Anomaly detection in cloud networks using machine learning algorithms

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LIST OF ABBREVIATIONS

Abbreviations	Definitions
DDoS	Distributed Denial of Service
PCA	Principal Component Analysis
CNN	Convolutional Neural Networks
DNN	Deep Neural Networks
AI	Artificial intelligence
LR	Logistic Regression
RF	Random Forest

ABSTRACT

This project focuses on developing an anomaly detection system using machine learning to identify and classify potential cyber threats, specifically Distributed Denial of Service (DDoS) attacks. The application features a user-friendly interface that allows users to register and log in securely. Once authenticated, users can input relevant dataset attributes to assess the likelihood of a DDoS attack occurring. The system leverages a comprehensive dataset, available in CSV or Excel format, which is preprocessed using the Pandas library to handle missing data and perform label encoding. Feature extraction is conducted through Principal Component Analysis (PCA) to enhance model efficiency. The processed data is split into training and testing sets, facilitating the implementation of hybrid classification algorithms, including Logistic Regression and a 1D Convolutional Neural Network (CNN). The output of the system classifies various types of cyber threats, and in the event of an attack, it identifies the source and destination IP addresses, notifying the administrator. Performance metrics such as accuracy, specificity, recall, precision, ROC curve analysis, and confusion matrices are employed to evaluate the effectiveness of the model, with visualization tools used for comparison. This project aims to provide an effective solution for real-time threat detection, enhancing cyber security measures for users and organizations.

CHAPTER 1
INTRODUCTION

1.1 General Introduction:

Background and Motivation

In today's digital landscape, the prevalence of cyber threats has increased dramatically, posing significant risks to individuals and organizations alike. Among these threats, Distributed Denial of Service (DDoS) attacks have emerged as one of the most common and disruptive forms of cyberattacks. A DDoS attack involves overwhelming a targeted server, service, or network with a flood of traffic, rendering it unavailable to legitimate users. Such attacks can lead to substantial financial losses, damage to reputation, and erosion of customer trust. Consequently, the need for effective anomaly detection systems has become critical in safeguarding digital infrastructure.

As organizations continue to migrate to cloud-based services and the Internet of Things (IoT) expands, the complexity of network traffic increases. This complexity makes it challenging to distinguish between normal and malicious activity, highlighting the importance of employing advanced detection techniques. Traditional security measures, such as firewalls and intrusion detection systems, often fall short in their ability to adapt to the evolving tactics used by cybercriminals. Thus, there is a growing recognition of the potential for machine learning (ML) techniques to enhance anomaly detection capabilities.

Machine Learning in Cybersecurity

Machine learning, a subset of artificial intelligence, involves training algorithms to identify patterns in data and make predictions based on these patterns. In the context of cybersecurity, ML techniques can analyze large volumes of network traffic data to detect anomalies indicative of potential threats. Unlike traditional methods, ML-based systems can learn from historical data, improving their accuracy over time and adapting to new attack vectors.

Several ML algorithms, including supervised, unsupervised, and semi-supervised learning, can be utilized for anomaly detection. Supervised learning requires labeled datasets, while unsupervised learning identifies patterns in unlabeled data. This flexibility makes ML particularly suited for cybersecurity applications, where labeled data may be scarce or difficult to obtain.

The Importance of Anomaly Detection

Anomaly detection plays a crucial role in cybersecurity by enabling organizations to identify unusual patterns that may indicate an attack. By detecting anomalies early, organizations can take proactive measures to mitigate risks, such as implementing countermeasures or informing affected parties. Effective anomaly detection systems can significantly reduce the impact of cyberattacks, ensuring the continuity of business operations.

Incorporating machine learning into anomaly detection systems enhances their ability to identify novel attack patterns. Traditional signature-based approaches rely on known attack patterns and are often ineffective against new, sophisticated attacks. In contrast, ML-based systems can adapt to new threats in real-time, providing a dynamic defense mechanism.

Challenges and Future Directions

While machine learning presents significant advantages for anomaly detection, several challenges must be addressed. These include the need for high-quality labeled datasets, the potential for model overfitting, and the requirement for continuous monitoring and updating of models to adapt to evolving threats. Future research could explore the integration of additional data sources, such as user behavior analytics and threat intelligence feeds, to further enhance detection capabilities.

