

**A Project Report
on
REAL-TIME INTRUSION DETECTION SYSTEM
USING MACHINE LEARNING ALGORITHM**

Submitted in partial fulfillment of the requirements

for the award of degree of

BACHELOR OF TECHNOLOGY

in

Information Technology

by

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(NAAC 'A' Grade & NBA Accredited- ECE, EEE, CSE, IT)

June, 2023

DECLARATION

We hereby declare that the work presented in this project entitled “**Real-Time Intrusion Detection System Using Machine Learning Algorithm**” submitted towards completion of the Project in IV year II sem of B.Tech IT at “BVRIT HYDERABAD College of Engineering for Women”, Hyderabad is an authentic record of our original work carried out under the esteemed guidance of Mr. K. Srikar Goud, Assistant Professor, Department of Information Technology.

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CERTIFICATE

This is to certify that the Major-Project report on **“Real-Time Intrusion Detection System using Machine Learning Algorithm”** is a bonafide work carried out by **M. Shivani (19WH1A1213), B. V. S. Selvi Reddy (19WH1A1215), Ch. Shravyasree (19WH1A1227) and J. Shreeya Reddy (19WH1A1234)** in the partial fulfillment for the award of B.Tech degree in **Information Technology, BVRIT HYDERABAD College of Engineering for Women, Bachupally, Hyderabad** affiliated to Jawaharlal Nehru Technological University, Hyderabad under my guidance and supervision.

The results embodied in the project work have not been submitted to any other university or institute for the award of any degree or diploma.

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ABSTRACT

Recent advancements in network technology and associated services have led to a rapid increase in data traffic. However, the detrimental effects caused by cyberattacks have also significantly increased. Network attacks are evolving in various forms. An essential instrument for monitoring and identifying intrusion threats is the intrusion detection system (IDS). With a focus on datasets, ML methods, and metrics, this study tries to analyse recent IDS research using a Machine Learning approach. The task is to build an intrusion detector, a predictive model capable of distinguishing between bad intrusions or attacks and good normal connections. We proposed an IDS algorithm based on supervised machine learning methods for developing such an efficient and flexible system that can detect intrusions from the data received in real-time. Finally, an intrusion detection system based on the Random Forest classifier is built using the optimal training dataset obtained by data sampling and the features selected by feature selection. The experiment will be carried out on the CICIDS2017 dataset. Compared with other algorithms, the model has obvious advantages in detecting rare anomalous behaviours.

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ABBREVIATIONS

Abbreviation	Meaning
IDS	Intrusion Detection System
SIEM	Security Information and Event Management
HIDS	Host-based IDS
NIDS	Network-based IDS
GPU	Graphics Processor Unit
SVM	Support Vector Machine
TCP	Transmission Control Protocol
VM	Virtual Machine
DOS	Denial Of Service Attack
DDOS	Distributed Denial Of Service Attack
HTTP	Hyper Text Transfer Protocol
IDPS	Intrusion Detection and Prevention Techniques
KNN	K-Nearest Neighbour
ANN	Artificial Neural Network
SMOTE	Synthetic Minority Over Sampling Technique
RST	Rough Set Theory
PCA	Principal Component Analysis

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1. INTRODUCTION

An intrusion detection system (IDS) is a tool for spotting unusual activity in network traffic and sending out alerts when it is found. It is software that checks a system or network for malicious activities. Any illegal activity or violation is often recorded either centrally using a security information and event management (SIEM) system or notified to an administrator. A SIEM system combines outputs from several sources and employs alarm filtering methods to distinguish between legitimate and erroneous alarms. While monitoring networks for potentially harmful behavior, intrusion detection systems are also prone to raising false alarms. Consequently, enterprises must adjust their IDS products after initial installation. It entails correctly configuring intrusion detection systems to distinguish between legitimate network traffic and malicious activities.

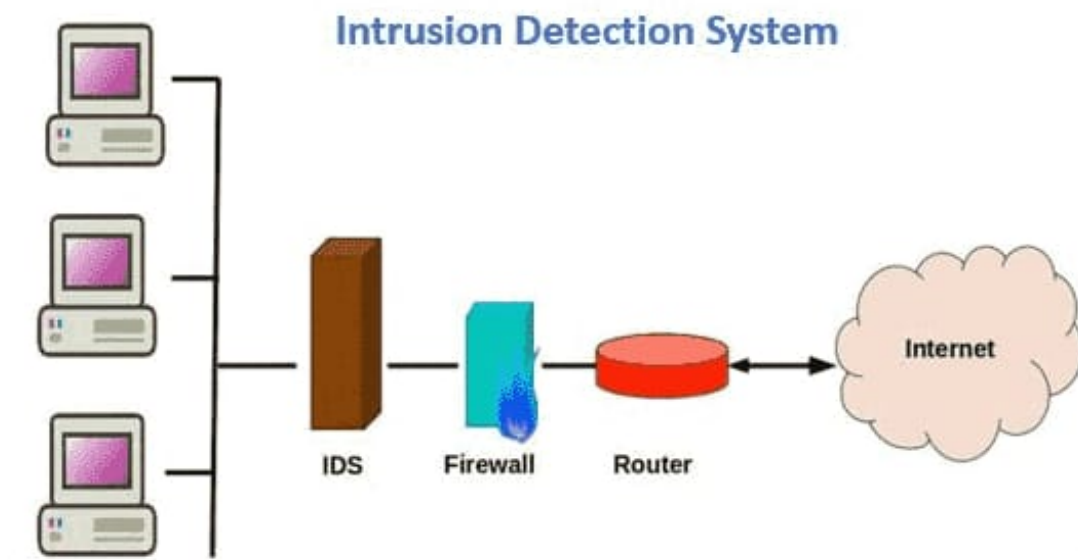


Figure 1.1: General idea of an IDS

IDS is a great way to protect your business' network environment from cyberattacks. Network-based and host-based intrusion detection systems are the two major classifications of an Intrusion Detection System. They are as follows:

1. Network Intrusion Detection System (NIDS): They are installed at a predetermined location within the network to monitor all network traffic coming from all connected devices. It carries out an observation of all subnet traffic passing through and compares that traffic to a database of known attacks. The alert can be delivered to the Administrator as soon as an attack is detected or unusual behaviour is noticed. Installing a NIDS on the subnet where firewalls are to check for attempts to breach the firewall is an example of a NIDS in action.

2. Host-based Intrusion Detection System (HIDS): Host intrusion detection systems (HIDS) are network applications that run on separate hosts or gadgets. Only the incoming and outgoing packets from the device are monitored by a HIDS, which 4 notifies the administrator of any unusual or malicious behaviour. It compares the current snapshot of the system files with the previous snapshot. An alert is given to the administrator to look into if the analytical system files were altered or deleted. On mission-critical devices, when the layout is not anticipated to change, HIDS is being used as an example.

Machine Learning in IDS

To fulfill the requirements of an effective IDS, the researchers have explored the possibility of using machine learning (ML) and deep learning (DL) techniques. Both ML and DL come under the big umbrella of artificial intelligence (AI) and aim at learning useful information from the big data. These techniques have gained enormous popularity in the field of network security, over the last decade due to the invention of very powerful graphics processor units (GPUs). Both ML and DL are powerful tools in learning useful features from the network traffic and predicting the normal and abnormal activities based on the learned patterns. The ML-based IDS depends heavily on feature engineering to learn useful information from the network traffic. While DL-based IDS do not rely on feature engineering and are good at automatically learning complex features from the raw data due to its deep structure.

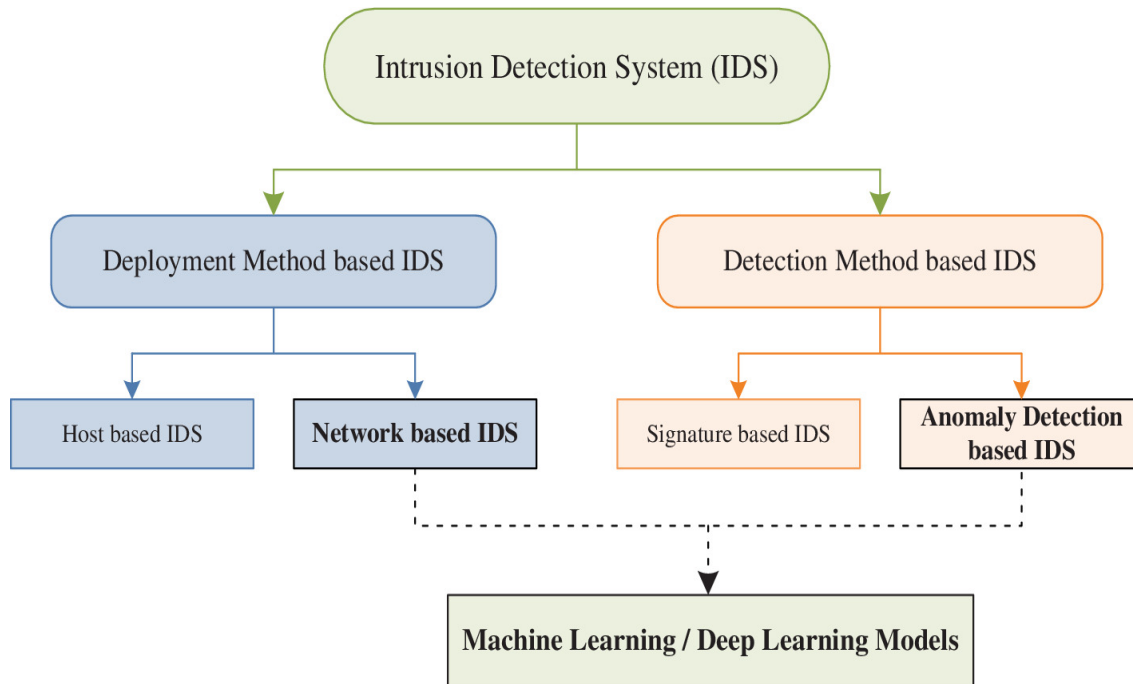


Figure 1.2: Classification of IDS based on Machine Learning

1.1 Objective

As it can be seen that the advancements in the technology of Computer Science not only is of beneficial purposes but it also comes with a cost of certain issues. If these are to be countered then we need newer types of security mechanisms and systems to protect computers as well as IOT nodes for a normal operating of the systems on a whole. So this leads to a need of stronger, faster and efficient Intrusion Detection and Prevention systems. This can be done in a real-time basis for enhanced protection and quicker response, using machine learning algorithms which reduce the manual labour and is better when compared to traditional IDS’.

The main objective of this project is to make a, “Real-Time Intrusion Detection System using Machine Learning algorithms”, such that examining machine learning methods for intrusion detection in order to improve accuracy, decrease false alarms, and shorten training time for intrusion detection, it is necessary to discover an appropriate machine learning algorithm.

1.2 Problem Definition

In order to enhance the effectiveness of Intrusion Detection Systems (IDS), finding an appropriate machine learning algorithm is crucial. IDS serves as a vital tool to monitor networks and systems for any signs of malicious activities or policy violations. By leveraging machine learning algorithms, IDS can improve accuracy, reduce false alarms, and expedite the training process. Machine learning algorithms enable IDS to analyze large volumes of data and identify patterns indicative of potential intrusions or anomalies. These algorithms can learn from historical data, identify regular network behavior, and detect deviations from normal patterns. Through continuous training and feedback loops, IDS can adapt to evolving threats and improve its detection capabilities over time. Selecting an appropriate machine learning algorithm is vital to the success of IDS. Different algorithms, such as decision trees, random forests, support vector machines, or deep learning models, have distinct strengths and weaknesses. The choice of algorithm depends on the specific requirements of the IDS, including the nature of the data, computational resources, and the desired trade-off between detection accuracy and training time. Ultimately, the discovery of an appropriate machine learning algorithm empowers IDS to effectively safeguard networks and systems by efficiently identifying and mitigating potential threats, reducing false positives, and optimizing detection accuracy.

2. LITERATURE SURVEY

Sharma, R., Verma, N. K. [2]. The objective of the research is to develop an IDS that combines multiple detection techniques to enhance the accuracy and efficiency of anomaly detection. The proposed IDS architecture consists of two main components: feature selection and ensemble-based classification. In the feature selection phase, a set of relevant features is extracted from the network traffic data. The authors employ a combination of statistical and information-theoretic measures to identify the most discriminative features for anomaly detection. After feature selection, the ensemble-based classification phase is employed to classify the network traffic as either normal or anomalous. The authors utilize an ensemble of classifiers, including k-nearest neighbors (KNN), support vector machines (SVM), and decision trees. Each classifier in the ensemble independently makes predictions, and the final classification is determined by combining the predictions through voting or weighted averaging. To evaluate the performance of the proposed IDS, the authors conducted experiments using several publicly available network traffic datasets. The performance metrics such as accuracy, precision, recall, and F1-score were used to assess the effectiveness of the system. The results were compared with other existing IDS methods.

Zhou, Y., Guo, L., Liu, R., Zhang, W. [3] introduces a deep learning-based real-time intrusion detection system (IDS) specifically designed for the Industrial Internet of Things (IIoT) environment. The objective of the research is to address the security challenges faced by IIoT systems and develop an effective IDS that can detect intrusions in real-time. The proposed IDS architecture incorporates deep learning techniques to enhance the accuracy and efficiency of intrusion detection in IIoT environments. It consists of three main components: data preprocessing, feature extraction, and intrusion detection. In the data preprocessing phase, raw data collected from IIoT devices is preprocessed to remove noise and outliers. Various techniques such as data normalization and denoising are applied to ensure the quality of the data. The feature extraction phase aims to extract meaningful features from the preprocessed data. Deep learning models, such as convolutional neural networks (CNNs) and long short-term memory networks (LSTMs), are employed to automatically

learn relevant features from the IIoT data. These models capture both spatial and temporal dependencies present in the data, allowing for effective representation learning.

Shamsi, J. A., Khayam, S. A., Karim, R. [4]. The objective of the research is to provide a thorough overview of the existing literature on intelligent IDS and analyze the various approaches, techniques, and technologies employed in this domain. The authors begin by discussing the importance of intrusion detection systems in safeguarding computer networks from malicious activities. They emphasize the need for intelligent IDS, which leverage advanced techniques to enhance the accuracy, efficiency, and adaptability of intrusion detection. The survey covers a wide range of topics related to intelligent IDS, including anomaly detection, misuse detection, machine learning-based approaches, ensemble methods, and hybrid models. The authors delve into each topic, discussing the underlying principles, methodologies, and advantages and disadvantages associated with different techniques. Anomaly detection is one of the primary approaches examined in the survey. It focuses on identifying deviations from normal behavior in network traffic or system activities. The authors discuss various anomaly detection techniques, such as statistical methods, clustering algorithms, and artificial intelligence-based approaches. Misuse detection, on the other hand, aims to detect known attack patterns or signatures. The authors provide insights into signature-based approaches, rule-based methods, and pattern matching techniques commonly used in misuse detection systems. Machine learning-based approaches play a significant role in intelligent IDS. The survey explores different machine learning algorithms, including decision trees, support vector machines, neural networks, and ensemble methods. The authors discuss the strengths and limitations of each algorithm in the context of intrusion detection.

Gwee, B. H., Koay, K. Y., Zaidan, B. B.[5] provides a comprehensive survey of intrusion detection systems (IDS) in the context of the Internet of Things (IoT). The authors aim to offer an overview of the existing IDS techniques specifically designed for IoT environments. The article begins by discussing the unique challenges and security concerns in IoT networks, highlighting the

need for robust IDS solutions to protect IoT devices and networks from intrusions. It emphasizes the limitations of traditional IDS approaches in the context of IoT, such as resource constraints, heterogeneity, and scalability. The authors survey a wide range of IDS techniques proposed for IoT networks, including anomaly-based detection, signature-based detection, hybrid approaches, and machine learning-based methods. They analyze the key features, advantages, and limitations of each approach, providing a comprehensive understanding of the state-of-the-art IDS techniques in IoT. The survey covers various aspects of IDS in IoT, including the types of data analyzed, detection methodologies, deployment strategies, and performance evaluation metrics. The authors also discuss the datasets commonly used for training and evaluating IDS in IoT, along with the challenges specific to IoT environments.

