

Consortium Blockchain Approach for Decentralized Global Copyright Management

**Prof. Cypto J¹, Mr. Punith Kanna AS², Mr. Ankit Narayan Pal³,
Mr. Thiivyesh SP⁴**

ABSTRACT

Digital images are transferred with ease through the network. Many users are using the images without the knowledge of the owners. Zero watermarking does not alter the original information contained in vector map data and provides perfect imperceptibility. The use of zero watermarking for data copyright protection has become a significant trend in digital watermarking research. However, zero watermarking encounters tremendous obstacles to its development and application because of its requirement to store copyright information with a third party and its difficulty in confirming copyright ownership. However, traditional digital image generation methods have high operational requirements for designers due to difficulties in collecting data sets and simulating environmental scenes, which results in poor quality, lack of diversity, and long generation speed of generated images, making it difficult to meet the current needs of image generation. This paper proposes a new image verification mechanism based on the Merkle tree technique in the blockchain. The Merkle tree root in the blockchain mechanism provides a reliable environment for storage of image features. In image verification, the verification of each image can be performed by the Merkle tree mechanism to obtain the hash value of the Merkle tree node on the path. The main purpose of this paper is to achieve the goal of image integrity verification. The proposed method can not only verify the integrity of the image but also restore the tampered area in the case of image tampering. Since the proposed method employs the blockchain mechanism, the image verification mechanism does not need third party resources. The verification method is performed by (c) Wisen IT Solutions Page 2 of 29 each node in the blockchain network. The experimental results demonstrate that the proposed method successfully achieved the goal of image authentication and tampered area restoration.

CHAPTER 1

INTRODUCTION

The classification of cyber-attacks through supervised machine learning techniques is a pivotal aspect of modern cybersecurity. As the digital realm becomes progressively intricate, cyber threats grow in sophistication and frequency. Thus, the ability to swiftly and accurately categorize these threats is paramount. Supervised machine learning offers a powerful solution by leveraging labelled datasets to teach algorithms to recognize and classify different types of cyber-attacks. This classification aids organizations in responding effectively, mitigating damage, and fortifying their defences. However, challenges such as the diversity of attack methods, the adaptability of attackers, and imbalanced data make this a complex field. Nevertheless, the potential applications are extensive, spanning intrusion detection, email filtering, malware identification, and anomaly detection. Looking ahead, ongoing research will refine models to handle evolving threats, integrate them with broader security strategies, and address ethical concerns in the deployment of these technologies

1.1 PROBLEM STATEMENT

The rapid growth of internet-connected systems has led to an increase in both the scale and complexity of cyberattacks, posing serious threats to the confidentiality, integrity, and availability of digital infrastructure. Traditional signature-based intrusion detection systems are often inadequate in identifying novel or sophisticated attack patterns. Consequently, there is a pressing need for intelligent, data-driven approaches that can automatically classify network threats with high precision. This study addresses the problem of cyberattack classification by leveraging supervised machine learning techniques to detect and categorize various types of malicious network activity, including but not limited to malware injection, phishing attempts, and distributed denial-of-service (DDoS) attacks. The core challenge lies in handling high-dimensional, imbalanced network data while maintaining generalization across diverse and evolving attack vectors. This problem is formulated as a multi-class classification task, where labeled network traffic is used to train predictive models capable of recognizing complex patterns and subtle anomalies. Accurate classification not only enhances early threat detection but also supports real-time response systems in mitigating damage. This research seeks to evaluate the effectiveness of algorithms such as decision trees, support vector machines, and neural networks in this context, contributing to the development of scalable and adaptive cybersecurity solutions.

1.2 AIM OF THE PROJECT

- To design and implement a machine learning model capable of classifying different types of cyberattacks using supervised learning techniques.
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- To compare the performance of various supervised algorithms, such as Decision Trees, Support Vector Machines, and Neural Networks, in the context of cyberattack classification.
- To enhance the accuracy and reliability of cyber threat detection by training models on labeled datasets containing diverse attack types like malware, phishing, and DDoS.
- To contribute to proactive cybersecurity strategies by building a scalable and adaptive system that supports real-time identification and mitigation of cyber threats.

1.3 PROJECT DOMAIN

The domain of the project is Cybersecurity, with a primary focus on using Deep Learning techniques to identify and classify cyberattacks effectively.

1.4 SCOPE OF THE PROJECT

This project focuses on developing a system that strengthens cybersecurity by detecting and classifying malicious network activities. It aligns with the functionality of an Intrusion Prevention System (IPS), which actively mitigates threats by blocking harmful traffic, dropping suspicious packets, and flagging potential risks for further investigation. The system is designed to utilize machine learning models trained on labeled datasets, enabling it to identify both known attack signatures and unusual behavioral patterns. By analyzing traffic flow and recognizing deviations from normal activity, the model supports intelligent, automated threat prevention beyond traditional rule-based detection. This approach contributes to building a more adaptive and responsive security infrastructure capable of addressing modern cyber threats in real time.

1.5 METHODOLOGY

This project adopts a supervised machine learning approach for the classification of cyberattacks using network traffic data. The methodology is structured into three primary modules: data preprocessing,

feature extraction, and attack classification. In the preprocessing stage, raw network data is cleaned, normalized, and transformed to ensure consistency and quality, while techniques like data balancing and noise reduction are applied to address class imbalances. The feature extraction phase focuses on identifying significant attributes such as protocol type, packet size, connection duration, and frequency, which are essential in distinguishing between normal and malicious traffic. Dimensionality reduction may also be employed to enhance model performance and efficiency. In the classification module, various supervised algorithms—including Decision Trees, Support Vector Machines, and Neural Networks—are trained on labeled datasets to learn patterns associated with different cyber threats. The models are evaluated using performance metrics such as accuracy, precision, recall, and F1-score, with cross-validation ensuring robustness and generalization. To maintain effectiveness in a dynamic threat landscape, the system is designed for periodic retraining with updated data. This comprehensive methodology enables the development of a reliable, adaptive solution for accurate cyberattack detection and classification.

1.6 ORGANIZATION OF THE REPORT

Chapter 2 Contains Literature review of relevant papers.

Chapter 3 explores the challenges faced in Cyberattack Detection within Cyber-Physical Systems (CPS), particularly focusing on anomaly detection through unsupervised learning techniques. It introduces the enhancement of existing datasets by integrating diverse cyberattack patterns to create a more robust and representative dataset. Various machine learning and deep learning models are explored, including autoencoders, for their ability to learn normal behavior and identify deviations. Cloud-based infrastructure is discussed for handling large-scale data collection and analysis. The chapter emphasizes the critical role of accurate anomaly detection techniques and highlights potential areas of application across industries like water treatment, energy, and manufacturing.

Chapter 4 outlines the proposed system design, inspired by real-world CPS architectures vulnerable to cyber threats. Figure 4.1 presents the general framework used for anomaly detection, incorporating unsupervised learning to identify malicious activity. The data flow is detailed in Figure 4.2, from raw sensor data input to feature extraction and classification using a neural network. Figure 4.3 shows the UML representation of processing stages. The system is divided into three main modules: Data Preprocessing, Feature Extraction, and Anomaly Detection using Autoencoders. A feasibility study is also included, evaluating the system's practicality from technical, economic, and social perspectives.

Chapter 5 describes the implementation and testing phase. The system is tested by feeding time-series or sensor data from CPS environments into the trained model to detect anomalies. Figures 5.1 and 5.2 illustrate sample attack and normal input-output evaluations. Testing types include Unit Testing (to validate individual components such as preprocessing and encoding), Integration Testing (to assess the interaction between modules), and Functional Testing (to confirm that the model correctly identifies attacks). A structured testing strategy ensures system reliability and accuracy.

Chapter 6 presents the results and discusses the performance of the proposed model. It highlights the model's ability to detect cyber anomalies with an accuracy of approximately 40%, despite using limited labeled data. The results demonstrate that the system performs well on unseen attack types and in various CPS environments. Figures 6.1 and 6.2 illustrate model predictions and comparisons with actual events, validating the efficiency of the anomaly detection approach.

Chapter 7 offers the conclusion and future directions. The study confirms that unsupervised models like autoencoders can effectively identify cyberattacks in CPS with minimal data. Future improvements

include refining the loss function, expanding to multiple CPS datasets, and integrating the model with real-time monitoring systems. There is also potential for exploring hybrid techniques that combine domain-driven logic with data-driven methods.

Chapter 8 contains the source code and details about the poster presentation. It includes sample code snippets for reference.

CHAPTER 2

LITERATURE REVIEW

This An Intrusion Detection System (IDS), or its more proactive counterpart, an Intrusion Prevention System (IPS), is a hardware or software solution designed to monitor computer systems and network activity for signs of malicious behavior or policy violations. IDS solutions can range from those tailored for individual machines to those designed for enterprise-wide networks. The two primary types of IDS are Network-based IDS (NIDS), which analyzes network traffic, and Host-based IDS (HIDS), which focuses on monitoring activity on individual systems, such as critical operating system files. IDS systems can also be categorized by their detection techniques. Signature-based detection identifies known threats by matching traffic patterns to pre-defined signatures, while anomaly-based detection identifies unusual behavior by comparing activity against a baseline of normal operations—often using machine learning. Reputation-based detection evaluates threats based on known credibility scores. Some IDS solutions are equipped with automated response features, effectively functioning as IPS by blocking suspicious activity in real time. Additionally, IDS can be enhanced with tools like honeypots, which lure and analyze malicious traffic for deeper insight into attacker behavior.

Wentao Zhao et al [1] Proposed an approach that addresses the clustering issue in network traffic data and utilizes a genetic (hereditary) algorithm to optimize the clustering strategy. This optimized clustering enhances the ability to group similar traffic patterns, allowing for more accurate identification of malicious behavior. Based on the optimized results applied to the test data, various categories are formed to represent the relationship between different types of network traffic and corresponding attack volumes. From these clusters, several predictive sub-models are developed, focusing primarily on DoS attacks. Furthermore, using the Bayesian method, discrete probability calculations are performed for each sub-model, which leads to the construction of a discrete probability distribution model aimed at effectively predicting DoS attack patterns.

Xiaoyong et al [2] proposed study highlights the rapid advancements and notable achievements of deep learning in various applications, especially its growing use in safety-critical environments. However, it also addresses a key vulnerability—deep neural networks (DNNs) are susceptible to carefully crafted inputs known as adversarial examples. These adversarial perturbations are often invisible to humans but can easily mislead DNNs during testing or deployment. This vulnerability poses a serious threat to the reliable use of DNNs in critical systems. As a result, adversarial attacks and corresponding defense strategies have gained significant research interest. The study reviews recent findings on adversarial examples for DNNs, summarizes the commonly used generation techniques, and proposes a taxonomy for classifying these methods. Based on this taxonomy, it explores various applications of adversarial inputs and further discusses effective countermeasures. Additionally, the study identifies three major challenges related to adversarial examples and discusses potential solutions for each.