1.2 Objectives:

This project aims to develop a comprehensive anomaly detection system specifically designed to identify DDoS attacks and other cyber threats. The key objectives include:

- User Authentication: Creating a secure interface for user registration and login to ensure that only authorized personnel can access the system.
- Data Handling: Implementing effective methods for data preprocessing, including handling missing values and performing label encoding.
- Feature Extraction: Utilizing techniques such as Principal Component Analysis (PCA) to reduce dimensionality and enhance model performance.
- Model Training and Testing: Splitting the dataset into training and testing sets, allowing for robust model evaluation.
- Hybrid Classification: Implementing a combination of classification algorithms, including Logistic Regression and 1D Convolutional Neural Networks (CNN), to improve predictive accuracy.
- Threat Classification: Developing a system that not only identifies potential DDoS attacks but also classifies other types of threats, such as insider threats and port scanning.
- Performance Evaluation: Analyzing the system's effectiveness using metrics like accuracy, precision, recall, and visualizations to compare performance.

CHAPTER 2
SYSTEM PROPOSAL

2.1 EXISTING SYSTEM:

In existing system, Autism Spectrum management often utilizes Support Vector Machines (SVM) as a machine learning technique to predict and classify threats based on IoT data. SVM is chosen for its ability to handle high-dimensional data and nonlinear relationships effectively. In this context, SVM is employed to build predictive models that can distinguish between type of threats = individuals, leveraging features such as IP address, source address, and destination address and so on.

2.1.1 DISADVANTAGES:

- It traditional approaches often lack the granularity and objectivity needed to capture the nuanced ways in which learner’s process information.
- They fail to provide real-time or dynamic insights into learners' cognitive processes, making it difficult to tailor educational interventions effectively.
- Additionally, these methods are not scalable for large populations, as they require significant time and effort to administer and analyze.
- Training time is high while increasing the dataset size.
- As a result, there is a pressing need for more objective, scalable, and accurate methods to identify threats, which can be addressed by leveraging advanced techniques in machine learning.

2.2 PROPOSED SYSTEM:

The proposed system for anomaly detection in DDoS attacks integrates several key components to create an effective framework for identifying and classifying cyber threats. The process begins with the input of a DDoS attack dataset, which can be sourced from a reliable dataset repository and is available in formats such as CSV or Excel (.xlsx). Upon receiving the dataset, the system employs the Pandas library for efficient data selection and manipulation, allowing for easy handling of the input data. Next, the collected data undergoes a rigorous preprocessing phase to ensure its readiness for analysis. This step addresses any missing values, applying appropriate techniques to handle gaps in the data, and performs label encoding to convert categorical variables into a numerical format suitable for machine learning algorithms. After preprocessing, the system extracts significant features from the data using Principal Component Analysis (PCA), which helps in reducing dimensionality while retaining essential information, thus enhancing the model's performance. Following feature extraction, the preprocessed dataset is divided into training and testing sets. The training data is utilized to evaluate the effectiveness of the machine learning models, while the testing data is reserved for making predictions. The classification phase involves implementing a hybrid approach that combines Logistic Regression (LR) and a 1D Convolutional Neural Network (CNN). This combination leverages the strengths of both algorithms, allowing the system to achieve robust classification capabilities. Once the classification is performed, the system outputs predictions regarding the presence of various types of threats, including DDoS attacks, insider threats, man-in-the-middle attacks, and port scanning. If a DDoS attack is detected, the system identifies the source and destination IP addresses and promptly sends notifications to the administrator for further action. To ensure the system's effectiveness, a performance estimation step is included, where various metrics such as accuracy, specificity, recall, precision, ROC curve analysis, and confusion matrices are analyzed. This comprehensive evaluation not only assesses the model's predictive

power but also aids in visualizing results through comparison graphs, enabling continuous improvement and refinement of the anomaly detection framework. Ultimately, the proposed system aims to provide organizations with a proactive and reliable solution for safeguarding their digital environments against evolving cyber threats.