Chiang, C.-C., Lin, C.-C., Huang, S.-C., Tsai, C.-F.[6] focuses on the application of Convolutional Neural Networks (CNN) for intrusion detection in Software-Defined Networking (SDN) networks. The authors propose an approach that utilizes CNNs to detect and classify various types of attacks in SDN environments. The article begins by discussing the challenges and security concerns in SDN networks, emphasizing the need for effective intrusion detection mechanisms to protect against cyber threats. It highlights the advantages of using machine learning techniques, particularly CNNs, for capturing patterns and identifying malicious activities in network traffic data. The proposed IDS utilizes CNNs to analyze network traffic data and identify patterns associated with different types of attacks. The authors describe the architecture of the CNN-based IDS and explain the training process involved. They also discuss the selection and preprocessing of network traffic data for training and evaluation. To evaluate the performance of the proposed IDS, the authors conducted experiments using real-world datasets with various types of attacks. They compare the results of the CNN-based IDS with other machine learning approaches, demonstrating the superior detection accuracy and performance of the CNN model.

Kumari, P., Reddy, B. E.[7] focuses on the development of a real-time intrusion detection system (IDS) using deep learning models. The authors propose an approach that leverages the capabilities of deep learning algorithms to detect and classify intrusions in a real-time manner. The article begins by highlighting the increasing sophistication of cyber attacks and the need for robust intrusion detection systems that can detect and respond to threats in real-time. It discusses the limitations of traditional rule-based and signature-based IDS approaches and the potential of deep learning models to overcome these limitations. The proposed IDS utilizes two deep learning models: a Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) network. The CNN model is employed to learn spatial features from network traffic data, while the LSTM model captures temporal dependencies. The combined output of these models is used to detect and classify intrusions. The authors conducted experiments using a real-world dataset to evaluate the performance of the proposed IDS. They compare the results with traditional machine learning algorithms, demonstrating the superior performance of the deep learning models in terms of accuracy, precision, recall, and F1-score.

Sridhar, A., Varma, V. S.[8] presents an approach for building an intrusion detection system (IDS) using an ensemble of hybrid classifiers. The authors address the challenge of accurately detecting network intrusions by combining multiple classifiers with different strengths and weaknesses. The proposed ensemble model combines three different classifiers: k-Nearest Neighbors (k-NN), Random Forest (RF), and Support Vector Machine (SVM). Each classifier is trained independently on a subset of the available dataset. The ensemble combines the individual classifier outputs using a weighted voting scheme to make the final intrusion detection decision. The authors evaluate the performance of the proposed ensemble model using several performance metrics such as accuracy, precision, recall, and F1-score. The experimental results demonstrate that the ensemble of hybrid classifiers outperforms individual classifiers in terms of overall detection accuracy and other evaluation measures. The authors attribute this improvement to the diversity and complementary nature of the individual classifiers in the ensemble.

Balachandar, R., Ramachandran, M.[9] provides a comprehensive review of intrusion detection systems (IDS) using machine learning techniques in the context of Internet of Things (IoT) networks. The authors aim to offer a comprehensive understanding of the existing machine learning-based IDS approaches and their applicability in IoT environments. The article begins by discussing the unique challenges and security concerns in IoT networks, highlighting the need for effective IDS solutions to protect IoT devices and networks from intrusions. It emphasizes the limitations of traditional rule-based and signature-based IDS approaches in the context of IoT. The authors review a wide range of machine learning algorithms and techniques applied in IDS for IoT networks, including decision trees, support vector machines, artificial neural networks, and ensemble methods. They analyze the strengths, weaknesses, and suitability of each approach in the context of IoT environments. The comprehensive review covers various aspects of machine learning-based IDS for IoT, including the types of data analyzed, feature selection techniques, classification methods, and performance evaluation metrics. The authors also discuss the datasets commonly used for training and evaluating IDS in IoT, along with the challenges specific to IoT environments.

Aryan, A. A., Ghorbani, A. A., and Shafiee,[10] introduces a novel approach for developing a real-time intrusion detection system (IDS) by combining deep learning techniques and a sparse autoencoder. The main objective of the research is to enhance the accuracy and efficiency of intrusion detection by leveraging the capabilities of deep learning. The proposed methodology consists of two main phases: unsupervised pre-training and supervised fine-tuning. In the unsupervised pre-training phase, a sparse autoencoder is utilized to learn representative features from unlabeled training data. A sparse autoencoder is a type of neural network that learns to reconstruct input data while also imposing sparsity constraints on the learned features. This pre-training phase helps in extracting meaningful and discriminative features from the input data. After the unsupervised pre-training, the model moves to the supervised fine-tuning phase. In this phase, the pre-trained model is further trained using labeled data, where the labels indicate whether the data is normal or malicious. The

model is fine-tuned using a deep neural network architecture, allowing it to learn more discriminative representations specific to the task of intrusion detection.

Borgohain, B., Mahanta, M. K., Mahanta, M. K.[11] presents an approach for building an intrusion detection system (IDS) using an ensemble of hybrid classifiers. The authors address the challenge of accurately detecting network intrusions by combining multiple classifiers with different strengths and weaknesses. The proposed ensemble model combines three different classifiers: k-Nearest Neighbors (k-NN), Random Forest (RF), and Support Vector Machine (SVM). Each classifier is trained independently on a subset of the available dataset. The ensemble combines the individual classifier outputs using a weighted voting scheme to make the final intrusion detection decision. The authors evaluate the performance of the proposed ensemble model using several performance metrics such as accuracy, precision, recall, and F1-score. The experimental results demonstrate that the ensemble of hybrid classifiers outperforms individual classifiers in terms of overall detection accuracy and other evaluation measures. The authors attribute this improvement to the diversity and complementary nature of the individual classifiers in the ensemble.

Ammar, M., Zainal, A., and Budiarto, R.[12] The primary objective of the research is to evaluate and compare the performance of various machine learning algorithms in detecting intrusions in computer networks. To conduct the study, the researchers utilized the NSL-KDD dataset, which is a widely adopted benchmark dataset in the field of intrusion detection. This dataset consists of both normal and attack network traffic data, making it suitable for training and testing IDS models. The authors selected several popular machine learning algorithms, including Support Vector Machines (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and Naive Bayes (NB). The first step in the research process involved preprocessing the NSL-KDD dataset and extracting relevant features. These features encompassed various aspects of network communication, such as network protocol types, service types, the number of failed login attempts, and the number of root accesses. The extracted features were then used to train the different machine learning models. Next, the researchers

performed extensive experiments to evaluate the performance of the selected algorithms.

Alom, M. Z., Yakopcic, C., Taha, T. M., Asari, V. K., Islam, M. R. [13] explores the application of one-class classifiers in the context of intrusion detection systems (IDS). Traditional IDS typically require a large amount of labeled training data to effectively distinguish between normal and anomalous network behaviors. However, obtaining such data can be challenging and time-consuming. The authors propose the use of one-class classifiers, which are capable of learning from only positive (normal) instances without requiring negative (anomalous) samples. They argue that this approach is particularly suitable for scenarios where limited training data is available. The study evaluates the performance of several one-class classifiers, including Support Vector Data Description (SVDD) and One-Class Random Forest (OCRF), using different evaluation metrics. The experimental results demonstrate that the proposed one-class classifiers exhibit promising performance even with limited training data. The classifiers achieve high detection rates and low false alarm rates, suggesting their effectiveness in identifying network intrusions.

Chen, Y., Lv, Q., Zhang, T., Wang, Y.[14] presents a comprehensive survey of real-time intrusion detection systems (IDS) using machine learning techniques. The authors aim to provide an overview of the state-of-the-art machine learning-based IDS approaches that operate in real-time to detect network intrusions. The article begins by discussing the significance of real-time IDS in the context of ever-evolving and sophisticated cyber threats. The authors then review a wide range of machine learning algorithms and techniques employed in real-time IDS, including decision trees, support vector machines, artificial neural networks, ensemble methods, and deep learning approaches. They analyze the strengths and weaknesses of each algorithm in the context of real-time intrusion detection. The survey also covers various datasets used for training and evaluating real-time IDS, along with the performance metrics employed to assess their effectiveness. The authors highlight the importance of benchmark datasets and standardized evaluation metrics for fair comparisons and advancements in the field.

Hodo, E., Bellekens, X., Hamilton, A., Tachtatzis, C. [15] presents a comprehensive survey of real-time intrusion detection systems (IDS) using machine learning techniques. The authors aim to provide an overview of the state-of-the-art machine learning-based IDS approaches that operate in real-time to detect network intrusions. The article begins by discussing the significance of real-time IDS in the context of ever-evolving and sophisticated cyber threats. The authors then review a wide range of machine learning algorithms and techniques employed in real-time IDS, including decision trees, support vector machines, artificial neural networks, ensemble methods, and deep learning approaches. They analyze the strengths and weaknesses of each algorithm in the context of real-time intrusion detection. The survey also covers various datasets used for training and evaluating real-time IDS, along with the performance metrics employed to assess their effectiveness. The authors highlight the importance of benchmark datasets and standardized evaluation metrics for fair comparisons and advancements in the field.

Khraisat, A., Khan, L.[16]presents a comprehensive survey of real-time intrusion detection systems (IDS) using machine learning techniques. The authors aim to provide an overview of the state-of-the-art machine learning-based IDS approaches that operate in real-time to detect network intrusions. The article begins by discussing the significance of real-time IDS in the context of ever-evolving and sophisticated cyber threats. The authors then review a wide range of machine learning algorithms and techniques employed in real-time IDS, including decision trees, support vector machines, artificial neural networks, ensemble methods, and deep learning approaches. They analyze the strengths and weaknesses of each algorithm in the context of real-time intrusion detection. The survey also covers various datasets used for training and evaluating real-time IDS, along with the performance metrics employed to assess their effectiveness. The authors highlight the importance of benchmark datasets and standardized evaluation metrics for fair comparisons and advancements in the field.

Kaur, J., Singh, N., Singh, D., Mishra, A.[17] presents a comprehensive review of intrusion detection systems (IDS) for Internet of Things (IoT) networks. The authors aim to provide insights into the existing IDS techniques, propose a taxonomy to categorize them, and highlight open research issues in this domain. The article begins with an overview of the IoT landscape and the need for IDS to secure IoT networks against various threats and attacks. The authors then review and analyze a wide range of IDS techniques proposed for IoT, including anomaly-based detection, signature-based detection, hybrid approaches, and machine learning-based methods. They discuss the key features, advantages, and limitations of each approach. To provide a structured understanding of the IDS techniques, the authors propose a taxonomy that classifies them based on several factors, such as the type of data analyzed (packet-level, flow-level, or event-level), detection methodology (behavioral or rule-based), and deployment location (edge, fog, or cloud). The article also identifies and discusses open research issues in the field of IDS for IoT networks.

3. SYSTEM DESIGN

3.1 UML Diagrams

UML is an acronym that stands for Unified Modeling Language. Simply put, UML is a modern approach to modeling and documenting software. In fact, it's one of the most popular business process modeling techniques. It is based on diagrammatic representations of software components. A UML diagram with the purpose of visually representing a system along with its main actors, roles, actions, artifacts or classes, in order to better understand, alter, maintain, or document information about the system.

3.1.1 Sequence Diagram

A sequence diagram is a valuable tool in UML (Unified Modeling Language) for visualizing and understanding the interactions and flow of messages between objects or components in a system. With its graphical representation, a sequence diagram captures the dynamic behavior of a system, providing insights into how different elements collaborate and communicate over time. At the heart of a sequence diagram are lifelines, which represent individual participants in the system. Lifelines are depicted as vertical lines, often labeled with the name of the participant. They serve as the visual entities through which the interactions occur. Along these lifelines, activations or execution occurrences are shown, indicating when an object or component is actively executing a method or processing a message. Activations are depicted as horizontal lines attached to the lifelines, often marked with a vertical dashed line to represent the completion of the execution.

The primary purpose of a sequence diagram is to illustrate the messages exchanged between lifelines. Messages can be synchronous or asynchronous, representing different types of communication. Synchronous messages, denoted by solid lines with arrowheads, indicate that the sender is blocked until a response is received. Asynchronous messages, on the other hand, are represented by dashed lines with open arrowheads, signifying that the sender continues its execution without waiting for a response. In addition to regular messages, sequence diagrams include return

messages to represent the response from the receiver back to the sender. Return messages signify the flow of control returning to the sender after the completion of an invoked operation. They are displayed as dashed lines with an open arrowhead pointing back to the sender, indicating the completion of the response.

To depict complex behaviors and control structures within a sequence diagram, combined fragments are used. Combined fragments allow the modeling of loops, conditionals, or parallel executions. They provide a way to represent different scenarios and constraints that govern the execution of the fragment. Interaction operands, which are part of combined fragments, define conditions or constraints for executing the fragment. They specify when and how many times the fragment should be executed based on the defined conditions.

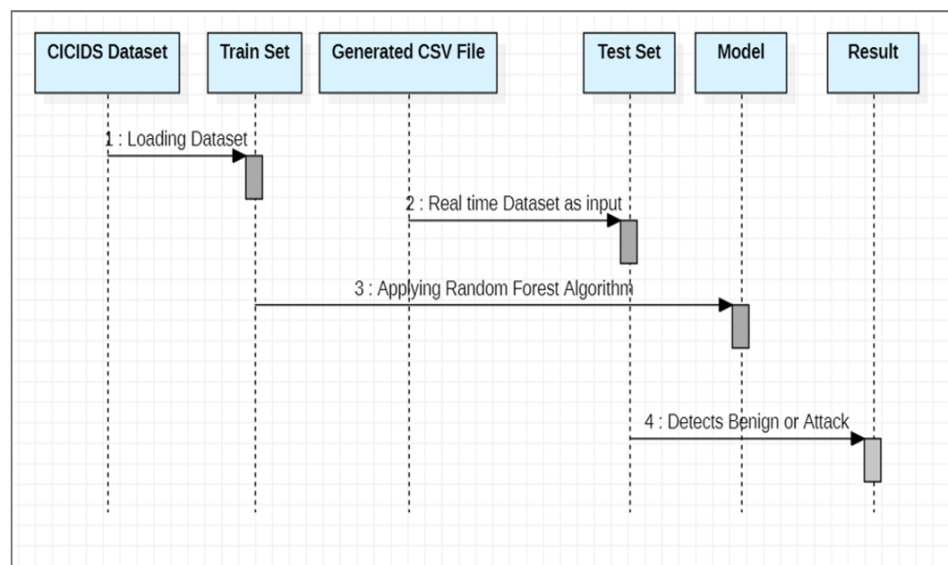


Figure 3.1.1.1: Sequence Diagram

3.1.2 Use Case Diagram

A use case diagram is a type of UML (Unified Modeling Language) diagram that helps visualize the functional requirements of a system from the perspective of its users or actors. It provides a high-level view of the system's behavior and illustrates the interactions between actors and the system through various use cases. With its graphical representation, a use case diagram serves as a communication tool between stakeholders, facilitating the understanding of system functionality and requirements. The key components of a use case diagram are actors, use cases, and relationships. Actors represent the roles that interact with the system. An actor can be a person, an external system, or even another software component. Actors are depicted as stick figures or labeled blocks outside the system boundary. Use cases represent the specific functionalities or tasks that the system provides to its actors. Each use case represents a distinct unit of functionality that the system can perform. Use cases are depicted as ovals within the system boundary and are labeled with descriptive names that reflect the actions performed by the system. The interactions between actors and use cases are illustrated through relationships.

There are two main types of relationships in a use case diagram:

- **Include relationship:** It signifies that one use case includes the functionality of another use case. It is represented by a dashed arrow from the including use case to the included use case.
- **Extend relationship:** It indicates that one use case extends the behavior of another use case under certain conditions. It is represented by a dashed arrow with the keyword *.extends* from the extending use case to the extended use case.

The use case diagram provides a high-level overview of the system's functionality and the interactions between actors and use cases. It helps stakeholders identify the different user roles and their requirements, as well as the various tasks the system needs to perform. By visualizing these interactions, the use case diagram aids in the understanding and documentation of the system's behavior and requirements. One of the key benefits of a use case diagram is its ability to facilitate communication among stakeholders. It provides a common visual language that can be easily

understood by both technical and non-technical team members. Use case diagrams serve as a basis for discussion and collaboration, enabling stakeholders to validate and refine the system's functionality and requirements.