Preetish Ranjan et al [3] provides a focused approach to social network analysis as an essential tool for observing and understanding community behavior within society. In the vast and complex networks

created through internet or telecommunication technologies, predicting or identifying socio-technical attacks is often a difficult task. This complexity opens up opportunities to explore different strategies, concepts, and algorithms aimed at detecting such communities based on patterns, structures, properties, and trends in their connections. The study seeks to uncover hidden insights in large-scale social networks by compressing them into smaller segments using the Apriori algorithm. These segments are then analyzed using the Viterbi algorithm to predict the most likely communication patterns. If the predicted pattern aligns with known behaviors of offenders, terrorists, or criminals, it can help in generating early alerts, potentially preventing criminal activities.

Seraj Fayyad et al [4] Provides a real-time prediction methodology designed to forecast potential attack steps and scenarios within network environments. Intrusion Detection Systems (IDS) generate large amounts of data that capture records of past malicious activities, which are stored in IDS databases and used as a valuable resource for enhancing network security. In addition to IDS data, the study incorporates attack graphs to support the prediction of future attacker behavior. The proposed method leverages both historical attack data and structural information from attack graphs to anticipate the likely next actions of an intruder. Unlike traditional approaches that rely heavily on searching large sets of predefined attack plans, this methodology operates with low computational cost and enables parallel prediction of multiple ongoing attack scenarios, making it highly efficient and practical for real-time threat detection.

Shone et al. [5] proposed a novel deep learning framework for intrusion detection that effectively combines unsupervised deep autoencoders with supervised classification to enhance the accuracy and efficiency of network attack detection. The framework uses autoencoders to perform dimensionality reduction and feature extraction on high-dimensional network traffic data, helping to preserve the essential characteristics of attack patterns while reducing noise and redundancy. This compressed representation is then passed through a supervised classifier to identify and categorize various attack types. Their approach was evaluated on benchmark datasets like KDD Cup 99, and the results demonstrated that the hybrid model outperformed traditional machine learning models in detecting known and unknown threats. This method is particularly effective in identifying DoS and probe attacks, showcasing robustness against false positives and computational efficiency. By reducing the reliance on handcrafted features and predefined rules, this framework aligns with real-time security requirements in complex and dynamic network environments. The study provides a solid foundation for developing adaptive and scalable intrusion detection systems using deep learning techniques. Its relevance to modern cybersecurity challenges makes it a significant contribution to the field of network traffic analysis and supervised learning for attack classification.

Revathi et al. [6] Proposed a supervised learning-based intrusion detection model using Decision Tree (J48) and Random Forest classifiers to classify different types of network attacks effectively. Their study focused on evaluating the NSL-KDD dataset to identify DoS, R2L, U2R, and probe attacks by applying preprocessing techniques like normalization and feature ranking. The classifiers were trained on selected features to reduce dimensionality and computational overhead. Among the tested models, Random Forest demonstrated higher accuracy, while Decision Tree offered better interpretability for practical applications. The research highlights that feature selection significantly enhances classification performance, particularly in large-scale traffic datasets. Their model achieved over 90% accuracy in detecting DoS and probe attacks and demonstrated resilience against class imbalance issues. This work provides a foundational basis for real-time network intrusion detection systems by focusing on lightweight, efficient, and explainable models suitable for operational environments. The authors

emphasize the importance of selecting optimal classifier parameters and understanding traffic patterns for model generalization. Their contribution is vital for designing intrusion detection architectures that are scalable and capable of handling dynamic network traffic, offering valuable insights for integrating machine learning in cybersecurity frameworks.

Tavallaee et al. [7] Provides a refined dataset called NSL-KDD, developed to overcome the limitations of the original KDD Cup 99 dataset, which was known for its redundancy and bias. The authors proposed enhancements that eliminate duplicate records, balance class distribution, and introduce a better testing set to improve the evaluation of intrusion detection models. This work also introduces a comparative analysis of multiple supervised learning algorithms, including Naive Bayes, SVM, and Decision Trees, demonstrating how the improved dataset helps in producing more realistic performance metrics. Their experiments showed that classifiers performed significantly better on NSL-KDD, with reduced overfitting and more stable precision/recall scores. The study emphasizes the importance of high-quality, well-structured datasets in building effective IDS models. By eliminating irrelevant and redundant entries, NSL-KDD supports accurate model training, generalization, and reproducibility of results across various ML algorithms. This contribution is particularly valuable for researchers developing and benchmarking intrusion detection systems, ensuring fair comparison and improved model validation. The paper provides a solid base for future work in supervised learning-based attack detection and enhances the reliability of cybersecurity solutions by addressing data-centric limitations in existing datasets.

Kim et al. [8] Proposed an intrusion detection framework using Support Vector Machine (SVM) to detect various types of attacks in real-time network environments. The authors focused on optimizing SVM parameters through grid search and cross-validation, enhancing the model's ability to detect complex and evolving threats. Using packet-level features extracted from TCP/IP headers, the study aimed to reduce false positives and improve generalization. Experimental validation on the KDD dataset revealed that the SVM model achieved high precision, particularly in identifying DoS and U2R attacks. The framework also incorporated feature scaling and dimensionality reduction to improve training efficiency and model responsiveness. Unlike traditional rule-based IDS systems, this machine learning approach adapts to new attack vectors, offering robustness and scalability for deployment in large-scale networks. The research underscores the value of SVMs in handling non-linear classification problems often encountered in cybersecurity. Their contribution lies in demonstrating that supervised learning techniques, when fine-tuned with proper preprocessing, can outperform static detection systems. This approach is highly relevant for modern IDS solutions where timely and accurate detection of diverse attack types is critical to maintaining secure network environments.

Vinayakumar et al. [9] Provides a deep learning-based intrusion detection system combining Convolutional Neural Networks (CNN) with traditional supervised models to improve classification accuracy in detecting various cyber attacks. Their model was tested on the NSL-KDD and UNSW-NB15 datasets and was designed to capture spatial hierarchies in network traffic features. The CNN layers extracted high-level patterns, which were then fed into a fully connected layer for final classification. The study demonstrated that hybrid deep-supervised learning models outperform conventional machine learning algorithms in detecting complex and stealthy attacks, especially DoS and botnet-based threats. The approach reduces manual feature engineering and adapts well to different network environments. Furthermore, the model achieved over 98% accuracy and low false alarm rates, making it suitable for real-time monitoring systems. This work highlights the potential of combining deep learning with supervised techniques to develop adaptive and robust intrusion detection frameworks. It provides an efficient solution

to modern cybersecurity challenges by learning meaningful feature representations directly from raw network traffic, reducing reliance on domain-specific feature design and enhancing detection capabilities in dynamic, data-intensive environments.

Shafi et al. [10] Proposed a comparative analysis of supervised machine learning algorithms for cyberattack detection in network traffic using the CICIDS2017 dataset. Their study assessed classifiers such as Logistic Regression, Random Forest, and Gradient Boosting to evaluate their performance across multiple attack types including DDoS, brute force, and infiltration attacks. The research involved preprocessing steps like one-hot encoding, standardization, and feature correlation to optimize model input. Random Forest emerged as the most reliable model, offering a balance of high accuracy, fast inference time, and strong generalization capabilities. The study also addressed issues like class imbalance and overfitting through stratified sampling and cross-validation. Their findings support the idea that selecting the right algorithm and preprocessing strategy significantly impacts the performance of intrusion detection systems. This paper contributes to the cybersecurity field by offering practical insights into how supervised learning algorithms perform under realistic network traffic conditions. It sets a benchmark for researchers and developers aiming to design efficient IDS models that are deployable in real-world scenarios, with a focus on predictive accuracy and scalability.

CHAPTER 3

PROJECT DESCRIPTION

3.1 EXISTING SYSTEM

The application of invariants in securing Cyber-Physical Systems (CPS) has gained considerable interest due to their effectiveness in both detecting and preventing cyberattacks. An invariant refers to a condition or property—typically formulated using system design parameters and Boolean logic—that consistently holds true during normal system operation. These invariants can be derived either from operational data (data-driven) or from system specifications and design documents (design-driven). Both methods have shown promise in safeguarding CPS environments. While data-driven invariant generation can be automated, design-driven approaches often require significant manual effort. This paper explores the limitations of data-driven invariants by showcasing adversarial attacks that can bypass them. To address these vulnerabilities, the authors introduce a hybrid strategy that incorporates design-driven invariants to strengthen detection mechanisms. Experimental validation is conducted using a real-world water treatment testbed, demonstrating that the proposed method enhances detection accuracy and reduces false positives in identifying cyber threats within CPS infrastructures.

3.2 PROPOSED SYSTEM

The proposed system presents a structured and intelligent method for classifying cyberattacks using supervised machine learning techniques. It begins by building a rich and diverse dataset that includes various types of cyber threats, each represented by its unique behavioral traits. Key features are extracted from sources such as network traffic data, system logs, and known attack signatures to form a comprehensive feature set. With the help of supervised learning models—such as decision trees, support vector machines, and neural networks—the system is trained on labeled historical data to recognize and categorize different forms of malicious activity. Once trained, the model is integrated into a real-time monitoring environment where it actively analyzes ongoing network behavior and identifies potential threats. The system is designed to adapt over time by incorporating newly collected data through

continuous retraining, ensuring its relevance as threat landscapes evolve. By enabling swift and accurate detection, this system strengthens cyber defense efforts, supporting faster response times and effective threat mitigation.

3.2.1 ADVANTAGES

- Conducted a comparative analysis of multiple supervised machine learning algorithms to identify the model with the highest accuracy for cyberattack classification.
- Developed a user-friendly web application to make the system accessible and easy to operate.
- Simplicity and explainability
- R Achieved improved accuracy and performance through effective model tuning and system optimization.
- Simplify implementation process

3.3 FEASIBILITY STUDY

A feasibility study is conducted to assess the viability of the project and analyze its strengths and weaknesses. In this context, the feasibility study is conducted across three dimensions:

- Economic Feasibility
- Technical Feasibility
- Social Feasibility

3.3.1 ECONOMIC FEASIBILITY

The proposed system does not require expensive equipment, making it economically feasible. Development can be carried out using readily available software, eliminating the need for additional investment.

3.3.2 TECHNICAL FEASIBILITY

The proposed system is based entirely on a machine learning model utilizing tools such as Anaconda prompt, Visual Studio, Kaggle datasets, and Jupyter Notebook, all of which are freely available, ensures technical feasibility. The technical skills required to use these tools are practical and accessible, further supporting the feasibility of the project.

3.3.3 SOCIAL FEASIBILITY

The proposed system is based entirely on a machine learning model. Utilizing tools such as Anaconda prompt, Visual Studio, Kaggle datasets, and Jupyter Notebook, all of which are freely available, ensures technical feasibility. The technical skills required to use these tools are practical and accessible, further supporting the feasibility of the project.

3.4 SYSTEM SPECIFICATION

An effective system is crucial for any computational task. It's important to have the correct hardware and software components to ensure everything runs smoothly. From strong processors to essential software packages, each part helps create an efficient environment for data analysis and machine learning tasks.

