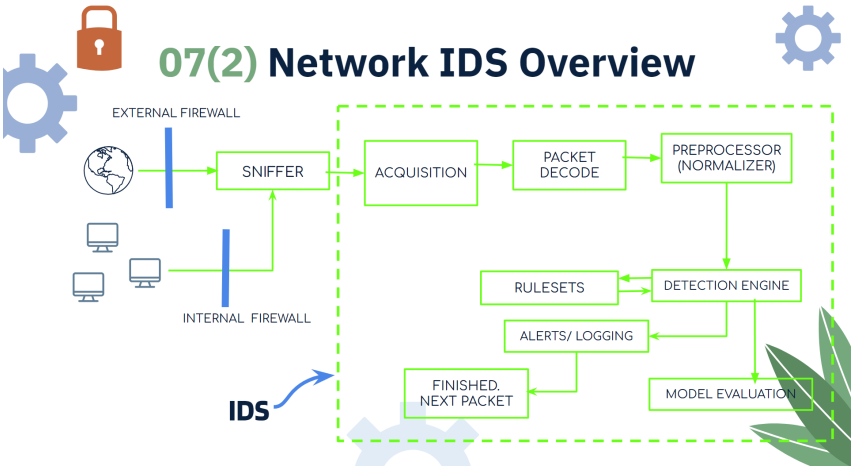
- Train the model with the CIC IDS 2017 and KDD Cup 99' dataset for the detection of bot, bruteforce, SQL injection and Denial of Service attacks.
- For the IDS, and rule-set formulation, we will use the libpcap library for SNORT, an Intrusion Prevention System and analyse traffic with the aid of Wireshark.