2.2.1 ADVANTAGES:

- Enhanced Detection Capabilities: The hybrid approach of combining Logistic Regression and 1D CNN improves accuracy in identifying DDoS attacks and other cyber threats.
- Real-Time Threat Identification: The system can quickly detect and classify threats, allowing organizations to respond promptly to potential attacks.
- Data Preprocessing: Robust preprocessing techniques ensure high-quality data input, improving the overall reliability of the predictions.
- Feature Reduction: Using Principal Component Analysis (PCA) minimizes dimensionality, reducing computational complexity while retaining critical information.
- User-Friendly Interface: The system includes an intuitive interface for user registration, login, and data input, making it accessible for users with varying technical backgrounds.
- Comprehensive Output: The system not only predicts DDoS attacks but also classifies other types of threats, providing a broader scope of security analysis.

2.3 LITERATURE SURVEY:

1. Title: "A survey of machine learning techniques for cyber security"

Year: 2023

Methodology:

This survey comprehensively reviews various machine learning techniques applied to cybersecurity, particularly focusing on intrusion detection systems (IDS). The authors categorize the methodologies into supervised, unsupervised, and semi-supervised learning. Each category is explored in detail, highlighting different algorithms like decision trees, support vector machines, and neural networks. The survey examines the effectiveness of these techniques in detecting cyber threats, emphasizing the importance of feature selection and data preprocessing. Furthermore, the authors discuss the challenges faced in real-world applications, including data scarcity and model interpretability. The survey concludes by outlining future research directions, such as the integration of deep learning and reinforcement learning to enhance detection capabilities.

Demerits:

- Limited focus on specific types of attacks (e.g., DDoS).
- May not cover the latest advancements in deep learning.
- Lack of practical implementation examples.
- Insufficient discussion on the computational costs involved.
- Potential bias in the selection of surveyed studies.

2. Title: "Deep learning-based DDoS detection in IoT networks: A review"

Year: 2022

Methodology:

This literature review investigates the application of deep learning techniques for DDoS detection in Internet of Things (IoT) environments. The authors analyze various deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), assessing their effectiveness in identifying DDoS attack patterns. The survey highlights the unique challenges posed by IoT, such as resource constraints and diverse data types. Through a systematic analysis, the authors categorize the existing literature based on methodologies used, datasets employed, and performance metrics reported. They also propose a framework for future research, emphasizing the need for hybrid models that combine deep learning with traditional machine learning techniques for improved accuracy.

Demerits:

- Limited generalizability to non-IoT environments.
- Emphasis on theoretical frameworks rather than practical implementations.
- Lack of discussion on dataset availability and quality.
- May overlook emerging threats beyond DDoS.
- Insufficient analysis of real-time detection capabilities.

3. Title: "Detection of DDoS attacks using machine learning and deep learning techniques: A review"

Year: 2023

Methodology: This comprehensive survey focuses on various machine learning and deep learning techniques employed for DDoS attack detection. The authors systematically categorize existing methodologies, including supervised learning, unsupervised learning, and hybrid approaches. They analyze the strengths and weaknesses of each technique, providing a comparative analysis of performance metrics such as accuracy, precision, and recall. The survey also discusses the role of feature selection and data preprocessing in enhancing model performance. Furthermore, the authors highlight the importance of real-time detection and propose a roadmap for future research, advocating for adaptive learning techniques to better address evolving DDoS threats.

Demerits:

- Overemphasis on theoretical aspects; lacks empirical validation.
- Limited exploration of ensemble methods.
- Inadequate focus on interpretability of models.
- Some methodologies may be outdated or underutilized.
- Challenges related to data imbalance are not sufficiently addressed.

4. Title: "A survey of DDoS detection techniques based on deep learning"

Year: 2022

Methodology: This survey presents a detailed examination of deep learning techniques specifically designed for DDoS detection. The authors review various architectures, including CNNs, RNNs, and autoencoders, and analyze their application in real-time traffic analysis. The study categorizes existing literature based on detection methodologies, datasets, and evaluation metrics, providing a clear overview of the effectiveness of different approaches. The authors emphasize the importance of feature extraction and model training, and they highlight common challenges faced in deploying these techniques in live environments. The survey concludes with recommendations for future research, focusing on the integration of adversarial training to enhance robustness.

Demerits:

- Focus on deep learning may exclude traditional techniques.
- Limited practical case studies or applications presented.
- Potential for overfitting in deep learning models.
- Challenges related to model deployment in resource-constrained environments are not thoroughly discussed.
- Lack of longitudinal studies to assess long-term effectiveness.