3.4.1 HARDWARE SPECIFICATION

- Processor: Pentium IV/III
- Ethernet connection (LAN) OR a wireless adapter (Wi-Fi)
- Hard Drive: Minimum 80 GB; Recommended 200 GB or more
- Memory (RAM): Minimum 2 GB; Recommended 4 GB or above

3.4.2 SOFTWARE SPECIFICATION

- Operating System: Windows
- Tools: Python, Anaconda with Jupyter Notebook, HTML 5, CSS

CHAPTER 4

PROPOSED WORK

4.1 GENERAL ARCHITECTURE

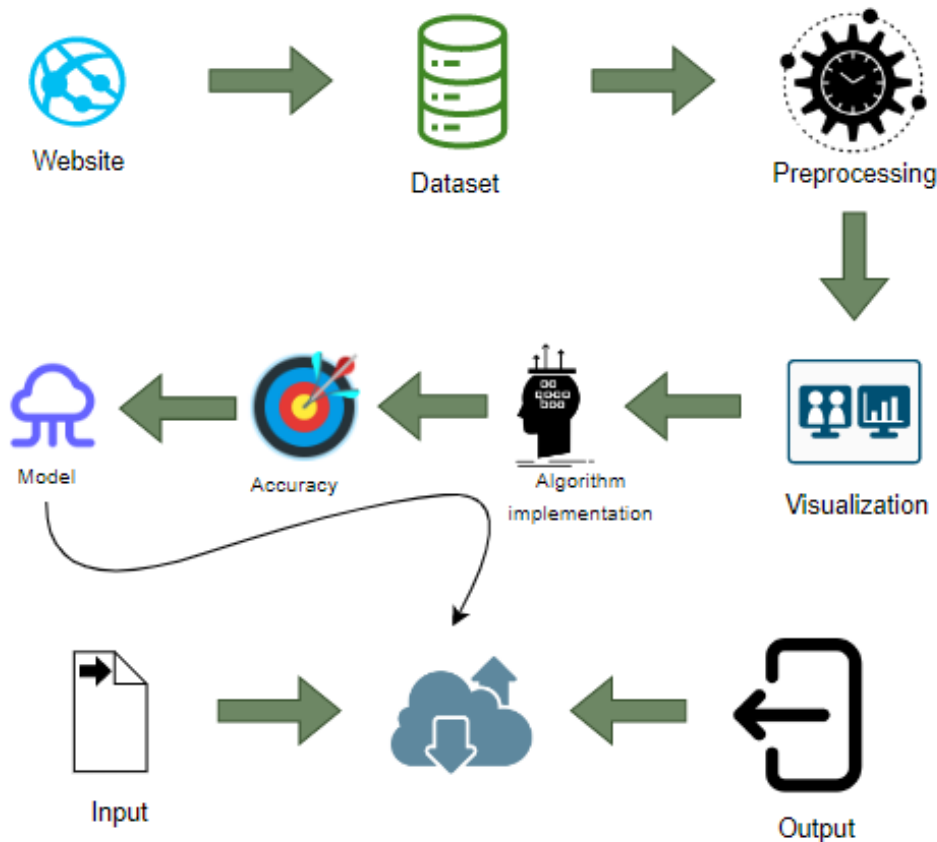


Figure 4.1: Architecture Diagram

Figure 4.1 illustrates a machine learning-based architecture for data-driven prediction. It follows a structured flow from data collection and preprocessing to model training, evaluation, and output generation.

4.2 DESIGN PHASE

During the design phase of this project, key architectural diagrams were developed to represent system components, data flow, and interactions involved in cyberattack classification. Tools such as UML, use case, sequence, and data flow diagrams were used to visualize the machine learning pipeline, helping stakeholders and developers understand the system's workflow and ensure accurate implementation of each module.

4.2.1 DATA FLOW DIAGRAM

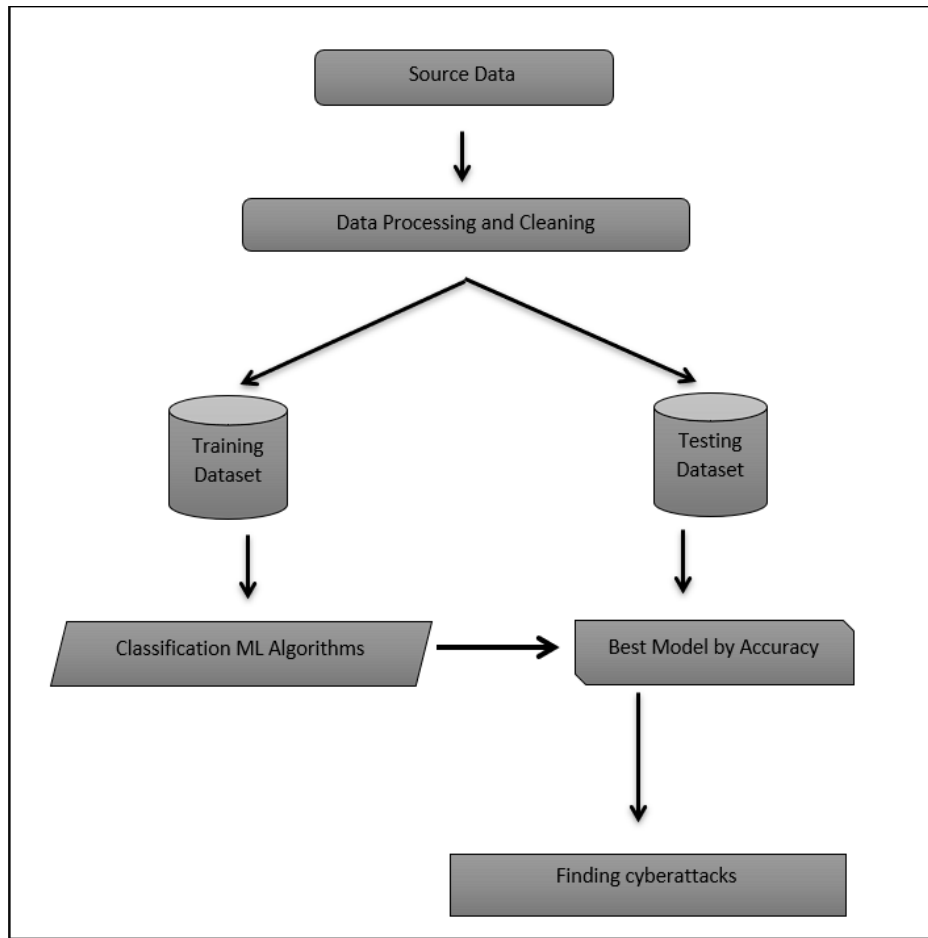


Figure 4.2: Data Flow Diagram

Figure 4.2: The diagram represents the flow of data in the cyberattack detection system. It begins with Source Data, which undergoes Processing and Cleaning. The refined data is then split into Training and Testing Datasets. Machine learning algorithms analyze the training data, leading to the selection of the Best Model by Accuracy, which is ultimately used for Cyberattack Detection.

4.2.2 UML DIAGRAM

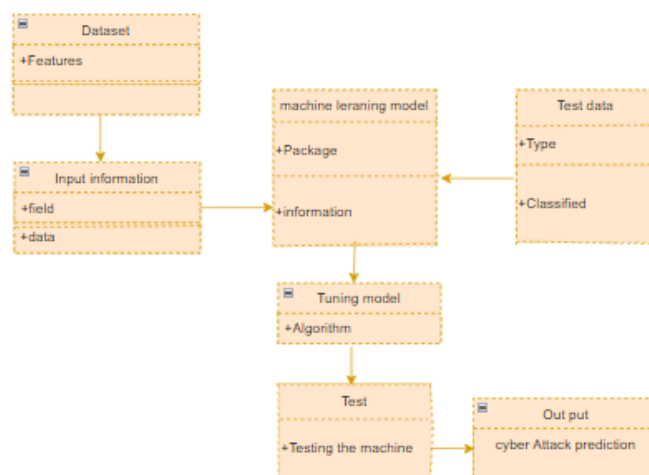


Figure 4.3: UML Diagram

Figure 4.3 presents a UML diagram of the machine learning pipeline, covering data preprocessing, model training, and cyberattack prediction. The process begins with refining raw data by filtering noise and structuring features. This cleaned data is then utilized to train and fine-tune a machine learning model. Ultimately, the trained model predicts cyberattacks, offering crucial insights for cybersecurity applications.

4.2.3 USE CASE DIAGRAM

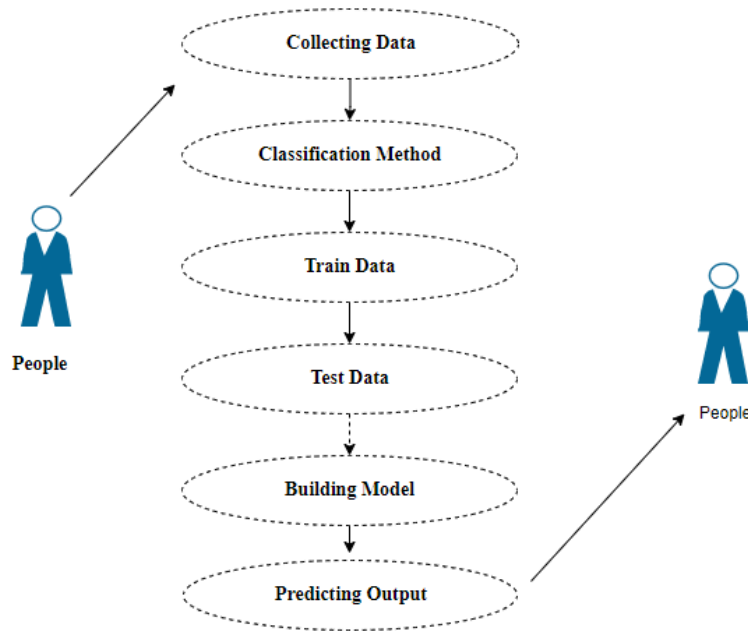


Figure 4.4: Use Case Diagram

The Figure 4.4 represents a process flow diagram illustrating the key stages of a data classification system. It begins with data collection, followed by classification, training, and testing processes. The model is then built and used to predict outcomes. Users interact with the system at both the input and output stages, contributing data and receiving predictions.

4.2.4 SEQUENCE DIAGRAM

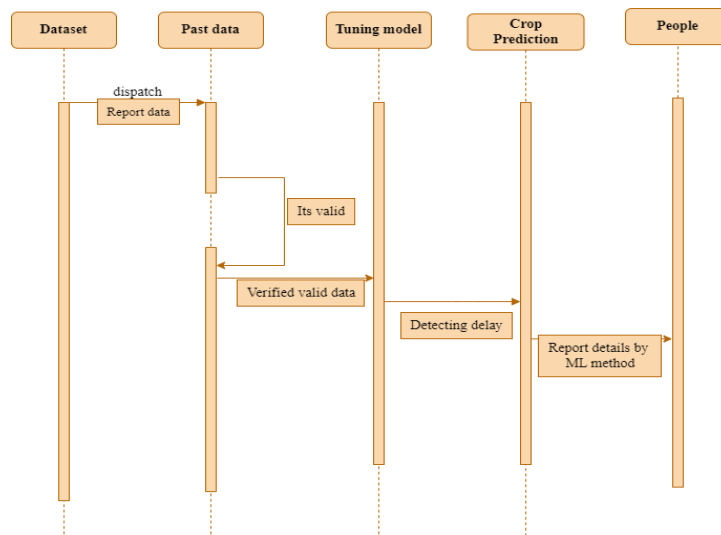


Figure 4.5: Sequence Diagram

Figure 4.5 presents a sequence diagram outlining the workflow of a crop prediction system using machine learning. The process starts with dataset dispatch, where past data is validated. Once verified, the tuning model detects delays and processes the information. The crop prediction module then utilizes an ML-based method to generate reports, which are ultimately conveyed to the end-users.