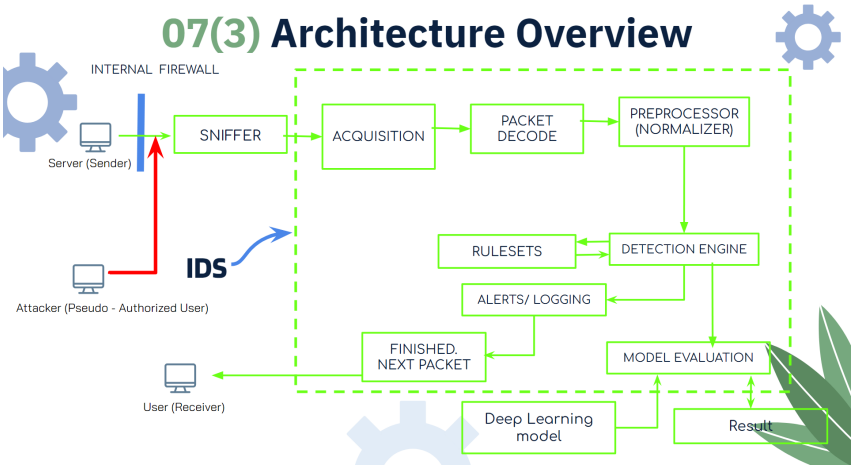
07 Architecture Diagram

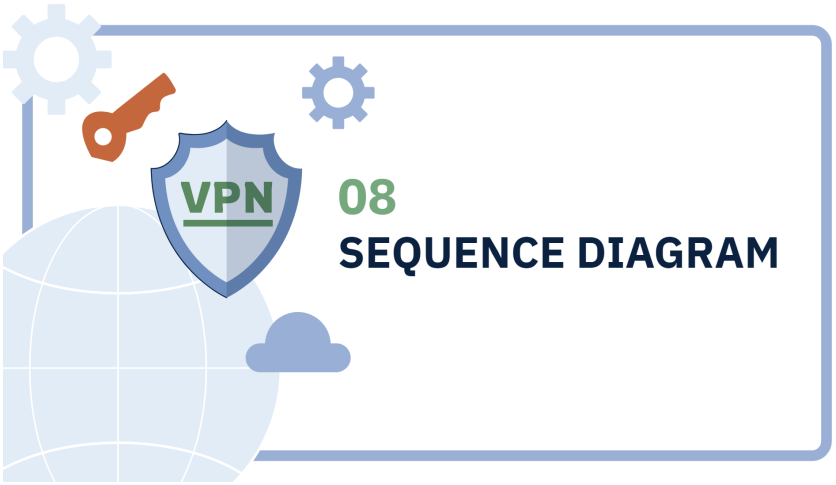
Describes how the ids model works

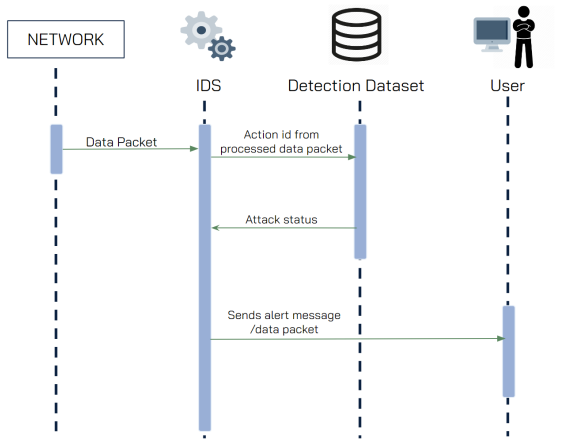
07(1) Deep Learning Model




07(2) Network IDS Overview
EXTERNAL FIREWALL
SNIFFER
ACQUISITION
PACKET DECODE
PREPROCESSOR (NORMALIZER)
RULESETS
DETECTION ENGINE
ALERTS/ LOGGING
FINISHED. NEXT PACKET
MODEL EVALUATION
INTERNAL FIREWALL
IDS


07(3) Architecture Overview
INTERNAL FIREWALL
Server (Sender)
SNIFFER
ACQUISITION
PACKET DECODE
PREPROCESSOR (NORMALIZER)
IDS
RULESETS
DETECTION ENGINE
ALERTS/ LOGGING
Attacker (Pseudo - Authorized User)
FINISHED. NEXT PACKET
MODEL EVALUATION
User (Receiver)
Deep Learning model
Result


VPN
08
SEQUENCE DIAGRAM

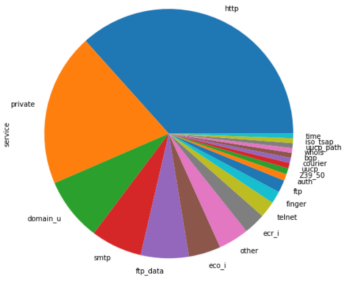


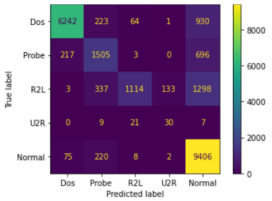
9 Module Division

Module	Topics	Content division
1	Obtaining the datasets	Tejas Ananthajith, Rahul
2	Coding the neural network	Thejus PS, Sleety
3	Training the neural network	Thejus PS, Rahul
4	Evaluation of neural network	Tejas Ananthajith, Thejus PS
5	Setting Up IDS rulesets	Sleety, Rahul
6	Integration of IDS with deep learning model	Sleety, Thejus

10 Module Wise Diagram

1. Deep Learning on NSL-KDD 1999:






```
TPR Normal: 96.85923179899083% - FPR Normal: 22.839554274136995%
TPR Dos: 83.67292225201072% - FPR Dos: 1.9557146645452135%
TPR Probe: 62.16439487814952% - FPR Probe: 3.9208865477314516%
TPR R2L: 38.61351819757365% - FPR R2L: 0.4883259575766824%
TPR U2R: 44.77611940298507% - FPR U2R: 0.6050629532410909%
```

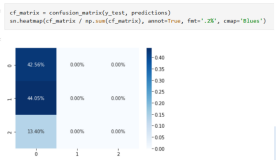
10 Module Wise Diagram

2. Deep Learning on CIC IDS 2018:

https://github.com/WhiteHatCyberus/Deep-Model-Evaluation-Intrusion-Detection-System-using-NSL-KDD-CIC-IDS-2018/blob/main/Group6_cicids_FFNN.ipynb

```
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model.fit(X_train, y_train, epochs=5)
model.save('drive/MyDrive/cicids/FFNN_MC')
```

```
Epoch 1/5
26215/26215 [==============================] - 59s 2ms/step - loss: 0.0174 - accuracy: 0.9971
Epoch 2/5
26215/26215 [==============================] - 58s 2ms/step - loss: 0.0117 - accuracy: 0.9983
Epoch 3/5
26215/26215 [==============================] - 61s 2ms/step - loss: 0.0115 - accuracy: 0.9983
Epoch 4/5
26215/26215 [==============================] - 57s 2ms/step - loss: 0.0114 - accuracy: 0.9983
Epoch 5/5
26215/26215 [==============================] - 59s 2ms/step - loss: 0.0114 - accuracy: 0.9983
```



11 Assumptions

- We are assuming that the dataset do not contain any duplicate values.
- It is free from noise
- There is no interference
- The integrity of the dataset is maintained.