Moreover, use case diagrams also assist in identifying potential system boundaries and scope. By analyzing the interactions between actors and use cases, stakeholders can determine which functionalities should be included or excluded from the system. This helps in defining the system's boundaries and ensuring that it addresses the specific needs of the users. Use case diagrams are not intended to provide detailed implementation or design information. They focus on the high-level requirements and functionality of the system. Use case diagrams can be used as a foundation for creating more detailed UML diagrams, such as activity diagrams or sequence diagrams, which provide a deeper understanding of the system's behavior and internal workings.

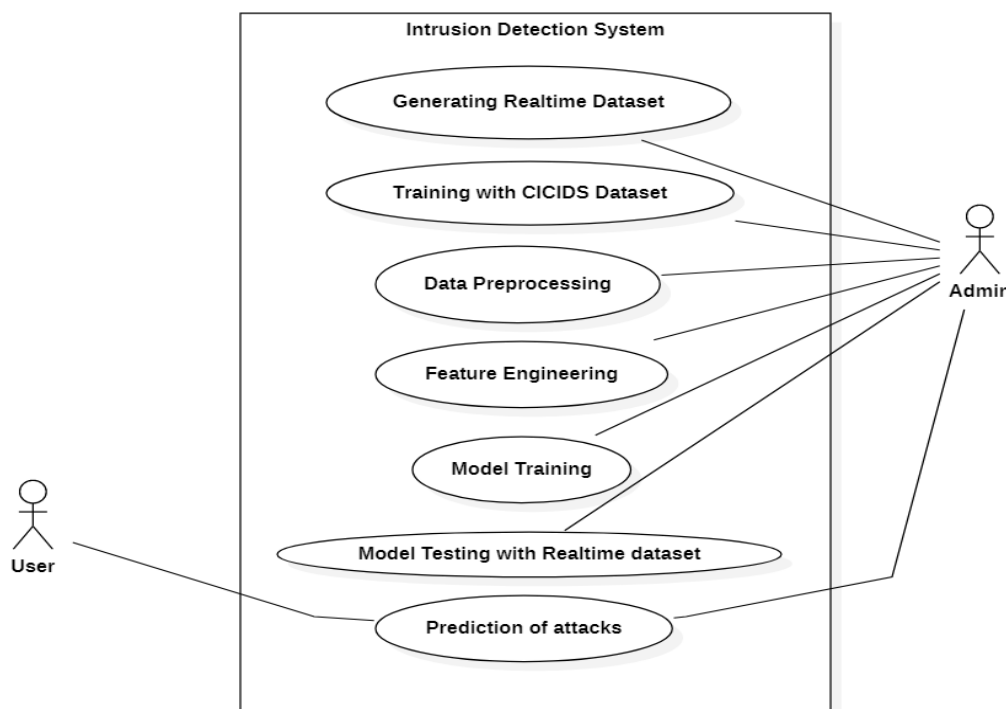


Figure 3.1.2.1: Use Case Diagram

3.2 Software & Hardware Requirements

Hardware Requirements

- Operating System: Windows 11
- Processor: Intel I5
- Hard disk: 1TB

Software Requirements

- Google Colaboratory
- Wireshark
- CIC Flowmeter
- VirtualBox
- Virtual Machines

3.2.1 Google Colaboratory

Google Colaboratory, also known as Google Colab, is a cloud-based development environment that enables users to write, execute, and share Python code in a Jupyter Notebook-like interface. It offers several key features such as free access to GPUs and TPUs, pre-installed libraries, and integration with Google Drive and GitHub. Colab allows users to work entirely in the cloud, eliminating the need for local setup and maintenance. It supports real-time collaboration, enabling multiple users to work on the same notebook simultaneously. Users can easily share their notebooks with others, making it a useful tool for collaboration and code sharing. One of the standout features of Colab is its provision of free GPU and TPU support. This allows users to leverage powerful hardware acceleration for computationally intensive tasks like deep learning.

The platform comes with pre-installed libraries commonly used in data science and machine learning, saving users the hassle of installing dependencies. Colab integrates seamlessly with Google Drive, allowing users to store and access their notebooks directly. It also offers integration with GitHub for version control and code sharing. With its user-friendly interface and powerful features, Google Colaboratory has become popular among data scientists, researchers, and developers for various coding and data analysis tasks.

3.2.2 Wire Shark

Wireshark is a network protocol analyzer that examines data packets over a network. Time, source and destination, protocol, and other factors can all be investigated. Filtering, searching based on set criteria, and data dump in a variety of formats for analysis are just a few of the capabilities that Wireshark offers. It is a packet sniffer and analysis tool. It captures network traffic on the local network and stores that data for offline analysis. Wireshark captures network traffic from Ethernet, Bluetooth, Wireless, Token Ring, Frame Relay connections, and more. You can narrow down and focus on the network trace that you're looking for with Wireshark by filtering the log either before the capture begins or while you're analyzing it.

You can configure a filter, for instance, to view TCP traffic between two IP addresses. You can configure it to only display packets sent by a single computer. One of the main reasons Wireshark became the industry standard tool for packet analysis is its filters. One device serves as the host in a real-world scenario and receives data via the internet. This data is then recorded using the wire shark tool and converted to '.pcap' format. Consequently, allowing the CICFlowMeter to extract the features from it. Wireshark is an open-source network protocol analyzer that allows users to capture, analyze, and inspect network traffic in real-time. It is widely used by network administrators, security professionals, and developers to troubleshoot network issues, perform network forensics, and analyze network protocols. With Wireshark, users can capture packets flowing across a network interface and view the details of each packet, including source and destination IP addresses, ports, protocols, and payload data.

It supports a wide range of network protocols and provides detailed information about the communication between network devices. Wireshark offers a powerful filtering and search functionality that allows users to focus on specific packets or protocols of interest. It also provides advanced features like protocol decodes, flow analysis, and statistics, which help in understanding network behavior and identifying anomalies or performance bottlenecks. One of the key advantages of Wireshark is its user-friendly graphical interface, which makes it accessible to both beginners and experienced users. It provides various display options and visualizations, including color-coded packet listings and interactive graphs, to aid in data analysis. Furthermore, Wireshark supports a large and active community, which contributes to its continuous development and provides access to a wide range of resources, including user guides, tutorials, and online forums. This community-driven nature ensures that Wireshark remains up-to-date with the latest network protocols and industry standards.

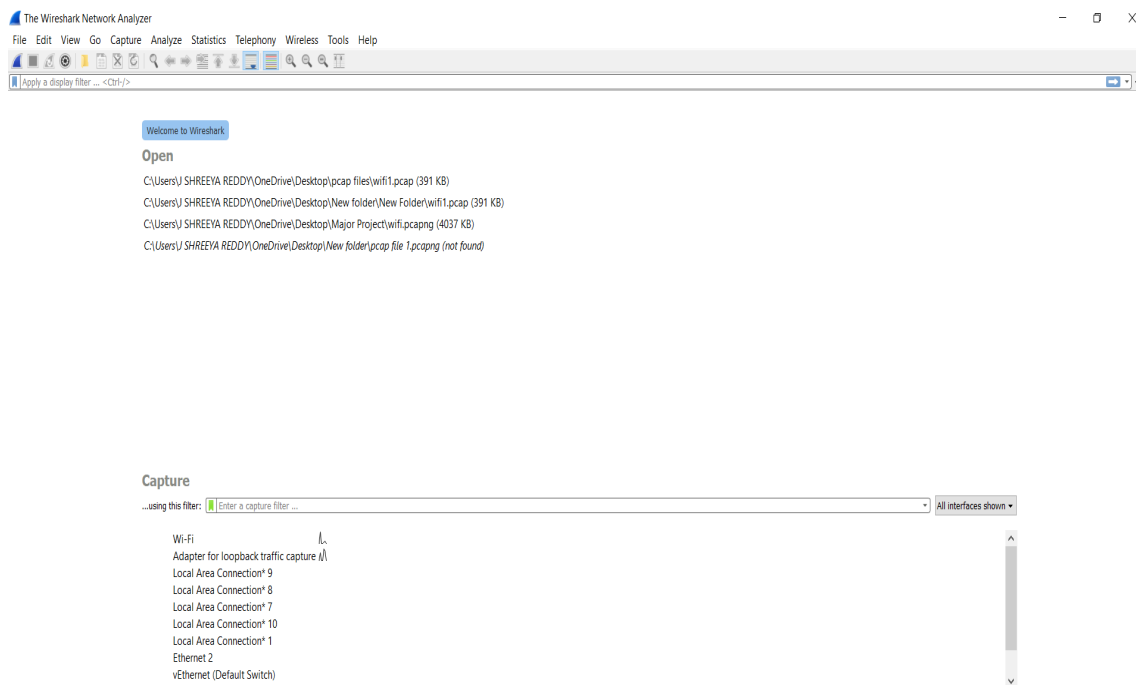


Figure 3.2.2.1 - Wireshark Tool

3.2.3 CIC Flow Meter

CIC Flow Meter is a network traffic flow generator and analyzer. More than 80 statistical network traffic features, such as Duration, Number of packets, Number of bytes, Length of packets, etc., can be calculated separately in the forward and backward directions when using it to generate bidirectional flows, where the first packet determines the forward (source to destination) and backward (destination to source) directions. Selecting features from a list of already-existing features, extracting new features, and adjusting the flow timeout period are additional functionalities. With more than 80 network traffic analysis capabilities, the application outputs a CSV file with six columns labelled for each flow (FlowID, SourceIP, DestinationIP, SourcePort, DestinationPort, and Protocol).

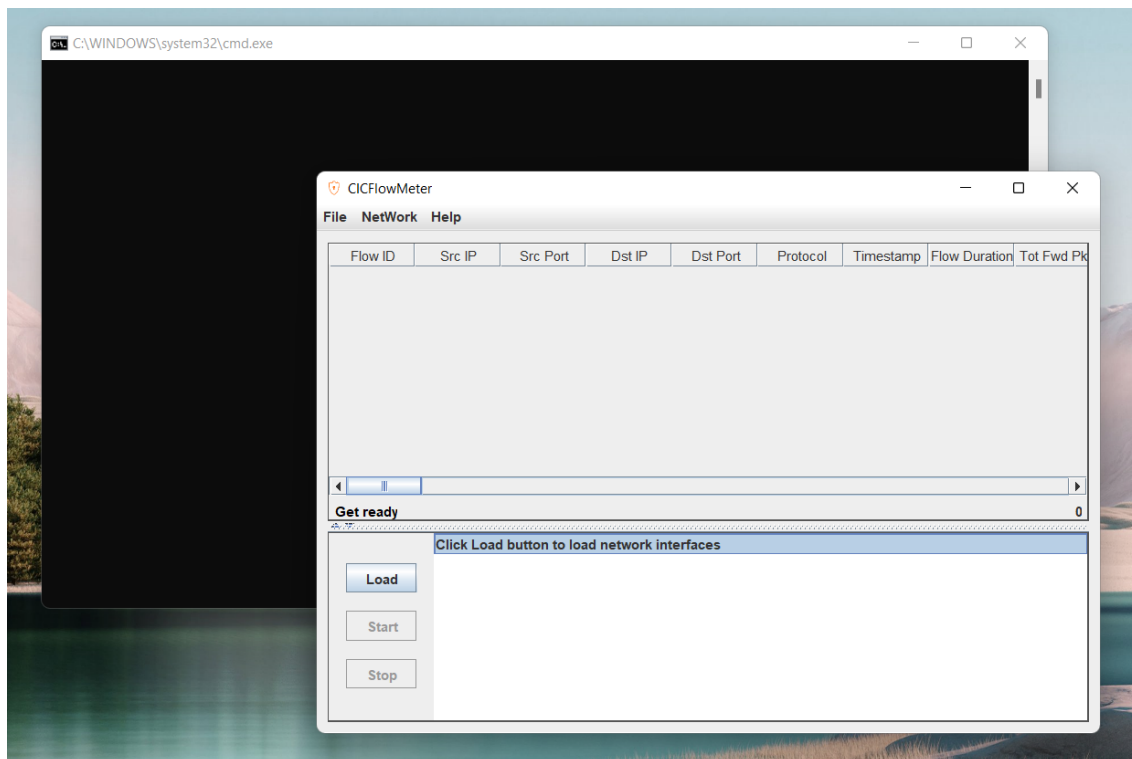


Figure 3.2.3.1: CIC flowmeter

3.2.4 VirtualBox

VirtualBox is an open-source virtualization software that allows users to create and run virtual machines on their computers. It provides a platform for running multiple operating systems simultaneously, enabling users to test software, set up development environments, and isolate applications or systems for security purposes. VirtualBox allows users to create virtual machines (VMs) that behave like independent computers within their host operating system. These VMs can run a wide range of operating systems, including Windows, Linux, macOS, and others. Users can allocate specific amounts of CPU, memory, and storage to each VM, tailoring their resources according to their needs. With VirtualBox, users can create snapshots of virtual machines, allowing them to save the current state of a VM and return to it later if needed. This feature is beneficial for testing and experimenting with software configurations without the risk of permanently modifying the system. VirtualBox also provides a variety of networking options, allowing users to configure network connectivity for their virtual machines. This includes bridged networking, where the VMs appear as separate entities on the network, and NAT (Network Address Translation), where the host acts as a gateway for the VMs to access the network. Another useful feature of VirtualBox is its ability to support guest additions. Guest additions are software packages that can be installed on the guest operating system to improve integration and performance.



Figure 3.2.4.1: VirtualBox

3.2.5 Virtual Machines

Virtual Machine (VM) is the virtualization of a computer system. Virtual machines are based on computer architectures and provide functionality of a physical computer. Their implementations may involve specialized hardware, software, or a combination. Virtual machines differ and are organized by their function. System virtual machines which is also known as full virtualization VMs provide a substitute for a real machine. They provide functionality needed to execute entire operating systems. A hypervisor uses native execution to share and manage hardware, allowing for multiple environments which are isolated from one another, yet exist on the same physical machine. Modern hypervisors use hardware-assisted virtualization, virtualization-specific hardware, primarily from the host CPUs. Process virtual machines are designed to execute computer programs in a platform-independent environment. Some virtual machine emulators, such as QEMU and video game console emulators, are designed to also emulate different system architectures thus allowing execution of software applications and operating systems written for another CPU or architecture.

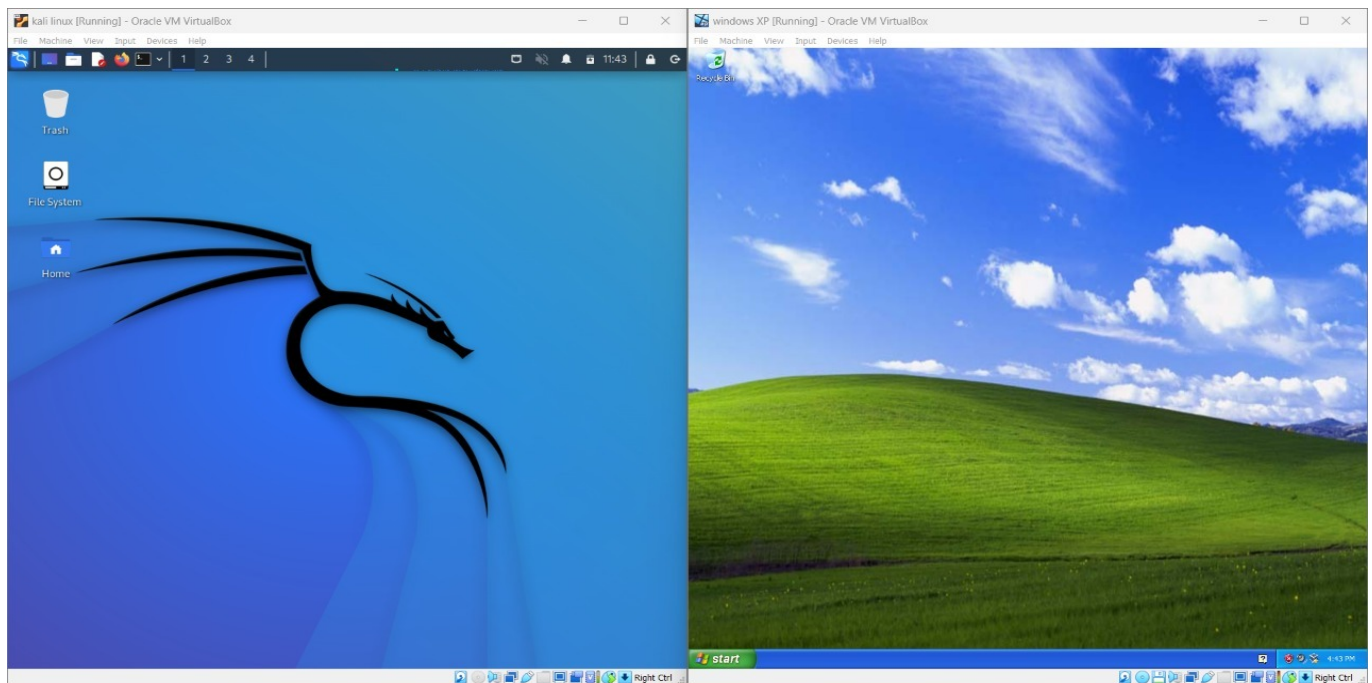


Figure 3.2.5.1: Virtual Machines

3.3 Libraries Used

3.3.1 Pandas

Pandas is a powerful and popular open-source library in Python for data manipulation and analysis. It provides high-performance, easy-to-use data structures and data analysis tools, making it a valuable tool for data scientists, analysts, and developers. At the core of Pandas are two primary data structures: Series and DataFrame. A Series is a one-dimensional labeled array that can hold any data type. It is similar to a column in a spreadsheet or a NumPy array. A DataFrame, on the other hand, is a two-dimensional table-like structure with rows and columns. It is akin to a spreadsheet or a SQL table, where each column can be of a different data type. DataFrames are particularly useful for handling structured data and are often used for data analysis tasks.