5. Title: "Machine Learning for Cyber Security: A Review of Recent Developments"

Year: 2023

Methodology: This review paper evaluates recent developments in the application of machine learning for cybersecurity, including DDoS detection. The authors provide a structured analysis of machine learning algorithms categorized by their learning paradigms. They assess the effectiveness of various models, including decision trees, random forests, and neural networks, while discussing their application in threat detection scenarios. The paper also emphasizes the significance of data preprocessing, feature selection, and the use of hybrid models that combine different algorithms to enhance detection accuracy. By summarizing recent research trends, the authors identify gaps in the existing literature and propose directions for future work.

Demerits:

- Limited focus on specific types of machine learning algorithms.
- May not address practical challenges faced in implementation.
- Potential lack of discussion on the ethical implications of machine learning in cybersecurity.
- Insufficient depth in exploring adversarial attacks on machine learning models.
- Inadequate analysis of computational efficiency and scalability.

6. Title: "Anomaly detection in network traffic using machine learning: An overview"

Year: 2022

Methodology: This overview paper discusses various machine learning techniques applied to anomaly detection in network traffic, with a particular focus on DDoS attacks. The authors categorize detection methods into supervised, unsupervised, and semi-supervised learning, providing a thorough analysis of algorithms used in each category. The survey highlights the importance of feature engineering and data preprocessing, as well as the role of visualization tools in understanding detection outcomes. By synthesizing findings from multiple studies, the authors identify common challenges and limitations in existing research, such as data scarcity and the dynamic nature of network traffic. The paper concludes with recommendations for future research, advocating for interdisciplinary approaches that integrate machine learning with domain-specific knowledge.

Demerits:

- Broad scope may dilute focus on DDoS-specific techniques.
- May not cover the latest algorithms or methodologies developed.
- Limited discussion on deployment challenges in real-world scenarios.
- Insufficient analysis of user behavior analytics integration.
- Potential for information overload due to the broad range of topics covered.

CHAPTER 3

SYSTEM DIAGRAMS

3.1 SYSTEM ARCHITECTURE:

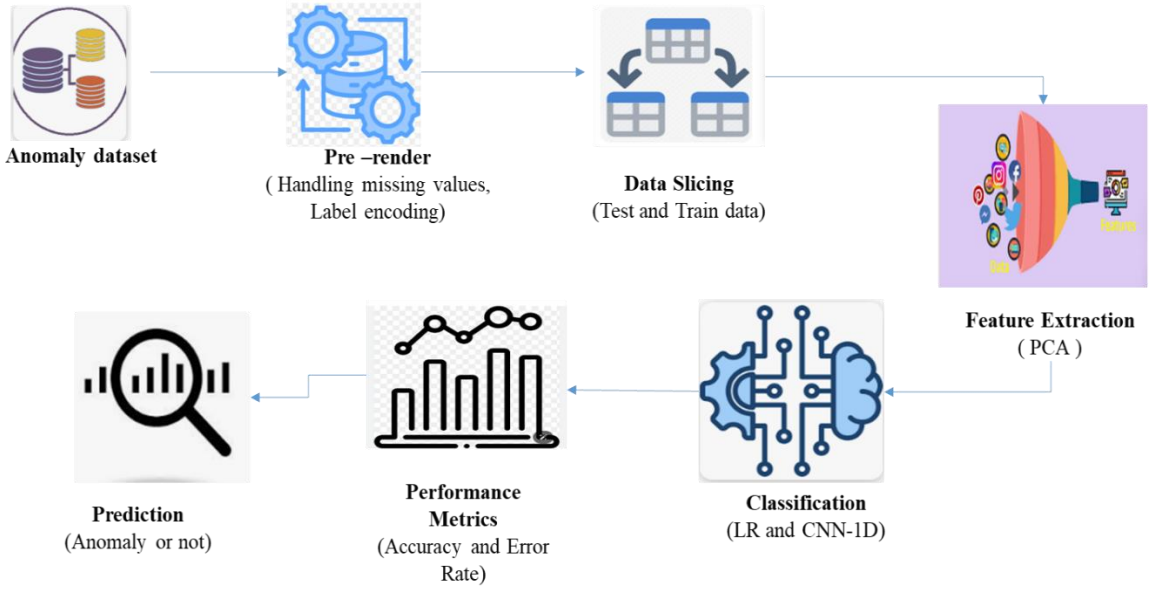


FIGURE 3.1: SYSTEM ARCHITECTURE

The architecture diagram outlines the workflow for processing and classifying anomaly dataset. Data Selection involves acquiring the dataset. Data Preprocessing handles missing values and label encoding.. The data is Split into training and test sets. Classification models are trained and evaluated. Result Generation computes performance metrics, and Prediction applies the trained models to classify new data, providing difficulty level insights.