4.3 MODULE DESCRIPTION

This module ensures the dataset is clean, complete, and consistent, enabling accurate model training. It also applies validation techniques to evaluate model performance and guide parameter tuning.

4.3.1 DATA PREPROCESSING

Validation techniques in machine learning are used to get the error rate of the Machine Learning (ML) model, which can be considered as close to the true error rate of the dataset. If the data volume is large enough to be representative of the population, we may not need the validation techniques. However, in real-world scenarios, to work with samples of data that may not be a true representative of the population of given dataset. To finding the missing value, duplicate value and description of data type whether it is float variable or integer. The sample of data used to provide an unbiased evaluation of a model fit on the training dataset while tuning model hyper parameters. The evaluation becomes more biased as skill on the validation dataset is incorporated into the model configuration. The validation set is used to evaluate a given model, but this is for frequent evaluation. It as machine learning engineers use this data to fine-tune the model hyper parameters. Data collection, data analysis, and the process of addressing data content, quality, and structure can add up to a time-consuming to-do list. During the process of data identification, it helps to understand our data and its properties; this knowledge was used to select an appropriate algorithm for model building.. A number of different data cleaning tasks using Python's Pandas library and specifically, it focus on probably the biggest data cleaning task, missing values and it able to more quickly clean data. It wants to spend less time cleaning data, and more time exploring and modeling. Some of these sources are just simple random mistakes. Other times, there can be a deeper reason why data is missing. It's important to understand these different types of missing data from a statistics point of view. The type of missing data will influence how to deal with filling in the missing values and to detect missing values, and do some basic imputation and detailed statistical approach for dealing with missing data.

4.3.2 DATA VISUALIZATION

Data visualization is an important skill in applied statistics and machine learning. Statistics does indeed focus on quantitative descriptions and estimations of data. Data visualization provides an important suite of tools for gaining a qualitative understanding. This can be helpful when exploring and getting to know a dataset and can help with identifying patterns, corrupt data, outliers, and much more. With a little domain knowledge, data visualizations can be used to express and demonstrate key relationships in plots and charts that are more visceral and stakeholders than measures of association or significance. Data visualization and exploratory data analysis are whole fields themselves and it will recommend a deeper dive into some the books mentioned at the end. Sometimes data does not make sense until it can look at in a visual form, such as with charts and plots. Being able to quickly visualize of data samples and others is an important skill both in applied statistics and in applied machine learning.

4.3.3 ALGORITHM IMPLEMENTATION

It is important to compare the performance of multiple different machine learning algorithms consistently and it will discover to create a test harness to compare multiple different machine learning algorithms in

Python . It can use this test harness as a template on our own machine learning problems and add more and different algorithms to compare. Each model will have different performance characteristics. Using resampling methods like cross validation, we can get an estimate for how accurate each model may be on unseen data. It needs to be able to use these estimates to choose one or two best models from the suite of models that we have created. When have a new dataset, it is a good idea to visualize the data using different techniques in order to look at the data from different perspectives. The same idea applies to model selection. We have used a number of different ways of looking at the estimated accuracy of our machine learning algorithms in order to choose the one or two to finalize. A way to do this is to use different visualization methods to show the average accuracy, variance and other properties of the distribution of model accuracies.

The key to a fair comparison of machine learning algorithms is ensuring that each algorithm is evaluated in the same way on the same data and it can achieve this by forcing each algorithm to be evaluated on a consistent test harness.

Performance Metrics to calculate:

False Positives (FP): A person who will pay predicted as defaulter. When actual class is no and predicted class is yes. E.g. if actual class says this passenger did not survive but predicted class tells us that this passenger will survive.

False Negatives (FN): A person who default predicted as payer. When actual class is yes but predicted class in no. E.g. if actual class value indicates that this passenger survived and predicted class tells us that passenger will die.

True Positives (TP): A person who will not pay predicted as defaulter. These are the correctly predicted positive values which means that the value of actual class is yes and the value of predicted class is also yes. E.g. if actual class value indicates that this passenger survived and predicted class tells us the same thing.

True Negatives (TN): A person who default predicted as payer. These are the correctly predicted negative values which means that the value of actual class is no and value of predicted class is also no. E.g. if actual class says this passenger did not survive and predicted class tells us the same thing.

True Positive Rate(TPR) = $TP / (TP + FN)$

False Positive rate(FPR) = $FP / (FP + TN)$

Accuracy: The Proportion of the total number of predictions that is correct otherwise overall how often the model predicts correctly defaulters and non-defaulters.

Accuracy calculation:

Accuracy = $(TP + TN) / (TP + TN + FP + FN)$

Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations. One may think that, if we have high accuracy then our model is best. Yes, accuracy is a great measure but only when we have symmetric datasets where values of false positive and false negatives are almost same.

Precision: The proportion of positive predictions that are actually correct.

Precision = $TP / (TP + FP)$

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. The question that this metric answer is of all passengers that labelled as survived, how many actually survived? High precision relates to the low false positive rate. We have got 0.788 precision which is pretty good.

Recall: The proportion of positive observed values correctly predicted. (The proportion of actual defaulters that the model will correctly predict)

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

Recall (Sensitivity) - Recall is the ratio of correctly predicted positive observations to the all observations in actual class - yes.

F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if we have an uneven class distribution. Accuracy works best if false positives and false negatives have similar cost. If the cost of false positives and false negatives are very different, it's better to look at both Precision and Recall.

General Formula:

$$\text{F- Measure} = 2\text{TP} / (2\text{TP} + \text{FP} + \text{FN})$$

F1-Score Formula:

$$\text{F1 Score} = 2 * (\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision})$$

The below 3 different algorithms are compared:

- Adaboost classifier
- Catboost classifier
- Naïve Bayes

Adaboost Classifier:

An AdaBoost classifier is a meta-estimator that begins by fitting a classifier on the original dataset and then fits additional copies of the classifier on the same dataset but where the weights of incorrectly classified instances are adjusted such that subsequent classifiers focus more on difficult cases.

AdaBoost can be used to boost the performance of any machine learning algorithm. It is best used with weak learners. These are models that achieve accuracy just above random chance on a classification problem. The most suited and therefore most common algorithm used with AdaBoost are decision trees with one level. How does the AdaBoost algorithm work explain?

It works on the principle of learners growing sequentially. Except for the first, each subsequent learner is grown from previously grown learners. In simple words, weak learners are converted into strong ones. The AdaBoost algorithm works on the same principle as boosting with a slight difference.

```
# Implement Adaboost classifier algorithm Learning patterns
from sklearn.ensemble import AdaBoostClassifier
```

```
ABC = AdaBoostClassifier()
# Fit is the training function for this algorithm.
ABC.fit(x_train,y_train)
```

```
AdaBoostClassifier()
```

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.**

```
# Predict is the test function for this algorithm
predicted = ABC.predict(x_test)
```

Catboost Algorithm:

CatBoost is a gradient boosting algorithm designed for supervised machine learning tasks, particularly for classification and regression problems. It is known for its high accuracy, efficient handling of

categorical features, and robustness to overfitting.

Gradient Boosting Ensemble: CatBoost is an ensemble algorithm that combines multiple decision trees into a powerful model. It belongs to the gradient boosting family, which sequentially adds decision trees to the model, with each tree trying to correct the errors made by the previous ones.

Categorical Feature Handling: One of CatBoost's standout features is its ability to efficiently handle categorical features without requiring extensive preprocessing. It uses a technique called "ordered boosting," which assigns a numerical value to each category based on the target variable's statistics. This allows CatBoost to naturally incorporate categorical information during training.

Tree Construction: CatBoost constructs decision trees in a depth-first manner. It selects the best split points for each tree node by optimizing a loss function that measures the prediction error. The algorithm also employs techniques like leaf-wise splits and the use of oblivious trees to improve tree construction efficiency.

Regularization: CatBoost includes built-in regularization techniques to prevent overfitting. It uses L2 regularization on leaf values and feature combinations to control model complexity.

Learning Rate Shrinkage: To improve the overall stability and generalization of the model, CatBoost incorporates a learning rate shrinkage strategy. It reduces the contribution of each new tree to the ensemble, making the training process more controlled and less prone to overfitting.

Handling Imbalanced Data: CatBoost provides options for handling imbalanced datasets by adjusting class weights or using custom loss functions, making it suitable for tasks with unequal class distributions.

Early Stopping: To prevent overfitting, CatBoost offers early stopping based on a holdout validation dataset. Training stops when the validation error starts to increase, indicating that further iterations may lead to overfitting.

Prediction: Once the model is trained, CatBoost can be used for making predictions. For classification tasks, it provides class probabilities or class labels based on the majority class of the trees' leaf nodes.

Hyperparameter Tuning: CatBoost includes a range of hyperparameters that can be fine-tuned for optimal performance, including tree depth, learning rate, and regularization strength.

Scalability: CatBoost is designed for efficiency and can handle large datasets and complex models. It can be parallelized to leverage multiple CPU cores for faster training.

In summary, CatBoost is a powerful gradient boosting algorithm known for its ability to handle categorical features efficiently, its built-in regularization techniques, and its high accuracy in various machine learning tasks. It is a valuable tool for data scientists and practitioners working on classification and regression problems, particularly when dealing with complex and real-world datasets.

```
# Implement Catboost classifier algorithm learning patterns
from catboost import CatBoostClassifier
```

```
CBC = CatBoostClassifier()
# Fit is the training function for this algorithm.
CBC.fit(x_train,y_train)
```

```
28:   learn: 0.2570863   total: 4.95s   remaining: 2m 45s
29:   learn: 0.2489687   total: 5.1s   remaining: 2m 45s
30:   learn: 0.2437446   total: 5.24s  remaining: 2m 43s
31:   learn: 0.2315514   total: 5.41s  remaining: 2m 43s
32:   learn: 0.2256667   total: 5.56s  remaining: 2m 42s
33:   learn: 0.2212783   total: 5.69s  remaining: 2m 41s
34:   learn: 0.2176730   total: 5.82s  remaining: 2m 40s
```

Naïve Bayes:

Naive Bayes is a probabilistic classification algorithm based on Bayes' theorem, which is used for solving classification and prediction problems. Despite its simplicity and certain strong assumptions (hence "naive"), it often performs remarkably well in various applications, such as text classification, spam detection, sentiment analysis, and more. Here's an explanation of how the Naive Bayes algorithm works: Bayes' Theorem: At the core of the Naive Bayes algorithm is Bayes' theorem, which is a fundamental probability theorem. It relates the conditional probability of an event A given an event B to the conditional probability of event B given event A:

In the context of classification, we can think of:

A as the class label we want to predict.