Pandas provides a wide range of functionalities for data manipulation and transformation. You can filter and sort data, merge and join datasets, reshape and pivot tables, and perform various aggregations and statistical calculations. These operations can be performed efficiently even on large datasets, thanks to Pandas' underlying implementation using optimized data structures and algorithms. Data cleaning is another crucial aspect of data analysis, and Pandas offers several tools for this purpose. It allows you to handle missing data by either dropping or filling in the missing values. You can also remove duplicates from datasets and handle outliers.

Additionally, Pandas provides functions for data imputation, enabling you to estimate missing values based on various strategies like mean, median, or interpolation. Pandas supports reading and writing data in different formats, including CSV, Excel, JSON, SQL databases, and more. It simplifies the process of loading and saving data, making it easy to integrate Pandas with various data sources. You can read data into a DataFrame, perform data analysis, and write the results back to a file or a database. Indexing and selection in Pandas are flexible and powerful. You can select specific rows and columns based on labels or positions, perform boolean indexing using conditions, and apply complex queries to filter data. This allows you to extract and manipulate subsets of data efficiently.

Pandas integrates well with other popular libraries in the Python ecosystem. It works seamlessly with NumPy, allowing easy conversion between Pandas data structures and NumPy arrays. Moreover,

Pandas integrates with Matplotlib for data visualization, enabling you to create insightful plots and charts from your data. In summary, Pandas is a powerful library for data manipulation and analysis in Python. With its intuitive data structures, extensive functionality, and efficient performance, Pandas simplifies the process of working with structured data, making it an essential tool for anyone dealing with data analysis and manipulation tasks.

3.3.2 NumPy

NumPy, short for Numerical Python, is a fundamental open-source library for scientific computing in Python. It provides powerful data structures and efficient algorithms for performing numerical operations on arrays and matrices. NumPy serves as a foundation for many other libraries in the scientific Python ecosystem and is widely used in fields such as data analysis, machine learning, and scientific research. The core data structure in NumPy is the ndarray (n-dimensional array). It is a homogeneous container for elements of the same data type, allowing efficient storage and manipulation of large datasets. The ndarray provides a variety of mathematical operations that can be applied to entire arrays or individual elements, enabling fast and vectorized computations. NumPy offers a vast collection of functions for numerical operations, including mathematical, statistical, and linear algebra functions. These functions are optimized for performance and often execute much faster than equivalent operations implemented in pure Python. NumPy's efficient implementation is based on C and C++ code, making it suitable for handling large datasets and computationally intensive tasks. One of the key advantages of NumPy is its ability to perform vectorized operations.

Vectorization allows you to perform operations on entire arrays instead of iterating over individual elements, resulting in concise and efficient code. This feature not only improves code readability but also enhances performance by utilizing optimized low-level implementations. NumPy provides a wide range of array creation and manipulation functions. You can create arrays from Python lists or tuples, initialize arrays with zeros, ones, or random values, and reshape, concatenate, and split arrays. NumPy also supports various indexing and slicing techniques, allowing you to access and modify specific elements or subarrays within an ndarray. NumPy's capabilities extend beyond

basic numerical operations. It offers advanced functionalities for linear algebra, including matrix multiplication, eigenvalue decomposition, and solving linear equations. These operations are essential for applications such as machine learning algorithms, signal processing, and simulations. Furthermore, NumPy integrates seamlessly with other scientific computing libraries in Python. For instance, it can be used in conjunction with libraries like SciPy (Scientific Python) for advanced scientific computations, Matplotlib for data visualization, and Pandas for data manipulation and analysis. The interoperability between these libraries creates a powerful ecosystem for scientific computing and data analysis. Another noteworthy feature of NumPy is its support for broadcasting.

Broadcasting enables NumPy to perform operations between arrays of different shapes and sizes by implicitly replicating elements along the appropriate dimensions. This simplifies code and avoids unnecessary memory consumption, making it easier to work with multidimensional data. NumPy also provides facilities for reading and writing arrays to disk, allowing you to store and retrieve data in various file formats, including binary files and text files. Additionally, NumPy supports memory-mapped arrays, which provide an efficient way to work with large datasets that may not fit into memory entirely. In summary, NumPy is a fundamental library for numerical computing in Python. With its ndarray data structure, efficient numerical operations, and wide range of functionalities, NumPy enables efficient handling of arrays and matrices. It serves as a building block for many other scientific computing libraries and provides a solid foundation for various scientific and data-related applications.

3.3.3 Sklearn

The scikit-learn library, often referred to as sklearn, is a widely used open-source machine learning library for Python. It provides a comprehensive set of tools and algorithms for various machine learning tasks, including classification, regression, clustering, dimensionality reduction, and model selection. Sklearn is built on top of other scientific computing libraries, such as NumPy, SciPy, and matplotlib, and offers a unified and intuitive API for performing machine learning tasks. Sklearn provides a diverse range of algorithms that can be applied to different types of machine learning

problems. It includes popular supervised learning algorithms such as support vector machines (SVM), random forests, k-nearest neighbors (KNN), decision trees, and logistic regression. These algorithms are implemented in a consistent manner, making it easy to compare and evaluate different models. For regression tasks, sklearn offers algorithms such as linear regression, support vector regression (SVR), random forest regression, and gradient boosting regression. These algorithms can handle both simple and complex regression problems and provide accurate predictions.

Clustering is another important aspect of unsupervised learning, and sklearn provides several clustering algorithms, including k-means, hierarchical clustering, and DBSCAN. These algorithms help identify natural groupings or clusters within the data, enabling insights into the underlying patterns and structures. Sklearn also includes algorithms for dimensionality reduction, which is useful for reducing the number of features in high-dimensional datasets. Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE) are popular techniques implemented in sklearn that can reduce the dimensionality while preserving important information. One of the strengths of sklearn is its robustness and scalability. The library is designed to handle large datasets efficiently. Sklearn supports parallel processing, allowing it to take advantage of multiple cores or distributed computing environments. It also provides tools for preprocessing data, including scaling, encoding categorical variables, handling missing values, and feature selection. These preprocessing techniques ensure that the data is in the appropriate format for the machine learning algorithms.

Sklearn emphasizes model evaluation and selection by providing various metrics and evaluation methods. It includes functions for computing accuracy, precision, recall, F1-score, and many other evaluation metrics depending on the task at hand. Furthermore, sklearn provides utilities for model persistence, allowing trained models to be saved and loaded for later use. This is particularly useful in production environments where models need to be deployed and used to make predictions on new data. Sklearn is widely adopted by the machine learning community due to its ease of use, versatility, and extensive documentation. It is well-maintained and constantly updated with new features and improvements. The sklearn library has become a go-to choice for many data scientists and machine learning practitioners for building, training, and evaluating machine learning models.

3.3.4 Matplotlib

Matplotlib is a powerful and widely used plotting library in Python. It provides a comprehensive set of tools and functions for creating static, animated, and interactive visualizations. Matplotlib is highly flexible and customizable, making it suitable for a wide range of plotting requirements. At the core of Matplotlib is the pyplot module, which provides a MATLAB-like interface for creating plots and visualizations. It allows you to create figures, add axes, plot data, and customize various aspects of the plot, such as labels, titles, colors, and styles. The pyplot module provides a high-level interface that simplifies the creation of common plot types. Matplotlib supports various types of plots, including line plots, scatter plots, bar plots, histograms, pie charts, box plots, and many more. You can create single plots or combine multiple plots to create complex figures with subplots.

Matplotlib provides fine-grained control over every aspect of the plot, allowing you to customize the appearance and behavior to suit your needs. One of the key features of Matplotlib is its ability to create publication-quality plots with precise control over every element. You can customize the line styles, markers, color maps, fonts, and sizes to match your desired aesthetics. Matplotlib also supports LaTeX typesetting, enabling the inclusion of mathematical expressions and symbols in the plot labels and titles. Matplotlib supports various output formats, including PNG, JPEG, PDF, SVG, and more. This flexibility allows you to save the plots in different file formats for use in reports, presentations, or web applications. Additionally, Matplotlib integrates well with Jupyter Notebooks, allowing the creation of interactive plots that can be embedded within the notebook itself.

Matplotlib also provides advanced features for creating animations and interactive visualizations. The animation module allows you to create animations by updating the plot data at regular intervals. This is particularly useful for visualizing dynamic or time-based data. Matplotlib also supports interactivity through features like zooming, panning, and adding widgets for user interaction. Beyond the pyplot interface, Matplotlib provides a more object-oriented approach for creating plots. This allows for greater control and flexibility in customizing the plot elements.

3.3.5 Seaborn

Seaborn is a popular Python data visualization library that is built on top of Matplotlib. It provides a high-level interface for creating visually appealing and informative statistical graphics. Seaborn is widely used in data analysis, machine learning, and scientific research to explore and communicate insights from complex datasets. One of the key advantages of Seaborn is its improved aesthetics. It offers visually pleasing default styles and color palettes that enhance the overall look of plots. This allows users to create attractive visualizations with minimal effort. Seaborn's default styles are designed to be easy on the eyes and optimized for data visualization, providing a consistent and professional appearance across different types of plots.

Seaborn also offers a high-level interface, which makes it easier for users to create complex statistical plots. It provides a set of functions that encapsulate many details of the underlying plot creation process. Users can create various types of plots, such as scatter plots, line plots, bar plots, box plots, violin plots, heatmaps, and more, with just a few lines of code. Seaborn handles many aspects, such as data grouping, aggregation, and color mapping, automatically, allowing users to focus on the data and the desired visual representation. Seaborn integrates statistical functionalities into its visualization framework. It supports the creation of plots that incorporate statistical measures, such as confidence intervals, kernel density estimation, and regression models. These statistical features enable users to gain insights into the underlying patterns and relationships within the data. For example, Seaborn's regression plots can visualize the relationship between two variables and fit a regression model to the data, providing a clear understanding of the trend and the associated uncertainty. Another strength of Seaborn is its ability to handle categorical data visualization effectively.

It provides specialized plots for categorical variables, including categorical scatter plots, bar plots, count plots, and categorical distribution plots. These plots make it easier to explore and compare categorical variables, allowing users to gain insights into the distribution, frequency, and relationships between different categories. Seaborn seamlessly integrates with the popular data

manipulation library, Pandas. It can directly accept Pandas DataFrames as input, enabling users to leverage the power of both libraries to quickly visualize and analyze data. This integration simplifies the workflow and allows users to seamlessly switch between data manipulation and visualization tasks. Seaborn also offers a range of customization options to tailor the appearance of plots. Users can modify colors, axes labels, titles, legends, and other visual elements to suit their specific needs. Additionally, Seaborn provides features like grids, facets, and annotations to further enhance the clarity and interpretability of plots. Seaborn is widely adopted in various domains, including data science, social sciences, finance, biology, and more. Its rich set of visualization capabilities helps users gain insights from data, discover patterns, and communicate findings effectively. By leveraging Seaborn's powerful features, users can create publication-quality plots that enhance their data analysis and presentation workflows.

3.3.6 GridSearchCV

GridSearchCV is a popular function in the scikit-learn library that enables efficient hyperparameter tuning for machine learning models. In this process, hyperparameters, which are settings that are not learned from the data but rather set by the user, are optimized to find the best combination for a given model and dataset. GridSearchCV automates this search by exhaustively evaluating different hyperparameter combinations using cross-validation. The process of hyperparameter tuning is crucial for optimizing the performance of a machine learning model. Each hyperparameter controls specific aspects of the model's behavior, such as its complexity, regularization strength, or learning rate. By finding the best hyperparameter values, the model can achieve better predictive accuracy, generalization, or other desirable properties.

GridSearchCV simplifies this process by providing a systematic way to define a grid of hyperparameter values to explore. The user specifies the model and the hyperparameters of interest along with their possible values. For example, in a Support Vector Machine (SVM) model, one might want to tune the kernel type, regularization parameter (C), and gamma. These hyperparameters would be defined in a grid, and GridSearchCV would exhaustively search through the grid to evaluate

each combination. To evaluate each combination of hyperparameters, GridSearchCV employs cross-validation. Cross-validation is a technique that divides the training data into multiple subsets, or folds. The model is trained on a portion of the data and evaluated on the remaining portion, repeating this process for each fold. This allows for a more robust assessment of the model's performance. GridSearchCV performs the search by iterating over each hyperparameter combination and fitting the model using the specified hyperparameters. It then evaluates the model's performance using cross-validation and records the results. Once all combinations have been evaluated, GridSearchCV provides access to the best set of hyperparameters and the corresponding performance metrics.

The output of GridSearchCV includes several attributes that provide insights into the search process. It includes the best hyperparameter values found during the search, the associated performance score, and additional information like mean cross-validated scores for each combination. Users can access these attributes to understand the impact of different hyperparameters on the model's performance. After identifying the best hyperparameters, users can instantiate a new model object using these optimal values and train it on the entire training dataset. This model is then ready for deployment and can be used to make predictions on new, unseen data. It's worth noting that GridSearchCV can be computationally expensive, particularly with large parameter grids or complex models. To address this, users can reduce the search space by specifying a smaller parameter grid or employ techniques like random search, which randomly samples from the parameter space. Additionally, scikit-learn provides options for parallelizing the search process, allowing for faster computations by distributing the workload across multiple CPU cores or machines. GridSearchCV is a valuable tool in a data scientist's arsenal for optimizing machine learning models. It automates the process of hyperparameter tuning, saving time and effort. By systematically exploring different hyperparameter combinations and evaluating them using cross-validation, GridSearchCV helps users find the best hyperparameters for their models, leading to improved performance and better generalization on unseen data.

4. Methodology

4.1 Architecture

The goal of this work is to develop a real-time Intrusion Detection System (IDS). The CICIDS 2017 dataset is preprocessed and feature selection is performed. Training is conducted using Decision Tree and Random Forest algorithms to create a predictive model. The model is then tested on real-time data to detect attacks. By utilizing machine learning algorithms, the IDS aims to accurately and promptly identify malicious activities in network traffic, enabling proactive measures to be taken for maintaining network security.