3.2 FLOW DIAGRAM:

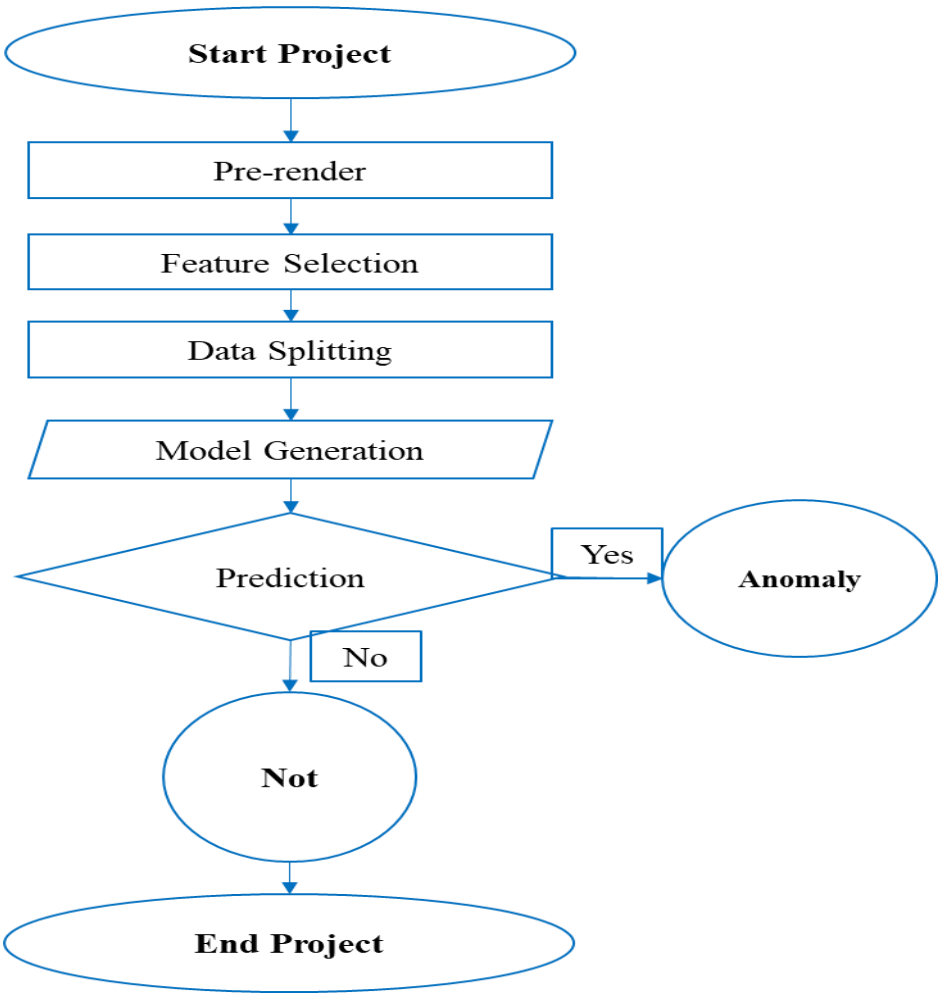
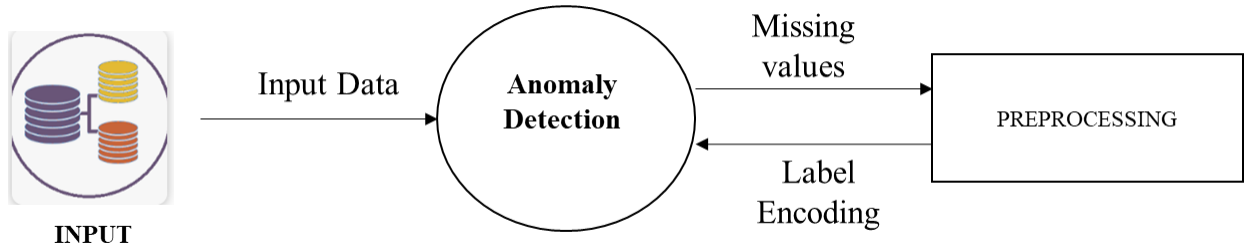