11 Assumptions

- The advancement in technology is static
- The real world conditions don't change drastically.

12 Work Breakdown

13(1) System Overview

1: Operating System
Windows / Unix / Linux

The IDS supports leading operating Systems used by Enterprises, gives flexibility and agility between servers.

2: Virtual Machine
Sender, Receiver, Attacker

VM to host multiple OS at the same time

3: Programming Language
Python / C

Python is used to study deep learning models and C is used for socket creation and network transmission purposes.

13(2) System Requirements

Hardware:

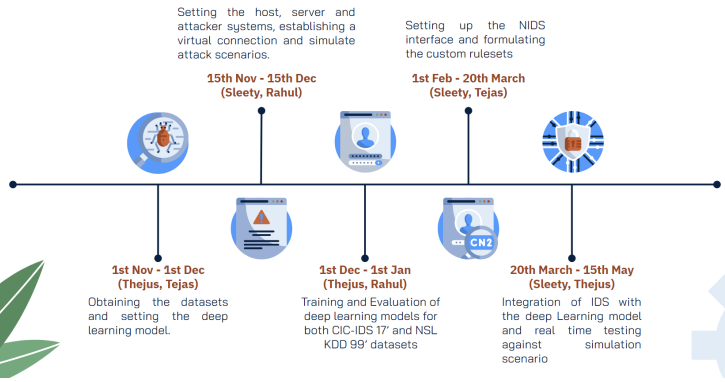
Devices: A computer, virtual machine, servers.
Processors: > Intel i3 8th gen
GPU: NViDia / AMD Ryzen (Preferred)
RAM: > 4 GB
Storage: > 20 GB

13(2) System Requirements

Software:

- **Programming Language: > Python 3.10** (100 MB)
- **OS: Kali Linux** (2.9 GB) **+ updates** (1.7 GB)
- **Oracle VirtualBox 7.0** (130 MB) **+ development kit** (2 MB)
- **Kali Tools:**
  - **Wireshark** (130 MB)
  - **Libpcap library** (13 KB)
  - **SNORT** (40 MB)
- **Databases:**
  - **NSL - KDD 99'** (2 GB)
  - **CICIDS 2017** (1.3 GB)

14 Schedules, Milestones and Deliverables



15 Project Timeline

TASKS	NOV				DEC				JAN				FEB				MARCH				APRIL			
WEEK	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
Dataset acquisition and deep learning model setup																								
Setting multiple virtual machines and establishing connection																								
Training and evaluation of DL model																								
Network IDS development and rule-set formulation																								
Integration and testing																								

Topics	Nov	Dec	Jan	Feb	March	April
Obtaining the datasets						
Coding the neural network						
Training the neural network						
Evaluation of neural network						
Setting Up IDS rulesets						
Integration of IDS with deep learning model						

Tejas,Rahul | Tejas,Thejus | Thejus,Sleety | Thejus,Rahul | Sleety,Rahul | Sleety,Thejus

17 Budget

- **IBM CYBERSECURITY ANALYST PROFESSIONAL CERTIFICATE** (Sleety George and Rahul C Karthik) - INR 4,399 per month
- **IBM AI ENGINEER PROFESSIONAL CERTIFICATE** (Thejus PS. and Tejas Anathajith) - INR 3,799 per month
- **D-LINK PORTABLE ROUTER**: INR 899
- **TOTAL**: 9,097

18 Conclusion

We have summarised five different research papers on Network Intrusion Detection Systems using Deep Learning as a Literature Survey and have designed our architecture and sequence model accordingly. This proposed method can implement a much better output by decreasing the rate of false positives.