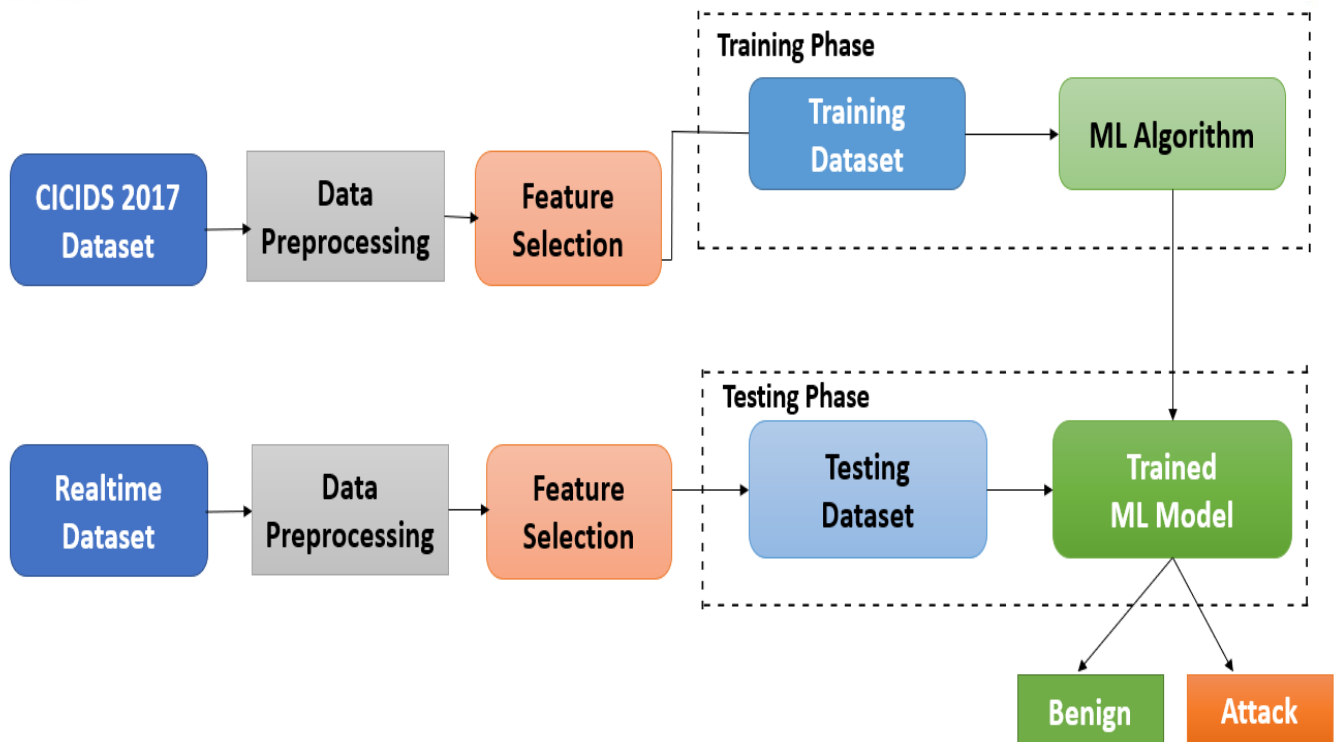


Figure 4.1.1: Project Flow

Dataset Description

The CICIDS 2017 dataset is a publicly available dataset that is widely used in the field of cybersecurity for research and development purposes. It contains network traffic data captured in a controlled environment and is designed to simulate realistic network traffic scenarios for analyzing and evaluating the performance of intrusion detection systems (IDS) and intrusion prevention systems (IPS).

The dataset was created as part of the Canadian Institute for Cybersecurity's (CIC) ongoing efforts to advance cybersecurity research. It consists of several days' worth of network traffic captured on a simulated network environment, including both normal and malicious activities. The dataset aims to provide a diverse range of network traffic patterns and attack scenarios to enable comprehensive testing and evaluation of security systems. The CICIDS 2017 dataset comprises different types of network traffic, including both benign and malicious traffic. The benign traffic consists of various types of legitimate activities, such as browsing, email communication, file transfers, and video streaming. On the other hand, the malicious traffic includes a wide range of cyber attacks, such as DoS (Denial of Service), DDoS (Distributed Denial of Service), port scanning, and malware propagation.

The dataset provides labeled data, with each network flow labeled as either normal or belonging to a specific attack category. The attack categories include brute force attacks, web attacks, denial of service attacks, reconnaissance attacks, infiltration attacks, and botnet attacks, among others. This labeling allows researchers and developers to train and evaluate their intrusion detection and prevention systems on real-world attack scenarios. The CICIDS 2017 dataset offers a rich set of features and attributes for each network flow, including source and destination IP addresses, port numbers, protocol type, packet sizes, and time duration. These features enable the analysis of network traffic patterns, the extraction of statistical measures, and the development of machine learning models for automated detection and classification of attacks.

Researchers and practitioners in the field of cybersecurity utilize the CICIDS 2017 dataset for various purposes. It serves as a benchmark dataset for evaluating the effectiveness of different intrusion detection and prevention techniques.

Name of Files	Day Activity	Attacks Found
Monday-WorkingHours.pcap_ISCX.csv	Monday	Benign (Normal human activities)
Tuesday-WorkingHours.pcap_ISCX.csv	Tuesday	Benign, FTP-Patator, SSH-Patator
Wednesday-workingHours.pcap_ISCX.csv	Wednesday	Benign, DoS GoldenEye, DoS Hulk, DoS Slowhttptest, DoS slowloris, Heartbleed
Thursday-WorkingHours-Morning-WebAttacks.pcap_ISCX.csv	Thursday	Benign, Web Attack – Brute Force, Web Attack – Sql Injection, Web Attack – XSS
Thursday-WorkingHours-Afternoon-Infiltration.pcap_ISCX.csv	Thursday	Benign, Infiltration
Friday-WorkingHours-Morning.pcap_ISCX.csv	Friday	Benign, Bot
Friday-WorkingHours-Afternoon-PortScan.pcap_ISCX.csv	Friday	Benign, PortScan
Friday-WorkingHours-Afternoon-DDos.pcap_ISCX.csv	Friday	Benign, DDoS

Figure 4.1.2: Description of files containing CICIDS-2017 dataset

SNo	S No	Feature Name	SNo	Feature Name	SNo	Feature Name	
1	Flow ID	22	Flow Packets/s	43	Fwd Packets/s	64	Fwd Avg Packets/Bulk
2	Source IP	23	Flow IAT Mean	44	Bwd Packets/s	65	Fwd Avg Bulk Rate
3	Source Port	24	Flow IAT Std	45	Min Packet Length	66	Bwd Avg Bytes/Bulk
4	Destination IP	25	Flow IAT Max	46	Max Packet Length	67	Bwd Avg Packets/Bulk
5	Destination Port	26	Flow IAT Min	47	Packet Length Mean	68	Bwd Avg Bulk Rate
6	Protocol	27	Fwd IAT Total	48	Packet Length Std	69	Subflow Fwd Packets
7	Timestamp	28	Fwd IAT Mean	49	Packet Length Variance	70	Subflow Fwd Bytes
8	Flow Duration	29	Fwd IAT Std	50	FIN Flag Count	71	Subflow Bwd Packets
9	Total Fwd Packets	30	Fwd IAT Max	51	SYN Flag Count	72	Subflow Bwd Bytes
10	Total Backward Packets	31	Fwd IAT Min	52	RST Flag Count	73	Init.Win_bytes.forward
11	Total Length of Fwd Packets	32	Bwd IAT Total	53	PSH Flag Count	74	Init.Win_bytes.backward
12	Total Length of Bwd Packets	33	Bwd IAT Mean	54	ACK Flag Count	75	act.data_pkt.fwd
13	Fwd Packet Length Max	34	Bwd IAT Std	55	URG Flag Count	76	min_seg_size.forward
14	Fwd Packet Length Min	35	Bwd IAT Max	56	CWE Flag Count	77	Active Mean
15	Fwd Packet Length Mean	36	Bwd IAT Min	57	ECE Flag Count	78	Active Std
16	Fwd Packet Length Std	37	Fwd PSH Flags	58	Down/Up Ratio	79	Active Max
17	Bwd Packet Length Max	38	Bwd PSH Flags	59	Average Packet Size	80	Active Min
18	Bwd Packet Length Min	39	Fwd URG Flags	60	Avg Fwd Segment Size	81	Idle Mean
19	Bwd Packet Length Mean	40	Bwd URG Flags	61	Avg Bwd Segment Size	82	Idle Std
20	Bwd Packet Length Std	41	Fwd Header Length	62	Fwd Header Length	83	Idle Max
21	Flow Bytes/s	42	Bwd Header Length	63	Fwd Avg Bytes/Bulk	84	Idle Min

Figure 4.1.3: Features of CICIDS-2017 Dataset

4.2 Modules

There are 4 modules

- Generating Real-time Dataset with attacks
- Data Preprocessing
- Training with Algorithms
- Testing the Model with Realtime Dataset

4.2.1 Generating Real-time Dataset with attacks

To generate a real-time dataset, you will need specific tools and virtual machines. The necessary tools include VirtualBox, Wireshark, and CICFlowmeter. Virtual machines such as Windows XP and Kali Linux are required for this process, and they should be installed within a virtual box environment. The objective is to conduct various attacks like Denial of Service (DoS), Distributed Denial of Service (DDoS), Slowloris, and Synflood attacks using these virtual machines. While performing these attacks, it is essential to have Wireshark running to capture the live traffic, which will generate a Pcap file. The next step involves using CICFlowmeter to convert the Pcap file into a CSV file. Finally, the two CSV files are merged for testing purposes.

Slowloris

Slowloris is a type of Denial of Service (DoS) attack that targets web servers. It exploits a vulnerability in the way web servers handle concurrent connections and can effectively render a targeted server unavailable to legitimate users. The Slowloris attack is named after the slow-moving animal "sloth" due to its gradual and persistent nature. The Slowloris attack works by initiating multiple connections to a target web server and keeping those connections open for an extended period. Instead of overwhelming the server with a high volume of traffic like other DoS attacks, Slowloris focuses on exhausting the server's available resources, such as concurrent connections or connection timeout limits.

Here's how the Slowloris attack typically unfolds:

- **Connection Initialization:** The attacker initiates a connection with the target web server, typically through HTTP. The initial connection request appears legitimate, including standard HTTP headers.
- **Slow Header Transmission:** After the initial connection is established, the attacker starts sending HTTP headers to the server. However, instead of sending the complete request at once, Slowloris sends the headers gradually and at a very slow pace. This technique is designed to keep the connection open for an extended period without triggering a timeout.
- **Persistent Connections:** Slowloris repeats the process of slowly transmitting headers and keeping connections open with the server. By opening multiple connections and maintaining them over time, the attack consumes the server's available resources, such as maximum concurrent connections, memory, and CPU resources.
- **Resource Exhaustion:** As the attacker continues to hold open connections and send headers at a slow pace, the server's resources become gradually depleted. Legitimate users may experience increased latency or even complete unresponsiveness from the targeted web server.

Slowloris takes advantage of the fact that many web servers allocate resources for each incoming connection and keep those resources active until the connection is closed. By prolonging the connection time with slow header transmission, Slowloris can tie up a significant number of server resources, leading to service degradation or complete denial of service.

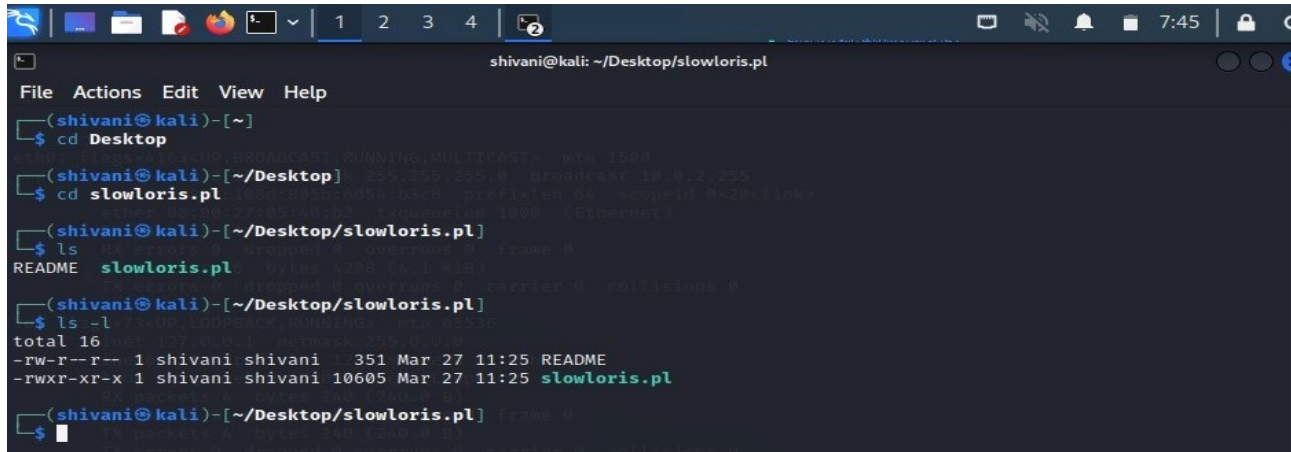
Performing Slowloris Attack

Step 1:

Open your Kali Linux and then Open your Terminal. Create a new Directory on Desktop named Slowloris using the following command. Move to the directory that you have to create (Slowloris). Now you have to clone the Slowloris tool from Github so that you can install it on your Kali Linux machine.

For that, you only have to type the following URL in your terminal within the Slowloris directory that you have created.

- <https://github.com/GHubgenius/slowloris.pl.git>



```
shivani@kali: ~/Desktop/slowloris.pl
File Actions Edit View Help
(shivani@kali)~[~]
$ cd Desktop
(shivani@kali)~/Desktop
$ cd slowloris.pl
(shivani@kali)~/Desktop/slowloris.pl
$ ls
README  slowloris.pl
(shivani@kali)~/Desktop/slowloris.pl
$ ls -l
total 16
-rw-r--r-- 1 shivani shivani 351 Mar 27 11:25 README
-rwxr-xr-x 1 shivani shivani 10605 Mar 27 11:25 slowloris.pl
(shivani@kali)~/Desktop/slowloris.pl
$
```

Figure 4.2.1.1: Installing Slowloris Tool

Step 2:

Now you have to check the IP address of your machine to do that type of following command. Now it's time to start the apache server, start the apache server using the following command.

- **sudo service apache2 start**

Now we have to check the status of your server whether it is active or not so to check the status of your server run the following command.

- **service apache2 status**

```

shivani@kali: ~
File Actions Edit View Help
(shivani@kali)-[~]
$ ifconfig
eth0: flags=4163<UP,BROADCAST,RUNNING,MULTICAST> mtu 1500
    inet 10.0.2.15 netmask 255.255.255.0 broadcast 10.0.2.255
    inet6 fe80::108d:805b:6d54:b3c8 prefixlen 64 scopeid 0<link>
    ether 08:00:27:05:46:b2 txqueuelen 1000 (Ethernet)
    RX packets 51 bytes 8798 (8.5 KiB)
    RX errors 0 dropped 0 overruns 0 frame 0
    TX packets 26 bytes 4208 (4.1 KiB)
    TX errors 0 dropped 0 overruns 0 carrier 0 collisions 0

lo: flags=73<UP,LOOPBACK,RUNNING> mtu 65536
    inet 127.0.0.1 netmask 255.0.0.0
    inet6 ::1 prefixlen 128 scopeid 0<host>
    loop txqueuelen 1000 (Local Loopback)
    RX packets 4 bytes 240 (240.0 B)
    RX errors 0 dropped 0 overruns 0 frame 0
    TX packets 4 bytes 240 (240.0 B)
    TX errors 0 dropped 0 overruns 0 carrier 0 collisions 0

(shivani@kali)-[~]
$ sudo service apache2 start

(shivani@kali)-[~]
$ service apache2 status
● apache2.service - The Apache HTTP Server
   Loaded: loaded (/lib/systemd/system/apache2.service; disabled; preset: disabled)
   Active: active (running) since Tue 2023-06-06 07:32:10 EDT; 8min ago
     Docs: https://httpd.apache.org/docs/2.4/
   Process: 2157 ExecStart=/usr/sbin/apachectl start (code=exited, status=0/SUCCESS)
  Main PID: 2174 (apache2)
    Tasks: 6 (limit: 4625)
   Memory: 19.3M
      CPU: 388ms
   CGroup: /system.slice/apache2.service
           └─2174 /usr/sbin/apache2 -k start
             └─2176 /usr/sbin/apache2 -k start
               └─2177 /usr/sbin/apache2 -k start
                 └─2178 /usr/sbin/apache2 -k start
                   └─2179 /usr/sbin/apache2 -k start
                     └─2180 /usr/sbin/apache2 -k start

Jun 06 07:32:09 kali systemd[1]: Starting The Apache HTTP Server...
Jun 06 07:32:10 kali apachectl[2173]: AH00558: apache2: Could not reliably determine the server's fully qualified >
Jun 06 07:32:10 kali systemd[1]: Started The Apache HTTP Server.
lines 1-20/20 (END)

```

Figure 4.2.1.2: Running apache2

Step 3:

Now it's time to run the tool using the following command.