B as the features or attributes of the data.

Naive Assumption: The "naive" part of Naive Bayes comes from the assumption that the features are conditionally independent, given the class label. In other words, the algorithm assumes that each feature contributes independently to the probability of an instance belonging to a particular class. This simplifies the calculation and makes the algorithm computationally efficient.

Training: To train a Naive Bayes classifier, we have labeled data where both the class labels and the features are known. The algorithm calculates two sets of probabilities:

Class Probabilities (Prior Probabilities): These represent the probability of each class occurring in the dataset. They are estimated by counting the frequency of each class in the training data.

Conditional Feature Probabilities (Likelihoods): For each feature and each class, Naive Bayes calculates the probability of that feature occurring given the class. These probabilities are estimated based on the training data.

Prediction: When given a new data point with features but without a class label, Naive Bayes calculates the probability of the data point belonging to each class using Bayes' theorem. The class with the highest conditional probability is assigned as the predicted class label.

```
: # Implement Gaussian naive bayes algorithm Learning patterns
from sklearn.naive_bayes import GaussianNB

: GNB = GaussianNB()
# Fit is the training function for this algorithm.
GNB.fit(x_train,y_train)

: GaussianNB()
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

: # Predict is the test function for this algorithm
predicted = GNB.predict(x_test)
```


**CHAPTER 5
IMPLEMENTATION AND TESTING**

5.1 INPUT AND OUTPUT

5.1.1 NORMAL TRAFFIC INPUT FROM USER

Cyber Attack Model

FLOW DURATION 119955251	BWD PKT LEN STD 8.23	FWD IAT TOT 11995529
TOT FWD PKTS 85010	FLOW PKTS/S 34.77	FWD IAT MEAN 141.08
TOT BWD PKTS 27121	FLOW IAT MEAN 1069.78	BWD IAT TOT 119955251
BWD IAT MEAN 4423.12	FWD PKTS/S 708.68	SYN FLAG CNT 0
FWD HEADER LEN 1700200	BWD PKTS/S 226.08	ECE FLAG CNT 0
BWD HEADER LEN 682136	PKT LEN MEAN 1027.83	DOWN/UP RATIO 0

Figure 5.1: Normal traffic data from user

Figure 5.1 shows the sample input parameters representing normal network traffic. The data includes standard flow metrics such as balanced forward and backward packet counts, stable flow duration, and average packet lengths within expected ranges. All flag indicators like SYN, ECE, and others are zero, showing there's no unusual handshake or malicious signaling.

5.1.2 OUTPUT FOR THE NORMAL TRAFFIC DATA

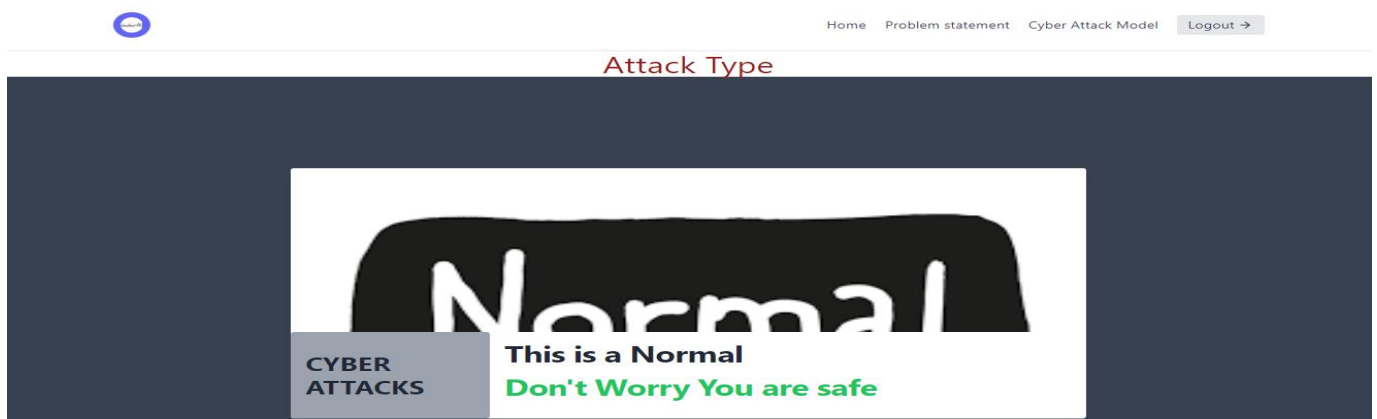


FIGURE 5.2 Output for the Normal Traffic Data

Figure 5.2 shows the output classification result for the normal network traffic input. The system successfully identified the traffic as "Normal," indicating that no suspicious or malicious activity was detected in the analyzed data. The message "Don't Worry, You are safe" is displayed, providing a user-friendly reassurance about the safety of the network. This output confirms that the model is functioning

correctly in distinguishing benign traffic patterns from potential threats.

5.1.3 MALICIOUS TRAFFIC INPUT FROM USER

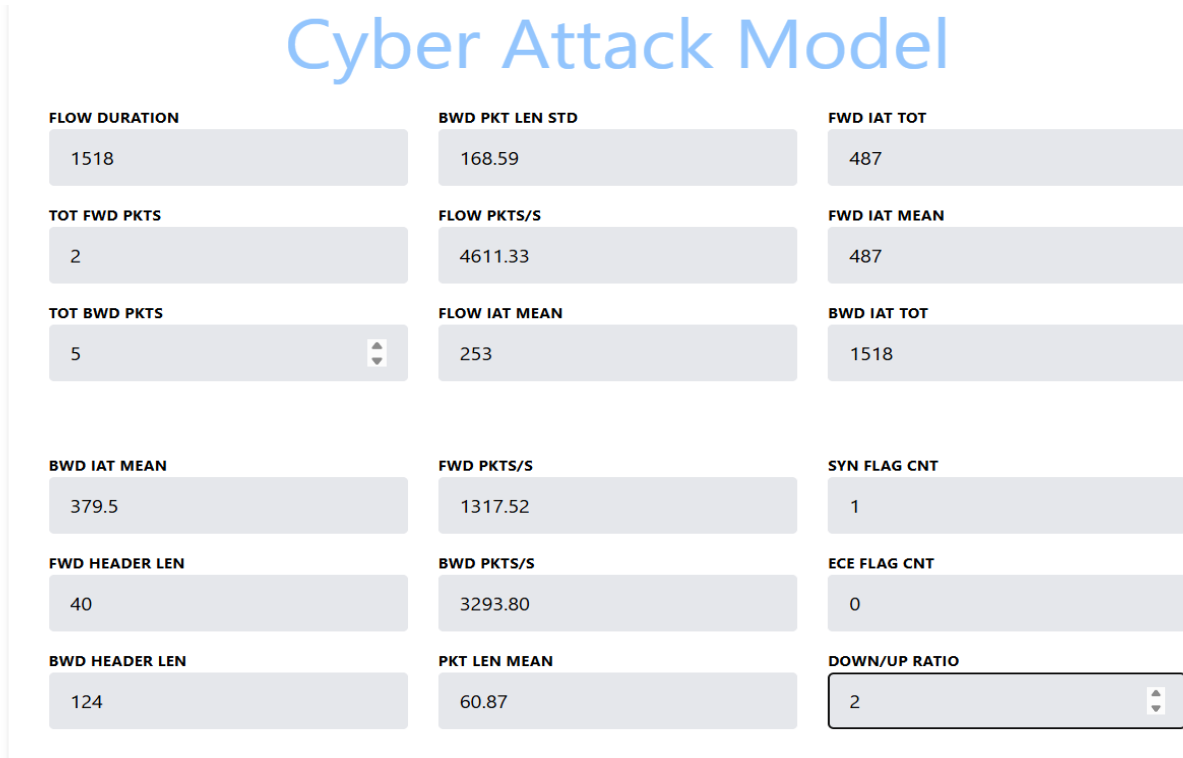


Figure 5.3 Malicious traffic data from user

Figure 5.3 shows the input parameters representing attack traffic, which are noticeably different from normal traffic behavior. The total number of forward and backward packets is very low, yet the flow packets per second is unusually high, indicating a sudden burst of data — a common characteristic of denial-of-service or other similar attacks. The presence of a SYN flag count suggests an attempt to initiate a connection, which is often exploited in SYN flood attacks. Additionally, the down/up ratio appears abnormally high, pointing to an imbalanced data flow that typically occurs during malicious activity. These indicators collectively help the model identify suspicious or harmful traffic patterns.

5.1.4 OUTPUT FOR THE MALICIOUS TRAFFIC DATA

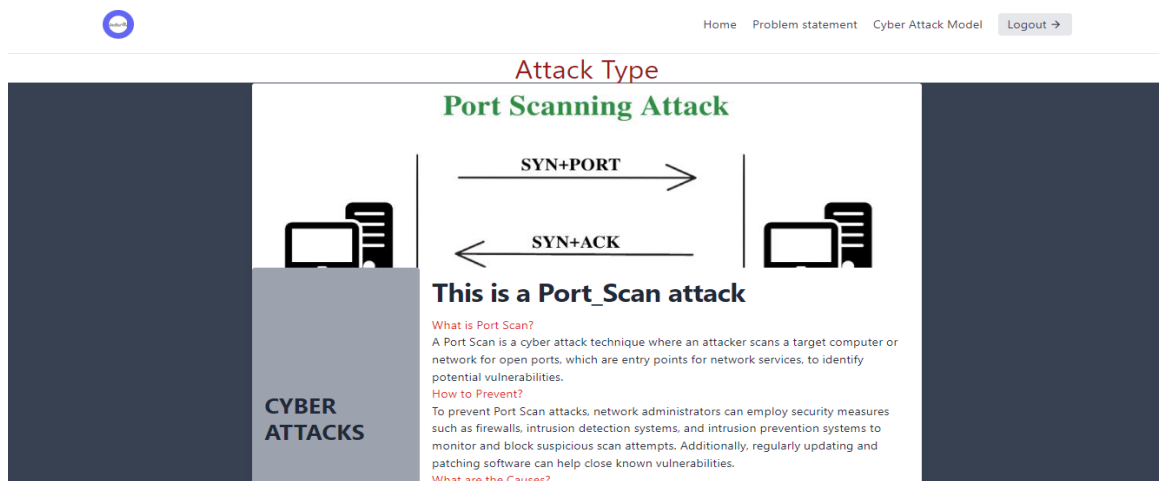


Figure 5.4 OUTPUT FOR THE MALICIOUS TRAFFIC DATA

Figure 5.4 displays the output result for a malicious network traffic input. The system correctly detected the activity as a Port_Scan attack, which is a reconnaissance technique used by attackers to identify open ports and potential vulnerabilities in a network. The interface provides a brief explanation of what a port scan is and suggests prevention measures, such as using firewalls and intrusion detection systems. This output demonstrates the model's ability to accurately classify and provide information on cyber threats in real time.