19 REFERENCES

1. Asmaa Halbouni, Teddy Surya Gunawan, Mohamed Hadi Habaebi, Murad Halbouni, Mira Kartiwi, And Robiah Ahmad: "Machine Learning and Deep Learning Approaches for CyberSecurity: A Review" [24 Feb, 2022], IEEE Access

2. Gozde Karatas, Önder Demir And Ozgur Koray Sahingoz: "Increasing the Performance of Machine Learning-Based IDSs on an Imbalanced and Up-to-Date Dataset" [24 Feb, 2020], IEEE Access

3. Juan Fernando Cañola Garcia, Gabriel Enrique Taborda Blandona: "Deep Learning-Based Intrusion Detection and Prevention System for Detecting and Preventing Denial-of-Service Attacks" [5 Aug, 2022], IEEE Access

4. Aechan Kim, Mohyun Park, And Dong Hoon Lee : "AI-IDS: Application of Deep Learning to Real-Time Web Intrusion Detection"[10 Apr, 2020], IEEE Access

5. H. Yang and F. Wang, "Wireless Network Intrusion Detection Based on Improved Convolutional Neural Network" [17 May 2019]

6. Gabriel Chukwunonso Amaizu, Cosmas Ifeanyi Nwakanma, Jae- Min Lee, and Dong-Seong Kim: "Investigating Network Intrusion Detection Datasets Using Machine Learning"[16 May, 2021], IEEE Access

7. Chao Liu, Zhaojun Gu, Jialiang Wang:" A Hybrid Intrusion Detection System Based on Scalable K-Means + Random Forest and Deep Learning"[20 May,2021], IEEE Access

8. FatimaEzzahra Lagrissi, Samira Douzi, Khadija Douzi and Badr Hssina:" Intrusion Detection System using Long Short Term Memory"[2021], Springler Open

9. Wooseok Seo And Wooguil Pak: "Real Time Network Intrusion Prevention System Based on Hybrid Machine Learning" [17 March, 2021]

20 CO-PO MAPPING

CO1	Model and solve real world problems by applying knowledge across domains (Cognitive knowledge level: Apply).
CO2	Develop products, processes or technologies for sustainable and socially relevant applications (Cognitive knowledge level: Apply).
CO3	Function effectively as an individual and as a leader in diverse teams and to comprehend and execute designated tasks (Cognitive knowledge level: Apply).
CO4	Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms (Cognitive knowledge level: Apply).
CO5	Identify technology/research gaps and propose innovative/creative solutions (Cognitive knowledge level: Analyze).
CO6	Organize and communicate technical and scientific findings effectively in written and oral forms (Cognitive knowledge level: Apply).

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
CO1	2	2	2	1	2	2	2	2	1	1	1	2
CO2	2	2	2		1	3	3	1	1			1
CO3									3	2	2	1
CO4					2			3	2	2	3	2
CO5	2	3	3	1	2							1
CO6					2			2	2	3	1	1

Appendix C

CO-PO AND CO-PSO MAPPING

CO1	Identify academic documents from the literature which are related to her or his areas of interest (Cognitive knowledge level: Apply).
CO2	Read and apprehend an academic document from the literature which is related to her/ his areas of interest (Cognitive knowledge level: Analyze).
CO3	Prepare a presentation about an academic document (Cognitive knowledge level: Create).
CO4	Give a presentation about an academic document (Cognitive knowledge level: Apply).
CO5	Prepare a technical report (Cognitive knowledge level: Create).

Table 6.1: Course outcomes

	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	P0 8	PO 9	PO 10	PO 11	PO 12
CO1	2	2	1	1		2	1					3
CO2	3	3	2	3		2	1					3
CO3	3	2			3			1		2		3
CO4	3				2			1		3		3
CO5	3	3	3	3	2	2		2		3		3

Table 6.2: Mapping of course outcome for PO1-PO12.

	PSO 1	PSO 2	PSO 3
CO1	1		1
CO2	1		1
CO3	1		1
CO4	1		1
CO5	1		1

Table 6.3: Mapping of course outcome for PSO1-PSO3.