- **perl slowloris.pl -dns 10.0.2.15 -options**


```

File Actions Edit View Help

(shivani@kali)-[~/Desktop/slowloris.pl]
$ perl slowloris.pl -dns 10.0.2.15 -options
Welcome to Slowloris - the low bandwidth, yet greedy and poisonous HTTP client by Laera Loris
Unknown option: options
Defaulting to port 80.
Defaulting to a 5 second tcp connection timeout.
Defaulting to a 100 second re-try timeout.
Defaulting to 1000 connections.
Multithreading enabled.
Connecting to 10.0.2.15:80 every 100 seconds with 1000 sockets:
Building sockets.
Sending data.
Building sockets.
Current stats: Slowloris has now sent 250 packets successfully.
This thread now sleeping for 100 seconds...
Building sockets.
Building sockets.
Building sockets.
Sending data.
Current stats: Slowloris has now sent 653 packets successfully.
This thread now sleeping for 100 seconds...
Building sockets.
Sending data.
Current stats: Slowloris has now sent 915 packets successfully.
This thread now sleeping for 100 seconds...
Sending data.
Current stats: Slowloris has now sent 1077 packets successfully.
This thread now sleeping for 100 seconds...
Building sockets.
Sending data.
Current stats: Slowloris has now sent 1463 packets successfully.
This thread now sleeping for 100 seconds...
Building sockets.
Sending data.
Current stats: Slowloris has now sent 1521 packets successfully.
This thread now sleeping for 100 seconds...
Building sockets.
Sending data.
Current stats: Slowloris has now sent 1962 packets successfully.
This thread now sleeping for 100 seconds...
Building sockets.
Sending data.
Current stats: Slowloris has now sent 2192 packets successfully.

```

Figure 4.2.1.3: Performing Slowloris Attack

Step 4:

Capture the live traffic data using wireshark.

No.	Time	Source	Destination	Protocol	Length	Info
1	0.000000000	fe80::e473:acf4:fe5...	ff02::1:ff21:dc29	ICMPv6	86	Neighbor Solicitation for
2	36.602466138	192.168.56.103	239.255.255.250	SSDP	217	M-SEARCH * HTTP/1.1
3	36.621002260	192.168.56.103	239.255.255.250	SSDP	217	M-SEARCH * HTTP/1.1
4	37.607379038	192.168.56.103	239.255.255.250	SSDP	217	M-SEARCH * HTTP/1.1
5	37.625135434	192.168.56.103	239.255.255.250	SSDP	217	M-SEARCH * HTTP/1.1
6	38.607349104	192.168.56.103	239.255.255.250	SSDP	217	M-SEARCH * HTTP/1.1
7	38.625363984	192.168.56.103	239.255.255.250	SSDP	217	M-SEARCH * HTTP/1.1
8	39.607961556	192.168.56.103	239.255.255.250	SSDP	217	M-SEARCH * HTTP/1.1
9	39.626784052	192.168.56.103	239.255.255.250	SSDP	217	M-SEARCH * HTTP/1.1
10	61.010657572	fe80::e473:acf4:fe5...	ff02::1:ff21:dc29	ICMPv6	86	Neighbor Solicitation for
11	62.728064737	fe80::108d:805b:6d5...	ff02::2	ICMPv6	62	Router Solicitation
12	69.261278922	192.168.56.103	224.0.0.251	MDNS	85	Standard query 0x0000 PTR
13	69.265658783	fe80::e473:acf4:fe5...	ff02::fb	MDNS	105	Standard query 0x0000 PTR
14	70.259335604	192.168.56.103	224.0.0.251	MDNS	85	Standard query 0x0000 PTR
15	70.259929418	fe80::e473:acf4:fe5...	ff02::fb	MDNS	105	Standard query 0x0000 PTR
16	122.010734453	fe80::e473:acf4:fe5...	ff02::1:ff21:dc29	ICMPv6	86	Neighbor Solicitation for
17	152.799144017	fe80::e473:acf4:fe5...	ff02::16	ICMPv6	90	Multicast Listener Report
18	152.799677404	192.168.56.103	224.0.0.22	IGMPv3	60	Membership Report / Leave
19	152.830525789	fe80::e473:acf4:fe5...	ff02::16	ICMPv6	90	Multicast Listener Report
20	152.832006614	fe80::e473:acf4:fe5...	ff02::16	ICMPv6	90	Multicast Listener Report
21	152.832006929	fe80::e473:acf4:fe5...	ff02::16	ICMPv6	90	Multicast Listener Report
22	152.832301691	192.168.56.103	224.0.0.22	IGMPv3	60	Membership Report / Join
23	152.832826818	192.168.56.103	224.0.0.22	IGMPv3	60	Membership Report / Leave

Frame 1: 86 bytes on wire (688 bits), 86 bytes captured (688 bits) on interface eth0, id 0
 Ethernet II, Src: 0a:00:27:00:00:0f (0a:00:27:00:00:0f), Dst: IPv6mcast_ff:21:dc:29 (33:33:ff:21:dc:29)
 Internet Protocol Version 6, Src: fe80::e473:acf4:fe57:acf, Dst: ff02::1:ff21:dc29
 Internet Control Message Protocol v6

Figure 4.2.1.4: Generating live traffic data

Step 5:

A Pcap file will be generated from wireshark tool. Convert the Pcap file to CSV file using CICFlowmeter tool.

Synflood Attack

A SYN flood attack is a type of Denial of Service (DoS) attack that targets the TCP (Transmission Control Protocol) handshake process, which is the method by which two devices establish a connection over a network. The attacker floods the target server with a large number of TCP SYN (synchronization) requests, overwhelming its resources and rendering it unable to respond to legitimate connection requests.

Here's how a typical SYN flood attack unfolds:

- **TCP Handshake:** When two devices, such as a client and a server, want to establish a TCP connection, they go through a three-way handshake process. The client sends a SYN packet to the server, requesting to initiate a connection.
- **SYN Flood Initiation:** In a SYN flood attack, the attacker sends a flood of SYN packets to the target server, but they do not complete the handshake by sending the final ACK (acknowledgment) packet. This leaves the server waiting for ACK packets from the attackers, consuming server resources and creating a backlog of incomplete connections.
- **Resource Exhaustion:** As the server waits for the final ACK packets, it consumes resources such as memory, processing power, and connection table entries for each incomplete connection. The server allocates resources for each incoming SYN packet and keeps them reserved until the handshake process is complete or times out. With a massive influx of SYN packets, the server's resources become exhausted, causing it to slow down, become unresponsive, or even crash.
- **Connection Queue Saturation:** In addition to consuming server resources, the flood of SYN packets overwhelms the server's connection backlog queue. This queue holds incoming SYN requests that are waiting for the handshake to complete. With a SYN flood, the queue fills up faster than the server can process and clear the connections, leading to a backlog of pending connections and a denial of service for legitimate users.

To defend against SYN flood attacks, various mitigation techniques can be implemented:

- **SYN Cookies:** SYN cookies are a technique used to prevent resource exhaustion in SYN flood attacks. Instead of allocating server resources for each incoming SYN packet, the server generates a cookie containing the necessary connection information and sends it back to the client in the SYN-ACK packet. The client includes this cookie in the final ACK packet, allowing the server to validate the connection without allocating resources until the handshake is complete.
- **Firewall and Traffic Filtering:** Firewalls and network devices can be configured to identify and block malicious SYN flood traffic. They can filter out excessive incoming SYN packets or detect patterns indicative of SYN flood attacks. Traffic filtering can be based on various factors such as the source IP address, SYN packet rate, or other anomaly detection techniques.
- **Rate Limiting and Connection Thresholds:** Implementing rate limiting mechanisms and connection thresholds can help mitigate SYN flood attacks. These measures can limit the number of incoming SYN packets from a single IP address or set maximum concurrent connections per IP, preventing a single attacker from overwhelming server resources.
- **Load Balancing and Redundancy:** Distributing incoming network traffic across multiple servers using load balancing techniques can help mitigate SYN flood attacks. By spreading the load among multiple servers, the impact of a flood attack can be minimized, and the available resources can be better utilized.
- **Intrusion Detection and Prevention Systems:** Employing intrusion detection and prevention systems (IDPS) can help identify and mitigate SYN flood attacks. IDPS systems can monitor network traffic, detect anomalies, and automatically block or mitigate the attack by applying appropriate countermeasures.

Performing Synflood Attack

Step 1:

Firstly, we should get IP address of 2 virtual Machines-WindowsXP and Kali-linux. Communication should be done for both VMs using ping command.

Step 2:

We should enter into Metasploit using the following command.

- **msfconsole**

Metasploit is a widely used penetration testing framework that provides a comprehensive set of tools and exploits for assessing the security of computer systems. It allows security professionals to identify vulnerabilities, launch attacks, and test the effectiveness of security measures. Metasploit simplifies the process of scanning, exploiting, and gaining access to target systems, helping to identify potential weaknesses before they can be exploited by malicious actors. With its extensive collection of exploits, payloads, and auxiliary modules, Metasploit is a powerful tool for ethical hacking and security assessment.

Step 3:

Next command is search synflood. Enter show options. It shows some options about rhosts, num, rport

Step 4:

Set RHOST to ipaddress of other virtual machine and enter exploit.

In Metasploit, RHOSTS, RPORT, and NUM are parameters used to specify the target host, target port, and the number of concurrent targets, respectively.

- **RHOSTS:** RHOSTS refers to the remote hosts, which are the target IP addresses or hostnames that you want to scan or attack. It can be a single host or a range of hosts specified using CIDR notation or wildcard characters.
- **RPORT:** RPORT stands for remote port and represents the target port number on the remote host. It is the port to which you want to establish a connection or attempt an exploit.

- **NUM:** NUM is an abbreviation for the number of concurrent targets. This parameter is typically used when launching attacks that require targeting multiple hosts simultaneously. By setting NUM to a specific value, you can control the number of concurrent targets that Metasploit will attack simultaneously, increasing the efficiency of the operation.
- **Set RHOSTS ipaddress**
- **Set RPORT 134**
- **Set NUM 50,000**

Step 5:

Capture the live traffic data using wireshark tool. A Pcap file will be generated from wireshark tool. Convert the Pcap file to CSV file using CICFlowmeter tool.

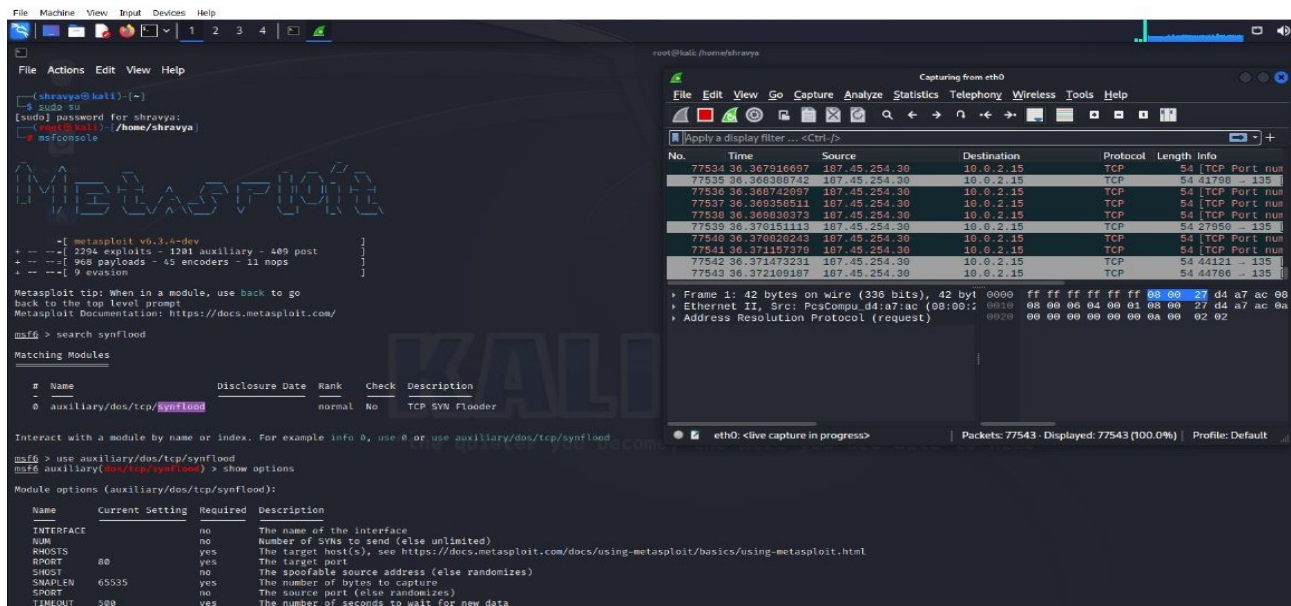


Figure 4.2.1.5: Performing Synflood Attack

4.2.2 Data Preprocessing

Data preprocessing is a vital step in developing a real-time intrusion detection system (IDS) using machine learning (ML) with the CICIDS 2017 dataset. The CICIDS 2017 dataset, a widely used benchmark, contains labeled network traffic data. In this paper, we focus on the key preprocessing steps for effective IDS implementation. The preprocessing process begins with data cleaning, addressing missing values, outliers, and inconsistent data. Feature selection techniques are then applied to reduce dimensionality and select the most relevant features. Feature scaling is performed to ensure that features are on a consistent scale. Categorical variables are encoded into numerical representations, and techniques are employed to handle imbalanced data, ensuring the dataset adequately captures both normal and attack samples. Finally, the preprocessed dataset is split into training and testing sets for model training and evaluation. These preprocessing steps ensure the quality, relevance, and compatibility of the CICIDS 2017 dataset with ML algorithms, ultimately enhancing the performance of the real-time IDS.

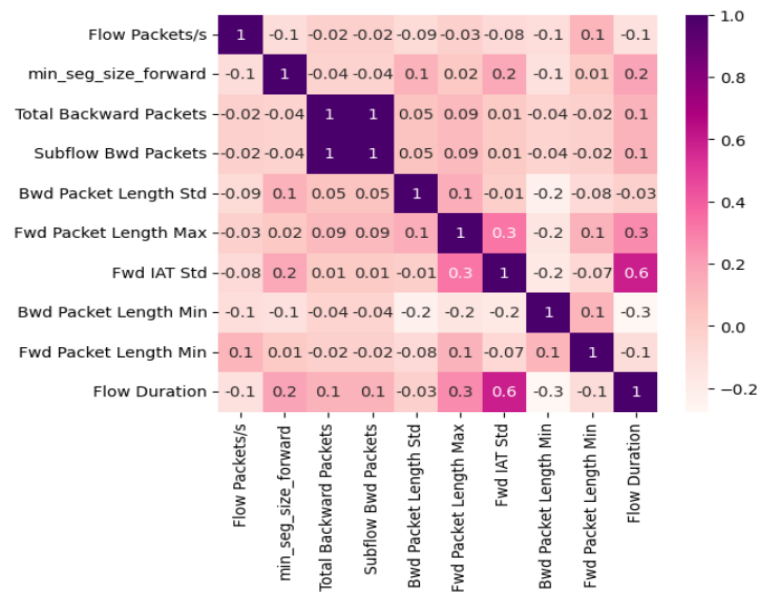


Figure 4.2.2.1: Top 10 features after Feature Selection

4.2.3 Training with Algorithms

a)Random Forest Classifier

The Random Forest classifier, initialized with 100 estimators, is a powerful algorithm used for classification tasks. It is trained on the training data, which consists of labeled examples of network traffic. During training, the classifier learns patterns and relationships in the data, enabling it to make accurate predictions. Once trained, the classifier is ready to make predictions on unseen data, known as the test data. To evaluate the performance of the Random Forest classifier, the confusion matrix is calculated. The confusion matrix provides a detailed breakdown of the predicted and actual class labels. It consists of four key elements: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). True positives are instances where the classifier correctly predicts the positive class (e.g., an intrusion). True negatives are instances where the classifier correctly predicts the negative class (e.g., normal network traffic). False positives occur when the classifier incorrectly predicts the positive class, and false negatives occur when the classifier incorrectly predicts the negative class. By analyzing the values in the confusion matrix, various performance metrics can be calculated. Accuracy is the proportion of correctly classified instances out of the total instances. Precision measures the proportion of true positives out of the predicted positives, indicating how precise the classifier is in identifying intrusions. Recall, also known as sensitivity or true positive rate, measures the proportion of true positives out of the actual positives, providing insights into the classifier's ability to detect intrusions. Another important metric is the F1 score, which combines precision and recall into a single value, providing a balanced measure of the classifier's performance. By following these steps and utilizing the scikit-learn library, the Random Forest classifier can effectively detect intrusions in real-time scenarios. The confusion matrix and the derived performance metrics allow for a comprehensive evaluation of the classifier's accuracy, precision, recall, and overall effectiveness in identifying intrusions. This information is crucial for assessing the performance of intrusion detection systems and making informed decisions in security applications.