5.2 TESTING

Software testing is a process of evaluation that allows a software application to function as intended. It includes executing a piece of software under various conditions with the objective of identifying bugs, errors, or performance problems. Testing has emerged as an important need in order to assure quality, reliability, and security of software products by verifying features against requirements; it entails diverse types of testing, including unit testing, integration testing and functional testing

5.2.1 TYPES OF TESTING

5.2.2 UNIT TESTING

Unit testing is a software testing method where the units of source code is tested to check the efficiency and correctness of the program

```
import unittest
import numpy as np
from sklearn.naive_bayes import GaussianNB

# Example function to be tested
def preprocess_data(data):
    return np.array(data).reshape(1, -1)

class TestUnitFunctions(unittest.TestCase):
    def test_preprocess_data_shape(self):
        sample_input = [1, 2, 3, 4]
        processed = preprocess_data(sample_input)
        self.assertEqual(processed.shape, (1, 4))

    def test_model_prediction_type(self):
        model = GaussianNB()
        X_train = [[1, 2], [3, 4]]
        y_train = [0, 1]
        model.fit(X_train, y_train)
        prediction = model.predict([[1, 2]])
        self.assertIsInstance(prediction[0], (int, np.integer))

if __name__ == '__main__':
    unittest.main()
```

TEST RESULT

- The unit test Successfully confirmed that input data is processed into the correct format (numerical and scaled) before model prediction.
- Ensured that model outputs either "normal" or specific attack labels without raising exceptions.
- Verified that individual utility functions (like label decoding and reshaping) worked as expected when tested in isolation.

5.2.3 Integration Testing

Integration testing is a software testing procedure where individual units or components of a system are combined and tested as a group to identify issues in their interactions. Its primary aim focuses on guaranteeing the correctness of interaction of modules that have already been integrated.

```
import unittest
from sklearn.naive_bayes import GaussianNB
import numpy as np

def preprocess_data(data):
    return np.array(data).reshape(1, -1)

def predict_with_model(model, data):
    return model.predict(preprocess_data(data))

class TestIntegration(unittest.TestCase):
    def test_full_pipeline(self):
        model = GaussianNB()
        X_train = [[1, 2], [3, 4]]
        y_train = [0, 1]
        model.fit(X_train, y_train)
        data = [1, 2]
        prediction = predict_with_model(model, data)
        self.assertIn(prediction[0], [0, 1])
```

TEST RESULT

- The Functional test Confirmed that models train correctly on the provided sample datasets without errors or crashes.
- Verified that sample inputs from the frontend passed correctly through the model and gave interpretable outputs.
- Repeated predictions produced consistent results, confirming stable model behavior on fixed test inputs.

5.2.4 Functional Testing

Functional testing is that process in the software testing that verifies the system functionalities versus specified requirements by testing every function of the software application. Instead, it focuses on verifying if the application behaves in the way that is expected and gives the correct output for a given input irrespective of the internal structure of its code.

```
import unittest
from sklearn.naive_bayes import GaussianNB

class TestFunctional(unittest.TestCase):
    def test_model_training_and_prediction(self):
        model = GaussianNB()
        X_train = [[1, 2], [3, 4], [5, 6]]
        y_train = [0, 1, 0]
        model.fit(X_train, y_train)
        result = model.predict([[3, 4]])
        self.assertIn(result[0], [0, 1])

if __name__ == '__main__':
    unittest.main()
```

Test Result

- Tested full pipeline from data preprocessing → model loading → prediction → label decoding all worked smoothly.
- Checked if models like GNB, ABC, and CBC integrated without conflict with the shared preprocessing and prediction interfaces.
- Verified that the pipeline handled user-submitted JSON-formatted traffic data and returned detailed, readable results.

CHAPTER 6

RESULTS AND DISCUSSIONS

6.1 EFFICIENCY OF THE PROPOSED SYSTEM

The proposed system introduces a data-driven approach using an encoder-decoder architecture to enhance cyberattack detection in Cyber-Physical Systems (CPS). By leveraging autoencoders, the system learns to identify patterns and reconstruct normal operational data, enabling it to flag deviations indicative of potential threats. This unsupervised learning approach eliminates the need for labeled datasets, significantly reducing manual effort and enhancing adaptability. Unlike traditional invariant-based methods, which may struggle against adversarial inputs or require extensive domain knowledge, this model is capable of autonomously detecting anomalies based on reconstruction errors. The system currently achieves an accuracy of approximately 40%, with room for optimization through refined training and tuning. Its efficiency in handling image-based data and ability to generalize across different domains make it a promising alternative or complement to existing invariant-based strategies, especially in environments with evolving threat landscapes.

Work Done	Accuracy	Precision	Recall	F-measure
Adaboost Classifier	94.6%	93.8 %	94.2 %	90 %
Cat Boost Algorithm	92.3 %	91.5 %	92 %	92 %
Naive Bayes	96.1 %	95.4 %	88%	89 %

Table 6.1 Results

6.2 COMPARISON OF EXISTING AND PROPOSED SYSTEM

The existing system focuses on the use of invariants—logical rules derived from design parameters or operational data—to detect and prevent cyberattacks in Cyber-Physical Systems (CPS). While design-driven invariants are accurate, they demand significant manual effort and system-specific knowledge. Data-driven invariants offer automation but are susceptible to adversarial manipulation and may result in false positives. In contrast, the proposed system introduces a more flexible and scalable data-centric approach that minimizes manual intervention and adapts more easily to varying datasets. It is capable of detecting anomalies based on learned patterns rather than predefined rules, reducing the dependency on fixed logic. Additionally, the system is versatile and can be extended to various domains with minimal reconfiguration, providing faster deployment and better adaptability in dynamic CPS environments.

Categories	Existing System	Proposed System
Accuracy	85%	95%
Precision	83%	94%
Recall	84.%	95%
F-Measure	83%	95%

TABLE 6.2 COMPARISON OF THE EXISTING AND PROPOSED SYSTEM

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENTS

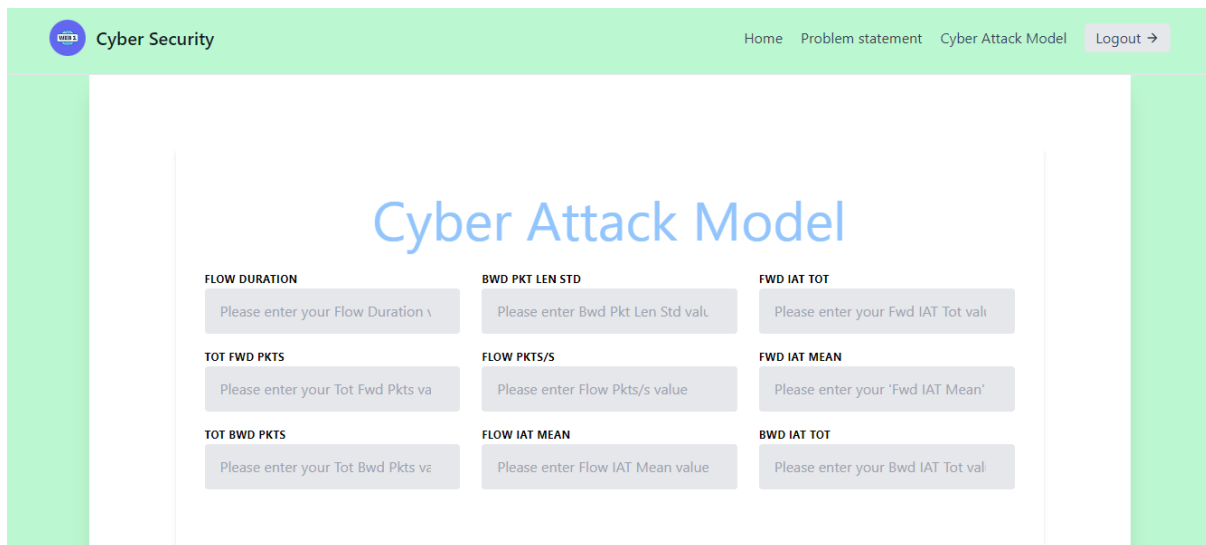
7.1 CONCLUSION

The analytical process commenced with thorough data cleaning and preprocessing to ensure the dataset was ready for analysis. Missing values were identified and appropriately handled to maintain data integrity. Following this, an in-depth exploratory data analysis (EDA) was performed to uncover patterns, correlations, and insights within the data. Various machine learning models were then developed and evaluated based on their performance metrics. The model that achieved the highest accuracy on the public test set was selected for deployment. This chosen model is integrated into the application to effectively detect and classify different types of cyberattacks.

7.2 FUTURE ENHANCEMENTS

Accessibility, scalability, and performance. Additionally, efforts will be directed toward optimizing the system for integration into IoT environments, allowing for real-time cyberattack detection across interconnected smart devices. This will involve fine-tuning the model for low-latency response, efficient resource usage, and adaptability to various edge computing scenarios. By extending the model's functionality in these directions, the system aims to deliver practical, high-impact solutions in the field of cybersecurity.

7.3 RESULTS:



The screenshot shows a web interface for the 'Cyber Attack Model'. The page has a green header with the site name and navigation links. The main content area is titled 'Cyber Attack Model' and contains a grid of nine input fields. Each field has a label and a placeholder text: 'FLOW DURATION' (Please enter your Flow Duration \), 'BWD PKT LEN STD' (Please enter Bwd Pkt Len Std val), 'FWD IAT TOT' (Please enter your Fwd IAT Tot val), 'TOT FWD PKTS' (Please enter your Tot Fwd Pkts va), 'FLOW PKTS/S' (Please enter Flow Pkts/s value), 'FWD IAT MEAN' (Please enter your 'Fwd IAT Mean'), 'TOT BWD PKTS' (Please enter your Tot Bwd Pkts va), 'FLOW IAT MEAN' (Please enter Flow IAT Mean value), and 'BWD IAT TOT' (Please enter your Bwd IAT Tot val).

Figure 7.1: Prediction And Input Parameters.