Mapping	LOW/ MEDIUM/ HIGH	Justification
CO1-PO1	2	Students will study the fundamentals in any specific domain of computer science by identifying academic documents from the literature.
CO1-PO2	2	The students will be able to analyze a given complex problem by identifying related academic documents from the literature.
CO1-PO3	1	The students will be able to develop and design solution to complex from related academic documents from the literature
CO1-PO4	1	The students will be able to understand the methodologies in design of experiments and interpretation of data through identified academic literature.
CO1-PO6	2	The students will be able to understand needs of the society through identified academic literature.

CO1-PO7	1	The students will be able to understand the environment and its sustainability through identified academic literature.
CO1-PO12	3	The students will be able to correlate to life long learning through identified academic literature.
CO1-PSO1	1	Students will be able to to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas through identified academic literature.
CO1-PSO3	1	Students will have the ability to apply the fundamentals of computer science in competitive research through academic literature.
CO2-PO1	3	Students will study the fundamentals in any specific domain of computer science by reading and apprehending an academic document from the literature.
CO2-PO2	3	The students will be able to analyze a given complex problem by reading and apprehending an academic document from the literature.
CO2-PO3	2	The students will be able to develop and design solution to complex problems by reading and apprehending an academic document from the literature.
CO2-PO4	3	The students will be able to understand the methodologies in design of experiments and interpretation of data by reading and apprehending an academic document from the literature.

CO2- PO6	2	The students will be able to understand needs of the society by reading and apprehending an academic document from the literature.
CO2- PO7	1	The students will be able to understand the environment and its sustainability by reading and apprehending an academic document from the literature.
CO2-PO12	3	The students will be able to correlate to life long learning by reading and apprehending an academic document from the literature
CO2-PSO1	1	Students will be able to to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas by reading and apprehending an academic document from the literature.
CO2-PSO3	1	Students will have the ability to apply the fundamentals of computer science in competitive research by reading and apprehending an academic document from the literature.
CO3-PO1	3	Students will study the fundamentals in any specific domain of computer science by preparing a presentation about an academic document.
CO3-PO2	2	Students will be able to analyze a given complex problem by preparing a presentation about an academic document.
CO3-PO5	3	Students will be able to familiarize the usage of a tool by preparing a presentation about an academic document.

CO3-PO8	1	Students will understand the principles of ethics while preparing a presentation about an academic document.
CO3-PO10	2	Students will develop communication skills while preparing a presentation about an academic document.
CO3-PO12	3	Students will be able to correlate to life long learning while preparing a presentation about an academic document.
CO3-PSO1	1	Students will be able to to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas while preparing a presentation about an academic document.
CO3-PSO3	1	Students will have the ability to apply the fundamentals of computer science in competitive research while preparing a presentation about an academic document.
CO4-PO1	3	Students will study the fundamentals in any specific domain of computer science by giving a presentation about an academic document.
CO4-PO5	2	Students will be able to familiarize the usage of a tool by giving a presentation about an academic document.
CO4-PO8	1	Students will understand the principles of ethics while giving a presentation about an academic document.
CO4-PO10	3	Students will develop communication skills while giving a presentation about an academic document.

CO4-PO12	3	Students will be able to correlate to life long learning while giving a presentation about an academic document.
CO4-PSO1	1	Students will be able to to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas while giving a presentation about an academic document.
CO4-PSO3	1	Students will have the ability to apply the fundamentals of computer science in competitive research while giving a presentation about an academic document.
CO5-PO1	3	Students will study the fundamentals in any specific domain of computer science while preparing a technical report.
CO5-PO2	3	Students will be able to analyze a given complex problem while preparing a technical report.
CO5-PO3	3	Students will be able to develop and design solution to complex problems while preparing a technical report.
CO5-PO4	3	Students will be able to understand the methodologies in design of experiments and interpretation of data while preparing a technical report.
CO5-PO5	2	Students will be able to familiarize the usage of a tool while preparing a technical report.
CO5-PO6	2	Students will be able to connect to the needs of the society while preparing a technical report.

CO5-PO8	2	Students will understand the principles of ethics while preparing a technical report.
CO5-PO10	3	Students will develop communication skills while preparing a technical report.
CO5-PO12	3	Students will be able to correlate to life long learning while preparing a technical report.
CO5-PSO1	1	Students will be able to to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas while preparing a technical report
CO5-PSO3	1	Students will have the ability to apply the fundamentals of computer science in competitive research while preparing a technical report