$$MSE = \frac{1}{N} \sum_{i=1}^N (f_i - y_i)^2$$

b) Gaussian Naive Bayes classifier

The classifier is initialized and trained on the training data, where it estimates the statistical parameters of the Gaussian distribution for each class. Subsequently, predictions are made on the test data by calculating the probability of each sample belonging to each class and selecting the class with the highest probability. The confusion matrix is then calculated to evaluate the model's performance, providing information on the predicted and actual class labels. This allows for the analysis of true positives, true negatives, false positives, and false negatives, enabling the assessment of accuracy, precision, recall, and other performance metrics. By utilizing the Gaussian Naive Bayes algorithm and following these steps, the classifier can effectively detect intrusions in real-time scenarios, providing valuable insights for IDS applications.

$$P(y|x_1, \dots, x_n) = \frac{P(y) \prod_{i=1}^n P(x_i|y)}{P(x_1)P(x_2) \dots P(x_n)}$$

c) Logistic Regression classifier

The data is first scaled using the StandardScaler to standardize the features and ensure consistent scaling across different variables. The Logistic Regression model is then initialized with increased max_iter to ensure convergence. The model is trained on the scaled training data, where it learns the coefficients for the logistic regression equation. Subsequently, predictions are made on the scaled test data by applying the learned coefficients. The confusion matrix is then calculated to evaluate the model's performance, providing insights into the predicted and actual class labels. The confusion matrix enables the analysis of true positives, true negatives, false positives, and false negatives, allowing for the assessment of accuracy, precision, recall, and other performance metrics. By utilizing the Logistic Regression algorithm and following these steps, the classifier can effectively detect intrusions in real-time scenarios, providing valuable insights for IDS applications.

$$z = (\sum_{i=1}^n w_i x_i) + b$$

4.2.4 Testing the Model with Realtime Dataset

During the testing phase, a real-time traffic dataset generated in the first module is utilized. The dataset needs to undergo preprocessing to ensure consistency with the features of the CICIDS2017 dataset. To achieve this, all features except for the top 10 features are removed. These 10 features include Flow IAT Mean, Flow Packets, Flow IAT Max, Flow Duration, min-seg-size-forward, Fwd IAT Mean, Bwd Packets, Total Backward Packets, Flow Bytes, and Subflow Bwd Packets. Once the dataset is prepared with the relevant features, the trained model is applied to predict whether the network traffic is categorized as an attack or benign.

The model leverages the information captured in the features to make accurate predictions based on patterns and anomalies observed in the real-time data. By focusing on the specified top 10 features and predicting the nature of the traffic, the testing phase enables the assessment of the model's effectiveness in identifying and distinguishing between malicious attacks and normal traffic.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X
1	Flow ID	Src IP	Src Port	Dst IP	Destination	Protocol	Timestamp	Flow Dura	Total Fwd	Total Back	Total Leng	Fwd Packe	Fwd Packe	Fwd Packe	Fwd Packe	Bwd Packe	Bwd Packe	Bwd Packe	Bwd Packe	Flow Bytes	Flow Packe	Flow IAT	N. Flc	
2	3.130.253.10.0.2.15	60056	3.130.253.	80	6	27-03-202	61147072	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.130832	0.049062	3.06E+07	4.	
3	3.130.253.10.0.2.15	34506	3.130.253.	80	6	27-03-202	62013610	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.129004	0.048376	3.10E+07	4.	
4	3.130.253.10.0.2.15	36664	3.130.253.	80	6	27-03-202	59708945	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.133983	0.050244	2.99E+07	4.	
5	3.130.253.10.0.2.15	40656	3.130.253.	80	6	27-03-202	59311088	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.134882	0.050581	2.97E+07	4.	
6	3.130.253.10.0.2.15	33356	3.130.253.	80	6	27-03-202	59090699	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.135385	0.050769	2.95E+07	4.	
7	3.130.253.10.0.2.15	38516	3.130.253.	80	6	27-03-202	57791402	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.138429	0.051911	2.89E+07	4.	
8	3.130.253.10.0.2.15	32808	3.130.253.	80	6	27-03-202	61436564	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.130216	0.048831	3.07E+07	4.	
9	3.130.253.10.0.2.15	33706	3.130.253.	80	6	27-03-202	58709821	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.136263	0.051099	2.94E+07	4.	
10	3.130.253.10.0.2.15	60820	3.130.253.	80	6	27-03-202	58248918	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.137342	0.051503	2.91E+07	4.	
11	3.130.253.10.0.2.15	34604	3.130.253.	80	6	27-03-202	60623161	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.131963	0.049486	3.03E+07	4.	
12	3.130.253.10.0.2.15	46932	3.130.253.	80	6	27-03-202	61363094	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.130372	0.048889	3.07E+07	4.	
13	3.130.253.10.0.2.15	38166	3.130.253.	80	6	27-03-202	5317	0	2	0	8	0	0	0	0	8	0	4	5.656854	1504.608	376.152	5317		
14	3.130.253.10.0.2.15	60406	3.130.253.	80	6	27-03-202	59530937	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.134384	0.050394	2.98E+07	4.	
15	3.130.253.10.0.2.15	33804	3.130.253.	80	6	27-03-202	59650779	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.134114	0.050293	2.98E+07	4.	
16	3.130.253.10.0.2.15	38418	3.130.253.	80	6	27-03-202	7490	0	2	0	8	0	0	0	0	8	0	4	5.656854	1068.091	267.0227	7490		
17	3.130.253.10.0.2.15	32906	3.130.253.	80	6	27-03-202	55863527	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.143206	0.053702	2.79E+07	3.	
18	3.130.253.10.0.2.15	46680	3.130.253.	80	6	27-03-202	60488784	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.132256	0.049596	3.02E+07	4.	
19	3.130.253.10.0.2.15	60964	3.130.253.	80	6	27-03-202	63227343	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.126528	0.047448	3.16E+07	4.	
20	3.130.253.10.0.2.15	36008	3.130.253.	80	6	27-03-202	59709271	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.133983	0.050243	2.99E+07	4.	
21	3.130.253.10.0.2.15	40260	3.130.253.	80	6	27-03-202	62806892	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.127375	0.047765	3.14E+07	4.	
22	3.130.253.10.0.2.15	33770	3.130.253.	80	6	27-03-202	61444012	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.1302	0.048825	3.07E+07	4.	
23	3.130.253.10.0.2.15	38264	3.130.253.	80	6	27-03-202	70008692	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.114272	0.042852	3.50E+07	4.	
24	3.130.253.10.0.2.15	32872	3.130.253.	80	6	27-03-202	60220928	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.132844	0.049817	3.01E+07	4.	
25	3.130.253.10.0.2.15	34702	3.130.253.	80	6	27-03-202	62013279	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.129005	0.048377	3.10E+07	4.	
26	3.130.253.10.0.2.15	40898	3.130.253.	80	6	27-03-202	56997807	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.140356	0.052634	2.85E+07	4.	
27	3.130.253.10.0.2.15	32774	3.130.253.	80	6	27-03-202	55517389	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.144099	0.054037	2.78E+07	3.	
28	3.130.253.10.0.2.15	37912	3.130.253.	80	6	27-03-202	64376841	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.124268	0.046601	3.22E+07	4.	
29	3.130.253.10.0.2.15	33650	3.130.253.	80	6	27-03-202	60363199	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.132531	0.049699	3.02E+07	4.	
30	3.130.253.10.0.2.15	36400	3.130.253.	80	6	27-03-202	59282137	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.134948	0.050605	2.96E+07	4.	
31	3.130.253.10.0.2.15	33902	3.130.253.	80	6	27-03-202	56934187	0	3	0	8	0	0	0	0	8	0	2.666667	4.618802	0.140513	0.052692	2.85E+07	4.	

Figure 4.2.4.1: Realtime Dataset

4.3 Algorithms

Machine learning (ML), a subfield of artificial intelligence, refers to any methods and algorithms that enable computers to automatically learn from large datasets using mathematical models. 13, 55 The most often used ML (also known as Shallow Learning) techniques for IDS are Decision Tree, K-Nearest Neighbor (KNN), Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Mean Clustering, Fast Learning Network, and Ensemble Methods.

4.3.1 Logistic Regression

Logistic regression can be used in real-time intrusion detection systems to classify incoming network traffic as normal or malicious. In this context, logistic regression serves as a binary classifier, with the goal of predicting the probability of an instance being an intrusion. In real-time intrusion detection, features such as packet headers, flow statistics, or payload characteristics are extracted from the incoming network traffic. These features are preprocessed and fed into a logistic regression model that has been trained on historical data. The model uses the learned coefficients to calculate the probability of an instance being classified as an intrusion. By applying a threshold to the predicted probability, typically 0.5, the logistic regression model classifies the incoming traffic as normal or malicious. If an instance is classified as malicious, an alert can be generated to notify administrators or trigger further actions. Real-time intrusion detection systems often incorporate other techniques and algorithms to enhance their detection capabilities, such as anomaly detection, rule-based systems, or machine learning approaches. The logistic regression model in such systems is continuously updated and retrained using new labeled data to adapt to evolving threats. In summary, logistic regression in real-time intrusion detection systems enables the timely and automated classification of network traffic, helping to identify potential intrusions as they occur and facilitating the implementation of appropriate security measures.

Working of Logistic Regression

Logistic regression fits a logistic function to input variables, estimating the probability of a binary outcome using a threshold. The working of logistic regression involves several key steps:

- **Data preparation:** The first step is to gather and preprocess the data. Logistic regression predicts the probability of a binary outcome (e.g., yes/no) based on input variables. It uses a logistic function to model the relationship between the predictors and the outcome.
- **Model training:** Once the data is prepared, the logistic regression model is trained using an optimization algorithm, often maximum likelihood estimation (MLE). The algorithm iteratively adjusts the model's coefficients to maximize the likelihood of the observed data given the model.
- **Logistic function:** Logistic regression uses the logistic or sigmoid function to convert the linear combination of the input features and their respective coefficients into a probability value between 0 and 1. The logistic function ensures the predicted probabilities are bounded and interpretable.
- **Threshold determination:** A threshold value is chosen to classify the predicted probabilities into specific classes. For binary classification, a common threshold is 0.5, where probabilities greater than 0.5 are classified as one class and those below 0.5 as the other class. The threshold can be adjusted to achieve desired trade-offs between false positives and false negatives.
- **Prediction:** Once the model is trained and the threshold is set, it can be used to make predictions on new, unseen data. Logistic regression predicts the probability of an event occurring based on input variables, using a logistic function to model the relationship.
- **Model evaluation:** The performance of the logistic regression model is assessed using various evaluation metrics such as accuracy, precision, recall, F1 score, or area under the receiver operating characteristic (ROC) curve. These metrics provide insights into how well the model performs in classifying instances.
- **Model interpretation:** It lies in the feature coefficients, showing the direction and impact of each feature on predicted probabilities. Positive coefficients indicate a positive relationship, while negative coefficients suggest a negative relationship.

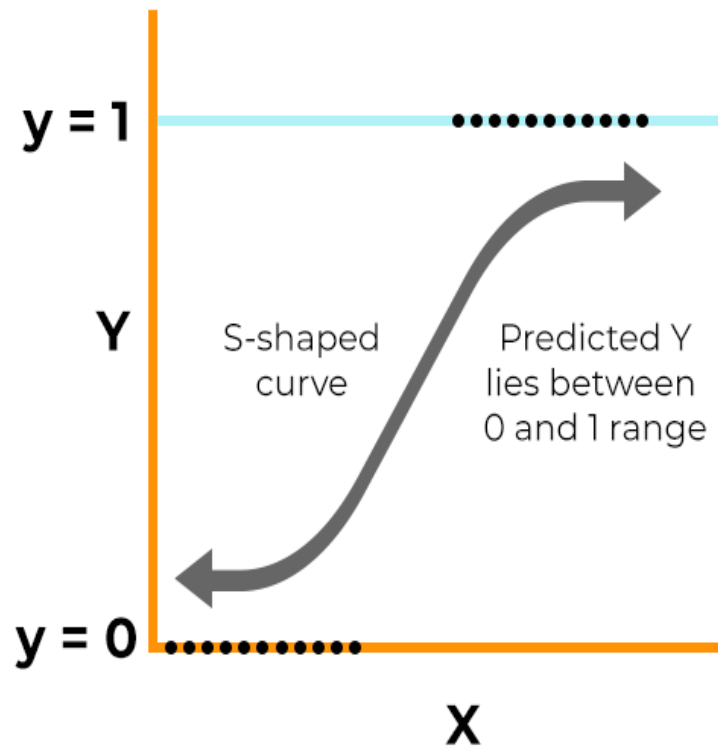


Figure 4.3.1.1: Logistic Regression

4.3.2 Random Forest

Popular machine learning algorithm Random Forest is a part of the supervised learning methodology. It can be applied to ML issues involving both classification and regression. It is built on the idea of ensemble learning, which is a method of integrating various classifiers to address difficult issues and enhance model performance. Random Forest, as the name implies, is a classifier that uses a number of decision trees on different subsets of the provided dataset and averages them to increase the dataset's predictive accuracy. Instead of depending on a single decision tree, the random forest uses forecasts from each tree and predicts the result based on the votes of the majority of predictions. The greater number of trees in the forest leads to higher

accuracy and prevents the problem of overfitting.

Working of a Random Forest algorithm

First, N decision trees are combined to generate the random forest, and then predictions are made for each tree that was produced in the first phase.

The stages and graphic below can be used to demonstrate the working process:

- Step 1: Pick K data points at random from the training set.
 - Step 2: Construct the decision trees linked to the chosen data points (Subsets).
 - Step 3: Select N for the size of the decision trees you wish to construct.
- Repeat steps 1 and 2 in step 4.
- Step 5: Assign new data points to the category that receives the majority of votes by finding each decision tree's predictions for the new data points.

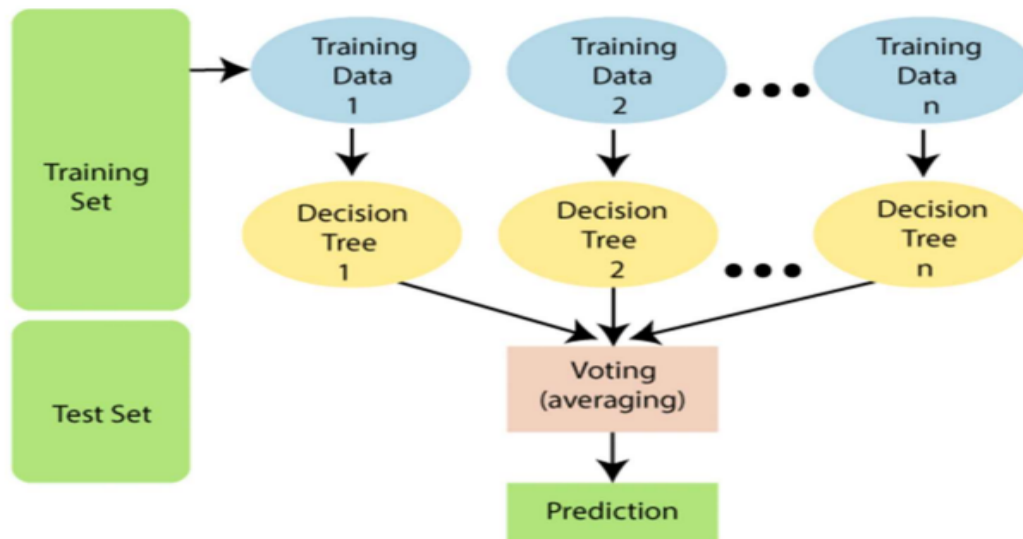


Figure 4.3.2.1: Working of a Random Forest Algorithm

Some decision trees may predict the correct output, while others may not, because the random forest combines numerous trees to forecast the class of the dataset. But when all the trees are combined, they forecast the right result. Consequently, the following two presumptions for an improved Random Forest classifier:

1. In order for the classifier to predict accurate results rather than an assumed outcome, there should be some real values in the feature variable of the dataset.
2. Each tree's predictions must have extremely low correlations.