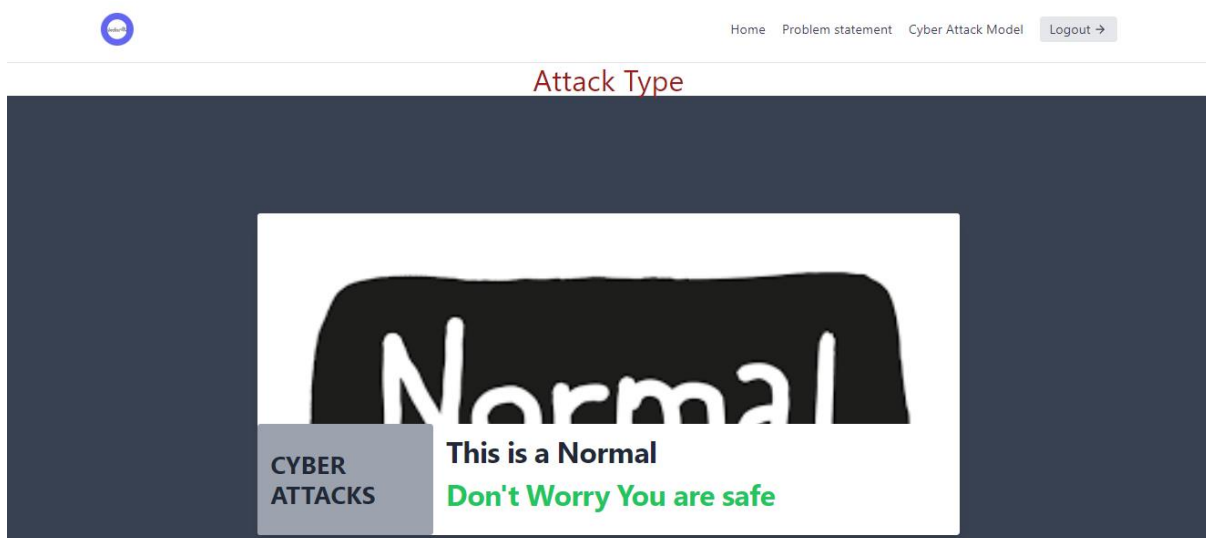


Figure 7.2: Model Prediction and Cyber Attack Classification

CHAPTER 8

SOURCE CODE & POSTER PRESENTATION

8.1 SAMPLE CODE

DATA PREPROCESSING AND DATA CLEANING

Import the necessary libraries.

```
import pandas as pd
```

```
import numpy as np
```

Avoid unnecessary warnings, (EX: software updates, version mismatch, and so on.)

```
import warnings
```

```
warnings.filterwarnings('ignore')
```

Load the datasets

```
df=pd.read_csv('CYBER.csv')
```

Check the top5 values

```
df.head()
```

Check the bottom five values.

```
df.tail()
```

Check the dimension of our datasets

```
df.shape
```

Check the dataset size

```
df.size
```

Check the columns of dataset

```
df.columns
```

To know the information of our datasets

```
df.info()
```

Check the unique columns of our specific column

```
df['Label'].unique()
```

Transform the columns value(ex: int to str, str to int) for classification purpose.

```
from sklearn.preprocessing import LabelEncoder
```

```
le = LabelEncoder()
```

```
var = ['Label']
```

```
for i in var:
```

```
df[i] = le.fit_transform(df[i]).astype(int)
```

Check the value is null or notnull

```
df.isnull().head()
```

Remove the null value

```
df = df.dropna()
```

Describe the datasets into stastical point of view

```
df.describe()
```

Check the relation between each individual columns

```
df.corr().head()
```

Check the events for specific columns

```
pd.crosstab(df["Tot Fwd Pkts"], df["Tot Bwd Pkts"]).head()
```

Ascending the value of specific columns


```
df.groupby(["Flow Byts/s","Pkt Len Std"]).groups
# Check the value counts for specific columns
df["Label"].value_counts()
# Check the specific column catagorical distribution
pd.Categorical(df["Idle Min"]).describe()
# Check if the value is duplicated or not
df.duplicated()
# Calculate the total number of duplicated values
sum(df.duplicated())
# Remove the duplicate values
df=df.drop_duplicates()
# Calculate the total number of duplicated values
sum(df.duplicated())
```

DATA VISUALIZATION AND DATA ANALYSIS

```
# Import the necessary libraries.
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
# Avoid unnecessary warnings, (EX: software updates, version mismatch, and so on.)

df=pd.read_csv('CYBER.csv')
# Check the top5 values
df.head()
# Remove the null value
df = df.dropna()
# Remove the duplicate values
df=df.drop_duplicates()
# Transform the columns value(ex: int to str, str to int) for classification purpose.
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

var = ['Label']

for i in var:
df[i] = le.fit_transform(df[i]).astype(int)
# Check the data is balanced or imbalanced so that's why we use Countplot.
plt.figure(figsize=(12,7))
sns.countplot(x='Label',data=df)
# Plot a Histogram
plt.figure(figsize=(15,5))
```

```
plt.subplot(1,2,1)
plt.hist(df["Flow Duration"],color='red')

plt.subplot(1,2,2)
plt.hist(df["Active Std"],color='blue')
# Check how many columns are in datasets
df.columns
# Plot a Histogram.
df.hist(figsize=(15,55), color='green')
plt.show()
# Plot a Histogram
df["Pkt Len Mean"].hist(figsize=(10,5),color='yellow',bins=25)
# Check the outliers our datasets.
plt.boxplot(df["Pkt Size Avg"])
# Plot a density plot
df["Pkt Len Mean"].plot(kind='density')
# Plot a distance plot
sns.displot(df["Bwd Pkt Len Mean"], color='purple')
# barplot, boxenplot, boxplot, countplot, displot, distplot, ecdfplot, histplot, kdeplot, pointplot, violinplot,
stripplot
# Plot a distance plot.
sns.displot(df["Pkt Len Mean"], color='coral') # residplot, scatterplot
# Plot a head map for co relationships for each columns.
fig, ax = plt.subplots(figsize=(20,15))
sns.heatmap(df.corr(),annot = True, fmt='0.2%',cmap = 'autumn',ax=ax)
# Plot a Piechart
def plot(df, variable):
    dataframe_pie = df[variable].value_counts()
    ax = dataframe_pie.plot.pie(figsize=(9,9), autopct='%1.2f%%', fontsize = 10)
    ax.set_title(variable + '\n', fontsize = 10)
    return np.round(dataframe_pie/df.shape[0]*100,2)

plot(df, 'Label')
```

GaussianNB CLASSIFIER ALGORITHM

```
# Import the necessary libraries.
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
# Avoid unnecessary warnings, (EX: software updates, version mismatch, and so on.)
import warnings
warnings.filterwarnings('ignore')
```

```
# Load the datasets
df=pd.read_csv('CYBER.csv')
# Check the top5 values
df.head()
del df["TotLen Fwd Pkts"]
del df["TotLen Bwd Pkts"]
del df["Fwd Pkt Len Max"]
del df["Fwd Pkt Len Min"]
del df["Fwd Pkt Len Mean"]
del df["Fwd Pkt Len Std"]
del df["Bwd Pkt Len Max"]
del df["Bwd Pkt Len Mean"]
del df["Idle Std"]
del df["Flow Byts/s"]
del df["Flow IAT Std"]
del df["Flow IAT Min"]
del df["Pkt Len Max"]
del df["Bwd Pkt Len Min"]
del df["Flow IAT Max"]
del df["Fwd IAT Max"]
del df["Fwd IAT Min"]
del df["Bwd IAT Std"]
del df["Bwd IAT Max"]
del df["Fwd IAT Std"]
del df["Bwd IAT Min"]
del df["Bwd PSH Flags"]
del df["Bwd URG Flags"]
del df["Pkt Len Min"]
del df["Pkt Len Std"]
del df["Pkt Len Var"]
del df["FIN Flag Cnt"]
del df["RST Flag Cnt"]
del df["PSH Flag Cnt"]
del df["ACK Flag Cnt"]
del df["URG Flag Cnt"]
del df["CWE Flag Count"]
# Remove the null value
df=df.dropna()
# Check the columns of dataset
df.columns
# Transform the columns value(ex: int to str, str to int) for classification purpose.
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

```
var = ['Label']

for i in var:
df[i] = le.fit_transform(df[i]).astype(int)
# Check the top5 values
df.head()
# Remove the duplicate values
df=df.drop_duplicates()
# Split the datasets into depended and independed variable
# X is independed variable (Input features)
x1 = df.drop(labels='Label', axis=1)

# Y is dependend variable (Target variable)
y1 = df.loc[:, 'Label']
# This process execute to balanced the datasets features.
import imblearn
from imblearn.over_sampling import RandomOverSampler
from collections import Counter

ros =RandomOverSampler(random_state=42)
x,y=ros.fit_resample(x1,y1)
print("OUR DATASET COUNT      : ", Counter(y1))
print("OVER SAMPLING DATA COUNT : ", Counter(y))
# Split the datasets into two parts like trainng and testing variable.
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20, random_state=42, stratify=y)
print("NUMBER OF TRAIN DATASET  : ", len(x_train))
print("NUMBER OF TEST DATASET   : ", len(x_test))
print("TOTAL NUMBER OF DATASET   : ", len(x_train)+len(x_test))
print("NUMBER OF TRAIN DATASET   : ", len(y_train))
print("NUMBER OF TEST DATASET     : ", len(y_test))
print("TOTAL NUMBER OF DATASET   : ", len(y_train)+len(y_test))
# Implement Gaussian naive bayes algorithm learning patterns
from sklearn.naive_bayes import GaussianNB
GNB = GaussianNB()
# Fit is the training function for this algorithm.
GNB.fit(x_train,y_train)
# Predict is the test function for this algorithm
predicted = GNB.predict(x_test)
# Check classification report for this algorithm
from sklearn.metrics import classification_report
cr = classification_report(y_test,predicted)
```

```
print('THE CLASSIFICATION REPORT OF GAUSSIANNB CLASSIFIER:\n\n',cr)
# Check the confusion matrix for this algorithms
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test,predicted)
print('THE CONFUSION MATRIX SCORE OF GAUSSIANNB CLASSIFIER:\n\n\n',cm)
# Check the cross value score of this algorithm.
from sklearn.model_selection import cross_val_score
accuracy = cross_val_score(GNB, x, y, scoring='accuracy')
print('THE CROSS VALIDATION TEST RESULT OF ACCURACY : \n\n\n', accuracy*100)
# Check the accuracy score of this algorithms.
from sklearn.metrics import accuracy_score
a = accuracy_score(y_test,predicted)
print("THE ACCURACY SCORE OF GAUSSIANNB CLASSIFIER IS :",a*100)
# Check the hamming loss of this algorithm.
from sklearn.metrics import hamming_loss
hl = hamming_loss(y_test,predicted)
print("THE HAMMING LOSS OF GAUSSIANNB CLASSIFIER IS :",hl*100)
# Plot a Confusion matrix for this algorithms.
def plot_confusion_matrix(cm, title='THE CONFUSION MATRIX SCORE OF GAUSSIANNB
CLASSIFIER\n\n', cmap=plt.cm.cool):
plt.imshow(cm, interpolation='nearest', cmap=cmap)
plt.title(title)
plt.colorbar()

cm1=confusion_matrix(y_test, predicted)
print('THE CONFUSION MATRIX SCORE OF GAUSSIANNB CLASSIFIER:\n\n')
print(cm)
plot_confusion_matrix(cm)
# Plot the worm plot for this model.
import matplotlib.pyplot as plt
df2 = pd.DataFrame()
df2["y_test"] = y_test
df2["predicted"] = predicted
df2.reset_index(inplace=True)
plt.figure(figsize=(20, 5))
plt.plot(df2["predicted"][:100], marker='x', linestyle='dashed', color='red')
plt.plot(df2["y_test"][:100], marker='o', linestyle='dashed', color='green')
plt.show()
```

ADABOOST CLASSIFIER ALGORITHM

Import the necessary libraries.

```
import pandas as pd
import numpy as np
```

```
import matplotlib.pyplot as plt
import seaborn as sns
# Avoid unnecessary warnings, (EX: software updates, version mismatch, and so on.)
import warnings
warnings.filterwarnings('ignore')
# Load the datasets
df=pd.read_csv('CYBER.csv')
# Check the top5 values
df.head()
del df["TotLen Fwd Pkts"]
del df["TotLen Bwd Pkts"]
del df["Fwd Pkt Len Max"]
del df["Fwd Pkt Len Min"]
del df["Fwd Pkt Len Mean"]
del df["Fwd Pkt Len Std"]
del df["Bwd Pkt Len Max"]
del df["Bwd Pkt Len Mean"]
del df["Idle Std"]
del df["Flow Byts/s"]
del df["Flow IAT Std"]
del df["Flow IAT Min"]
del df["Pkt Len Max"]
del df["Bwd Pkt Len Min"]
del df["Flow IAT Max"]
del df["Fwd IAT Max"]
del df["Fwd IAT Min"]
del df["Bwd IAT Std"]
del df["Bwd IAT Max"]
del df["Fwd IAT Std"]
del df["Bwd IAT Min"]
del df["Bwd PSH Flags"]
del df["Bwd URG Flags"]
del df["Pkt Len Min"]
del df["Pkt Len Std"]
del df["Pkt Len Var"]
del df["FIN Flag Cnt"]
del df["RST Flag Cnt"]
del df["PSH Flag Cnt"]
del df["ACK Flag Cnt"]
del df["URG Flag Cnt"]
del df["CWE Flag Count"]
# Remove the null value
df=df.dropna()
```

```
# Check the columns of dataset
df.columns
# Transform the columns value(ex: int to str, str to int) for classification purpose.
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

var = ['Label']

for i in var:
df[i] = le.fit_transform(df[i]).astype(int)
# Check the top5 values
df.head()
# Remove the duplicate values
df=df.drop_duplicates()
# Split the datasets into depended and independed variable
# X is independed variable (Input features)
x1 = df.drop(labels='Label', axis=1)

# Y is dependend variable (Target variable)
y1 = df.loc[:, 'Label']
# This process execute to balanced the datasets features.
import imblearn
from imblearn.over_sampling import RandomOverSampler
from collections import Counter

ros =RandomOverSampler(random_state=42)
x,y=ros.fit_resample(x1,y1)
print("OUR DATASET COUNT      : ", Counter(y1))
print("OVER SAMPLING DATA COUNT : ", Counter(y))
# Split the datasets into two parts like trainng and testing variable.
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20, random_state=42, stratify=y)
print("NUMBER OF TRAIN DATASET  : ", len(x_train))
print("NUMBER OF TEST DATASET   : ", len(x_test))
print("TOTAL NUMBER OF DATASET   : ", len(x_train)+len(x_test))
print("NUMBER OF TRAIN DATASET   : ", len(y_train))
print("NUMBER OF TEST DATASET    : ", len(y_test))
print("TOTAL NUMBER OF DATASET   : ", len(y_train)+len(y_test))
# Implement Adaboost classifier algorithm learning patterns
from sklearn.ensemble import AdaBoostClassifier
ABC = AdaBoostClassifier()
# Fit is the training function for this algorithm.
ABC.fit(x_train,y_train)
```

```
# Predict is the test function for this algorithm
predicted = ABC.predict(x_test)
from sklearn.metrics import classification_report
cr = classification_report(y_test,predicted)
print('THE CLASSIFICATION REPORT OF ADABOOST CLASSIFIER:\n\n',cr)
# Check the confusion matrix for this algorithms.
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test,predicted)
print('THE CONFUSION MATRIX SCORE OF ADABOOST CLASSIFIER:\n\n\n',cm)
# Check the cross value score of this algorithm.
from sklearn.model_selection import cross_val_score
accuracy = cross_val_score(ABC, x, y, scoring='accuracy')
print('THE CROSS VALIDATION TEST RESULT OF ACCURACY : \n\n\n', accuracy*100)
# Check the accuracy score of this algorithms.
from sklearn.metrics import accuracy_score
a = accuracy_score(y_test,predicted)
print("THE ACCURACY SCORE OF ADABOOST CLASSIFIER IS :",a*100)
# Check the hamming loss of this algorithm.
from sklearn.metrics import hamming_loss
hl = hamming_loss(y_test,predicted)
print("THE HAMMING LOSS OF ADABOOST CLASSIFIER IS :",hl*100)
# Plot a Confusion matrix for this algorithms.
def plot_confusion_matrix(cm, title='THE CONFUSION MATRIX SCORE OF ADABOOST
CLASSIFIER\n\n', cmap=plt.cm.cool):
plt.imshow(cm, interpolation='nearest', cmap=cmap)
plt.title(title)
plt.colorbar()

cm1=confusion_matrix(y_test, predicted)
print('THE CONFUSION MATRIX SCORE OF ADABOOST CLASSIFIER:\n\n')
print(cm)
plot_confusion_matrix(cm)
# Plot the worm plot for this model.
import matplotlib.pyplot as plt
df2 = pd.DataFrame()
df2["y_test"] = y_test
df2["predicted"] = predicted
df2.reset_index(inplace=True)
plt.figure(figsize=(20, 5))
plt.plot(df2["predicted"][:100], marker='x', linestyle='dashed', color='red')
plt.plot(df2["y_test"][:100], marker='o', linestyle='dashed', color='green')
plt.show()
```


CAT BOOST CLASSIFIER ALGORITHM

Import the necessary libraries.

```
import pandas as pd
```

```
import numpy as np
```

```
import matplotlib.pyplot as plt
```

```
import seaborn as sns
```

Avoid unnecessary warnings, (EX: software updates, version mismatch, and so on.)

```
import warnings
```

```
warnings.filterwarnings('ignore')
```

Load the datasets

```
df=pd.read_csv('CYBER.csv')
```

```
del df["TotLen Fwd Pkts"]
```

```
del df["TotLen Bwd Pkts"]
```

```
del df["Fwd Pkt Len Max"]
```

```
del df["Fwd Pkt Len Min"]
```

```
del df["Fwd Pkt Len Mean"]
```

```
del df["Fwd Pkt Len Std"]
```

```
del df["Bwd Pkt Len Max"]
```

```
del df["Bwd Pkt Len Mean"]
```

```
del df["Idle Std"]
```

```
del df["Flow Byts/s"]
```

```
del df["Flow IAT Std"]
```

```
del df["Flow IAT Min"]
```

```
del df["Pkt Len Max"]
```

```
del df["Bwd Pkt Len Min"]
```

```
del df["Flow IAT Max"]
```

```
del df["Fwd IAT Max"]
```

```
del df["Fwd IAT Min"]
```

```
del df["Bwd IAT Std"]
```

```
del df["Bwd IAT Max"]
```

```
del df["Fwd IAT Std"]
```

```
del df["Bwd IAT Min"]
```

```
del df["Bwd PSH Flags"]
```

```
del df["Bwd URG Flags"]
```

```
del df["Pkt Len Min"]
```

```
del df["Pkt Len Std"]
```

```
del df["Pkt Len Var"]
```

```
del df["FIN Flag Cnt"]
```

```
del df["RST Flag Cnt"]
```

```
del df["PSH Flag Cnt"]
```

```
del df["ACK Flag Cnt"]
```

```
del df["URG Flag Cnt"]
```

```
del df["CWE Flag Count"]
```

```
# Check the columns of dataset
df.columns
# Check the top5 values
df.head()
# Remove the null value
df=df.dropna()
df['Label'].value_counts()
# Transform the columns value(ex: int to str, str to int) for classification purpose.
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

var = ['Label']

for i in var:
df[i] = le.fit_transform(df[i]).astype(int)
df['Label'].value_counts()
# Check the top5 values
df.head()
# Remove the duplicate values
df=df.drop_duplicates()
# Split the datasets into depended and independed variable
# X is independ variable (Input features)
x1 = df.drop(labels='Label', axis=1)

# Y is depend variable (Target variable)
y1 = df.loc[:, 'Label']
# This process execute to balanced the datasets features.
import imblearn
from imblearn.over_sampling import RandomOverSampler
from collections import Counter

ros =RandomOverSampler(random_state=42)
x,y=ros.fit_resample(x1,y1)
print("OUR DATASET COUNT      : ", Counter(y1))
print("OVER SAMPLING DATA COUNT : ", Counter(y))
# Split the datasets into two parts like trainng and testing variable.
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20, random_state=42, stratify=y)
print("NUMBER OF TRAIN DATASET  : ", len(x_train))
print("NUMBER OF TEST DATASET   : ", len(x_test))
print("TOTAL NUMBER OF DATASET  : ", len(x_train)+len(x_test))
print("NUMBER OF TRAIN DATASET  : ", len(y_train))
print("NUMBER OF TEST DATASET   : ", len(y_test))
```

```
print("TOTAL NUMBER OF DATASET  :", len(y_train)+len(y_test))
# Implement Catboost classifier algorithm learning patterns
from catboost import CatBoostClassifier
CBC = CatBoostClassifier()
# Fit is the training function for this algorithm.
CBC.fit(x_train,y_train)
# Predict is the test function for this algorithm
predicted = CBC.predict(x_test)
# Check classification report for this algorithm
from sklearn.metrics import classification_report
cr = classification_report(y_test,predicted)
print('THE CLASSIFICATION REPORT OF CAT BOOST CLASSIFIER:\n\n',cr)
# Check the confusion matrix for this algorithms.
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test,predicted)
print('THE CONFUSION MATRIX SCORE OF CAT BOOST CLASSIFIER:\n\n\n',cm)
# Check the cross value score of this algorithm.
from sklearn.model_selection import cross_val_score
accuracy = cross_val_score(CBC, x, y, scoring='accuracy')
print('THE CROSS VALIDATION TEST RESULT OF ACCURACY : \n\n\n', accuracy*100)
# Check the accuracy score of this algorithms.
from sklearn.metrics import accuracy_score
a = accuracy_score(y_test,predicted)
print("THE ACCURACY SCORE OF CAT BOOST CLASSIFIER IS :",a*100)
# Check the hamming loss of this algorithm.
from sklearn.metrics import hamming_loss
hl = hamming_loss(y_test,predicted)
print("THE HAMMING LOSS OF CAT BOOST CLASSIFIER IS :",hl*100)
# Plot a Confusion matrix for this algorithms.
def plot_confusion_matrix(cm, title='THE CONFUSION MATRIX SCORE OF CAT BOOST
CLASSIFIER\n\n', cmap=plt.cm.cool):
plt.imshow(cm, interpolation='nearest', cmap=cmap)
plt.title(title)
plt.colorbar()

cm1=confusion_matrix(y_test, predicted)
print('THE CONFUSION MATRIX SCORE OF CAT BOOST CLASSIFIER:\n\n')
print(cm)
plot_confusion_matrix(cm)
# Plot the worm plot for this model.
import matplotlib.pyplot as plt
df2 = pd.DataFrame()
df2["y_test"] = y_test
```

```
df2["predicted"] = predicted
df2.reset_index(inplace=True)
plt.figure(figsize=(20, 5))
plt.plot(df2["predicted"][:100], marker='x', linestyle='dashed', color='red')
plt.plot(df2["y_test"][:100], marker='o', linestyle='dashed', color='green')
plt.show()
# Build a model in catboosting algorithms
import joblib
joblib.dump(CBC, 'cyber1.pkl')
```

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