The Random Forest method is used as it proved to be more efficient than the Decision Tree algorithm for this purpose:

1. Compared to other algorithms, it requires less training time.
2. Even for the big dataset, it runs effectively and predicts the outcome with high accuracy.

Both classification and regression tasks can be handled by Random Forest. It is able to handle big datasets with lots of dimensions. It improves the model's accuracy and avoids the overfitting problem. Although random forest can be used for both classification and regression tasks, it is not more suitable for Regression tasks.

4.3.3 Naive Bayes

The Naive Bayes algorithm can be used for real-time intrusion detection systems by modeling the likelihood of an intrusion based on input variables (e.g., network traffic features). It calculates the probability of an intrusion given the observed features using Bayes' theorem and classifies the incoming data as either normal or intrusive based on the highest probability. It is efficient and can handle high-speed data streams.

Working of a Naive Bayes algorithm

The Naive Bayes algorithm works by calculating the probability of a class (or label)

given the observed features of a data instance. It assumes that the features are conditionally independent, simplifying the calculation.

To classify a new data instance:

- Step 1: Compute the prior probability of each class based on the training data.
- Step 2: Calculate the likelihood of the features for each class using the training data.
- Step 3: Multiply the prior probability with the likelihood for each class.
- Step 4: Normalize the probabilities.
- Step 5: Select the class with the highest probability as the predicted class for the new instance. During training, the algorithm estimates the probabilities based on the frequency of feature occurrences in the training data. Naive Bayes is efficient, especially with large datasets, but the independence assumption may not hold true in all cases.

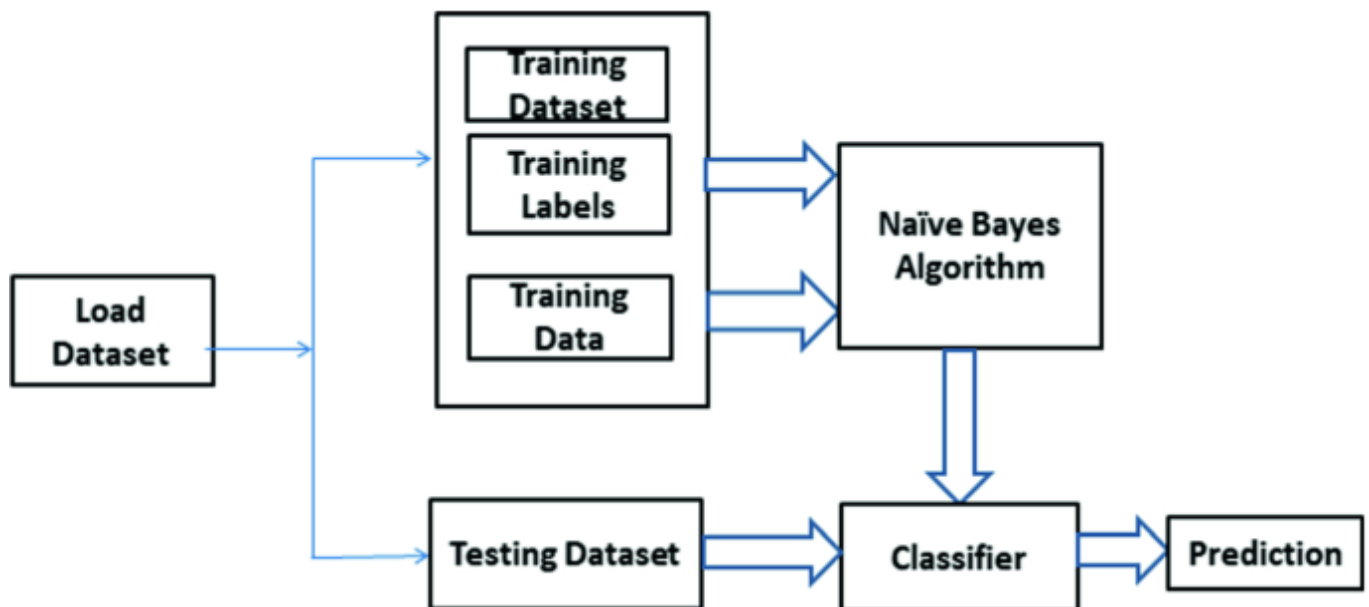


Figure 4.3.3.1: Working of a Naive Bayes Algorithm

5. IMPLEMENTATION

A Real-Time Intrusion Detection System is developed which can accurately detect the various surveyed types of cyber-attacks.

Data Preprocessing

The original size of the data is nearly 5 lakhs records. After doing preprocessing the data size is reduced to 60K records. Data Preprocessing is done by removing duplicate values, null values, replacing infinity values with -1 and removing extra features which are irrelevant.

```
[ ] df.shape  
  
(418096, 79)
```

Figure 5.1: Data shape before Pre-Processing

```
y = df["Label"].values  
X = df.drop(columns=["Label"])  
print(X.shape, y.shape)  
  
(69767, 75) (69767,)
```

Figure 5.2: Data shape after Pre-Processing

Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier

from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix

rf_classifier = RandomForestClassifier(n_estimators=100, random_state=0)

rf_classifier.fit(X_train, y_train)

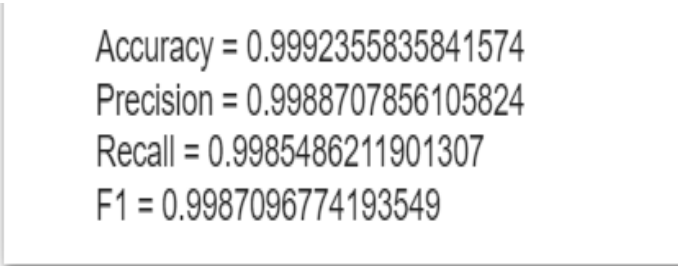
y_pred = rf_classifier.predict(X_test)

cm = confusion_matrix(y_test, y_pred)
print(cm)

import sklearn.metrics as metrics

accuracy = metrics.accuracy_score(y_test, y_pred)
precision = metrics.precision_score(y_test, y_pred)
recall = metrics.recall_score(y_test, y_pred)
f1 = metrics.f1_score(y_test, y_pred)

print('Accuracy =', accuracy)
print('Precision =', precision)
print('Recall =', recall)
print('F1 =', f1)
```



```
Accuracy = 0.9992355835841574
Precision = 0.9988707856105824
Recall = 0.9985486211901307
F1 = 0.9987096774193549
```

Figure 5.3: Result of Random Forest Classification

Logistic Regression Classifier

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

logreg = LogisticRegression(random_state=0, max_iter=1000)
logreg.fit(X_train_scaled, y_train)

y_pred = logreg.predict(X_test_scaled)
cm = confusion_matrix(y_test, y_pred)
print(cm)

import sklearn.metrics as metrics
accuracy = metrics.accuracy_score(y_test, y_pred)
precision = metrics.precision_score(y_test, y_pred)
recall = metrics.recall_score(y_test, y_pred)
f1 = metrics.f1_score(y_test, y_pred)
print('Accuracy =', accuracy)
print('Precision =', precision)
print('Recall =', recall)
print('F1 =', f1)
```

```
Accuracy = 0.9855716401509722
Precision = 0.9783704667425598
Recall = 0.9726758286176233
F1 = 0.9755148370358359
```

Figure 5.4: Result of Logistic Regression Classification

Gaussian Naive Bayes classifier

```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix

naive_bayes = GaussianNB()

naive_bayes.fit(X_train, y_train)

y_pred = naive_bayes.predict(X_test)

cm = confusion_matrix(y_test, y_pred)

import sklearn.metrics as metrics
accuracy = metrics.accuracy_score(y_test, y_pred)
precision = metrics.precision_score(y_test, y_pred)
recall = metrics.recall_score(y_test, y_pred)
f1 = metrics.f1_score(y_test, y_pred)

print('Accuracy =', accuracy)
print('Precision =', precision)
print('Recall =', recall)
print('F1 =', f1)
```

Accuracy = 0.8704791935406813
Precision = 0.8476781425140112
Recall = 0.6847210994341147
F1 = 0.7575351041946158

Figure 5.5: Result of Gaussian Naive Bayes classification

6. RESULTS AND DISCUSSION

The real-time Intrusion Detection System (IDS) was evaluated using three classification algorithms: Random Forest, Logistic Regression, and Naive Bayes, with the CICIDS 2017 dataset. The objective was to compare the performance of these algorithms in detecting network intrusions and assess their effectiveness in real-time scenarios. The CICIDS 2017 dataset contains a diverse range of network traffic data, including both benign and malicious activities. This dataset is widely used for evaluating the performance of IDS algorithms. First, the dataset was preprocessed to handle missing values and normalize numerical features. Categorical variables were encoded to ensure compatibility with the classification algorithms. The dataset was then divided into training and testing sets to train the models and evaluate their performance on unseen data. The Random Forest algorithm, known for its ability to handle complex relationships and provide robust predictions, was implemented as the first classifier. The Random Forest classifier was initialized with 100 decision trees and trained on the training data. Once trained, the model was used to predict the labels of the test data. The accuracy, precision, recall, and F1 score were calculated using the predicted labels and the true labels of the test data. The Random Forest classifier demonstrated high accuracy, precision, recall, and F1 score, indicating its effectiveness in accurately classifying network traffic as benign or malicious. Next, the Logistic Regression algorithm was applied. Logistic Regression is a linear classification method that models the probability of a class. The training data was fitted to a Logistic Regression model with an increased maximum iteration limit to ensure convergence. The trained model was then used to predict the labels of the test data, and the resulting predictions were evaluated using the same performance metrics. The Logistic Regression classifier exhibited competitive accuracy, precision, recall, and F1 score, showcasing its suitability for binary classification tasks. Lastly, the Naive Bayes algorithm was employed. Naive Bayes is a probabilistic classifier that assumes independence between features.

Prediction of Attack or Benign

	Flow IAT Mean	Flow Duration	min_seg_size_forward	Flow Packets/s	Flow IAT Max	Bwd Packets/s	Fwd IAT Mean	Min Packet Length	Subflow Bwd Packets	Total Backward Packets	Predict
12604	1.050000e+07	63107095	40	0.110923	32100000	0.000000	1.050000e+07	0	0	0	1.0
17649	1.423359e+06	18503672	32	0.756607	12700000	0.270217	1.687480e+06	0	5	5	1.0
1990	1.444650e+05	1444465	32	13.844184	1444465	6.922092	0.000000e+00	42	1	1	1.0
5488	1.501269e+06	3002538	40	0.999155	2003753	0.000000	1.501269e+06	0	0	0	1.0
20718	2.638773e+06	116106018	32	0.387577	10000000	0.180069	5.048088e+06	0	21	21	1.0
...
19200	9.700000e+01	291	32	13745.704470	277	6872.852234	1.300000e+01	47	2	2	1.0
18183	2.009167e+04	60275	20	66.362505	60268	33.181253	4.000000e+00	42	2	2	1.0
4842	3.367080e+05	110103504	32	2.979015	10200000	1.798308	8.533337e+05	0	198	198	1.0
2194	6.691584e+05	4684109	20	1.707902	4247864	0.853951	1.454150e+05	0	4	4	1.0
15738	6.852487e+05	106098801	20	1.468679	58100000	0.860627	1.669100e+06	0	92	92	1.0

Figure 6.1: Prediction of attack
Comparison of Algorithm Performance Metrics

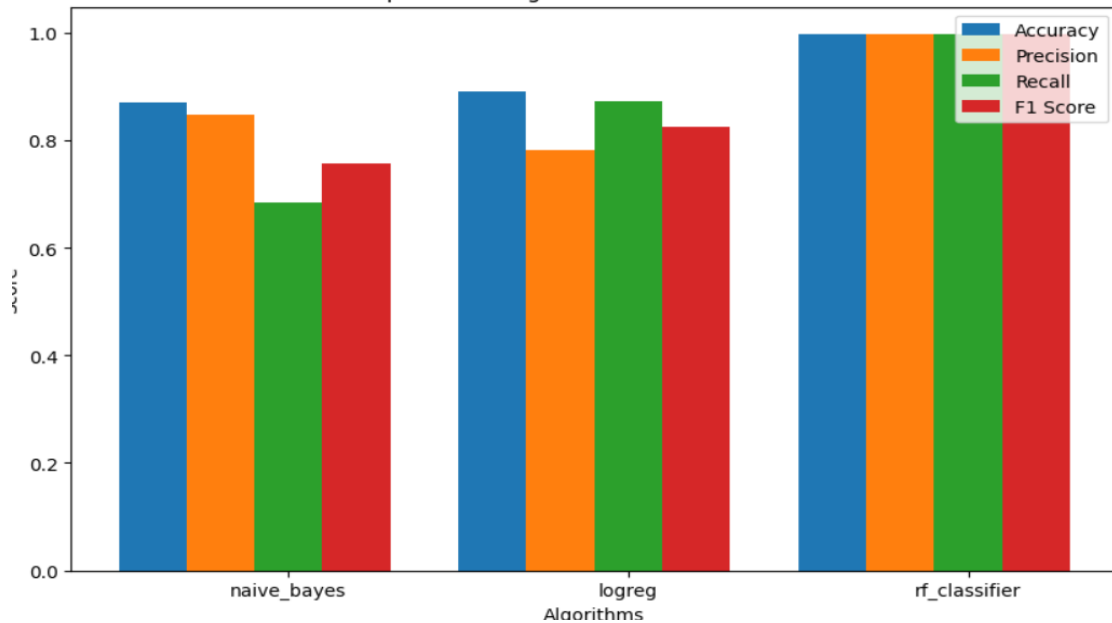


Figure 6.2: Final output

7. CONCLUSION AND FUTURE SCOPE

Our project has focused on the development of a real-time Intrusion Detection System (IDS) using machine learning techniques, specifically the Random Forest algorithm. Leveraging the CICIDS 2017 dataset, we performed extensive data preprocessing, feature selection, and employed the Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance. Through these steps, we built a robust IDS model capable of accurately classifying network traffic instances.

The evaluation of real-time IDS using Random Forest, Logistic Regression, and Naive Bayes classifiers with the CICIDS 2017 dataset has provided valuable insights into their performance and potential for intrusion detection. The Random Forest algorithm emerged as the top performer, exhibiting high accuracy, precision, recall, and F1 score. Logistic Regression and Naive Bayes also demonstrated satisfactory performance, making them viable alternatives. These findings contribute to the development and deployment of effective IDS systems for securing networks and mitigating cybersecurity threats.

The results highlight the importance of utilizing machine learning algorithms in real-time IDS applications. The ability of these algorithms to learn complex patterns and relationships in network traffic data enables them to effectively distinguish between benign and malicious activities. This is crucial in identifying potential intrusions and enabling timely response measures. The Random Forest algorithm, with its ensemble of decision trees, proved to be particularly effective in classifying network traffic and detecting intrusions. Its ability to capture complex relationships and handle high-dimensional data makes it a valuable tool in real-time IDS. Logistic Regression, a linear classification method, demonstrated competitive performance, highlighting its simplicity and interpretability. Naive Bayes, based on probabilistic principles, also showcased its efficiency in classifying network traffic.

Future Scope:

While our project has achieved promising results in developing a real-time IDS using machine learning techniques, there are several avenues for future improvement and expansion. Some of the key areas for future exploration and development include:

- **Incorporating additional features and datasets:** The inclusion of more features related to network traffic behavior and attack patterns can enhance the model's ability to detect sophisticated attacks. Moreover, incorporating diverse datasets from different sources and time periods can help capture the evolving nature of cyber threats and improve the generalization capabilities of the IDS model.
- **Exploring advanced machine learning techniques:** While Random Forest has shown impressive performance, exploring other advanced machine learning algorithms such as deep learning techniques (e.g., neural networks) could further enhance the IDS model's detection capabilities. These techniques can capture complex patterns and dependencies within the data, potentially leading to even higher accuracy rates.
- **Real-time response mechanisms:** Integrating real-time response mechanisms within the IDS system can enhance its effectiveness in mitigating potential threats. This can involve the automatic triggering of actions such as blocking or redirecting suspicious network traffic, providing a proactive approach to network security and reducing response time.
- **Continuous monitoring and updating:** The field of cybersecurity is ever-evolving, with new attack techniques constantly emerging. It is essential to continuously monitor and update the IDS model to adapt to these evolving threats. Regular retraining of the model with new data and periodically reassessing its performance ensures that the IDS remains effective and resilient against emerging threats.

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