FIGURE 3.2: FLOW DIAGRAM

The flow diagram illustrates the process for anomaly prediction and management using machine learning. It starts with Data Selection, where a diabetes dataset in CSV format is sourced. This is followed by Data Preprocessing, which includes handling missing values and applying label encoding. Feature selection through PCA reduces data dimensionality. The dataset is then divided into Training and Testing sets for model evaluation. Classification models are applied to the training data. Result Generation evaluates model performance using accuracy metrics. Finally, Prediction determines if an individual is affected by autism based on the trained models' outputs.

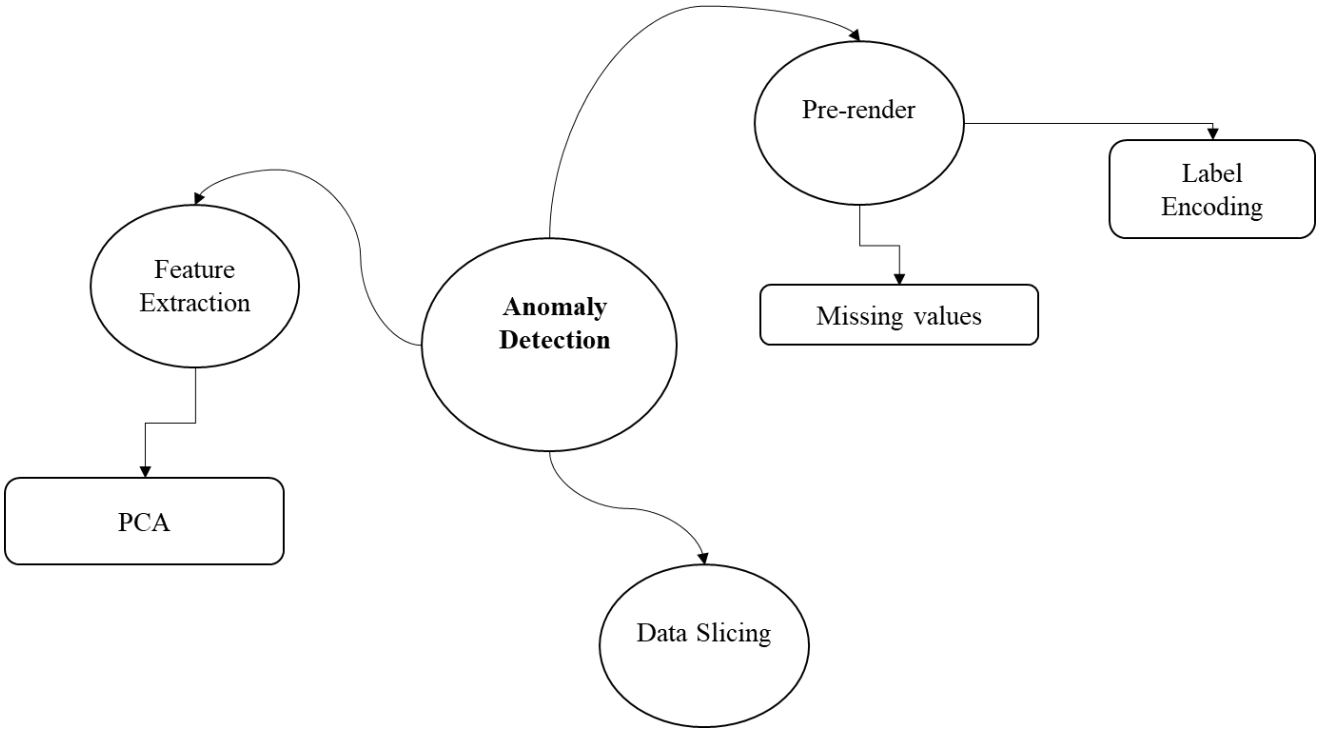
3.3 DATA FLOW DIAGRAM:

3.3.1 Level 0:



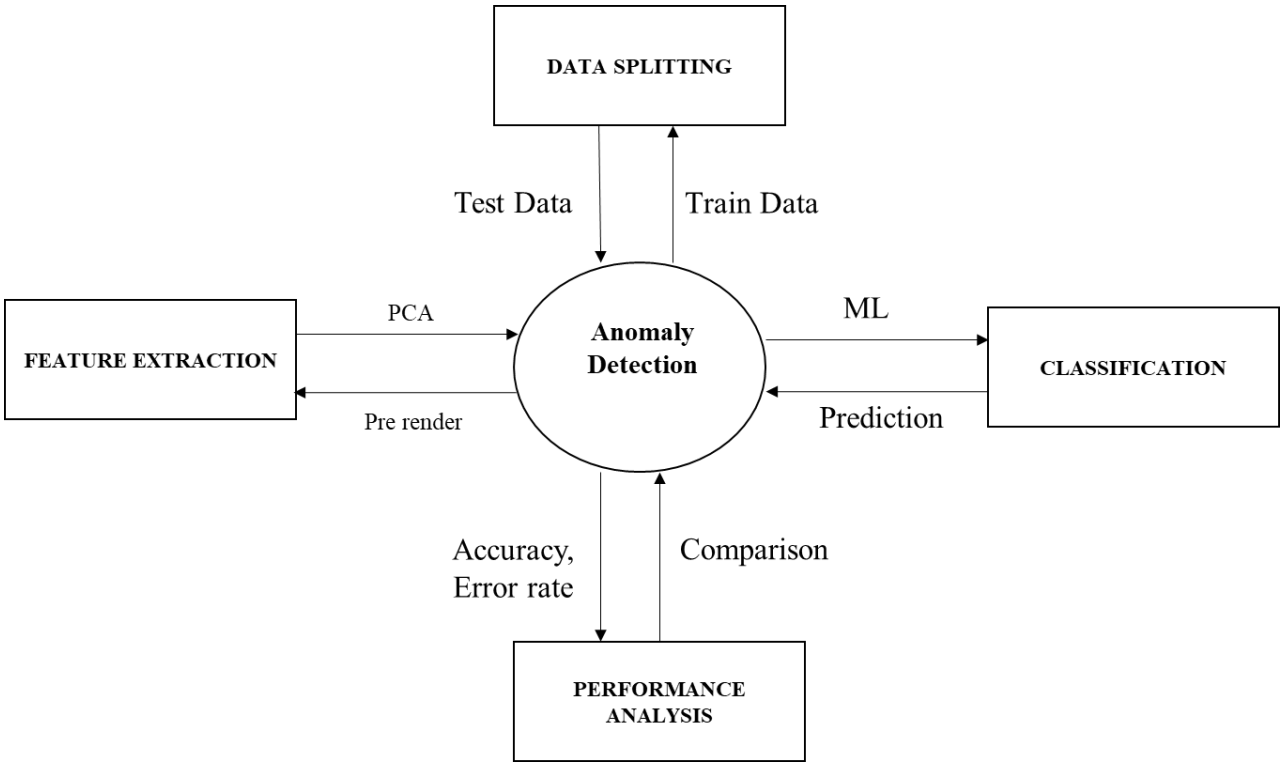
The Data Flow Diagram (DFD) Level 0 provides a high-level overview of the anomaly prediction system's primary processes. It starts with **Data Selection**, where the ND dataset in CSV format is imported into the system. The diagram then shows the **Data Preprocessing** phase, which includes handling missing values and applying label encoding to standardize the data. The diagram illustrates the flow of data between these key processes and highlights the inputs and outputs involved. This level of abstraction captures the essential functions of data handling and preparation, setting the stage for more detailed process analysis in subsequent DFD levels.

3.3.2 Level 1:



The Data Flow Diagram (DFD) Level 1 expands on the high-level overview by detailing the specific processes involved in the anomaly prediction system. It begins with **Data Selection**, where the autism dataset in CSV format is imported. This data is then passed to the **Data Preprocessing** module, which handles missing values and applies label encoding. The diagram continues with **Feature selection**, where PCA select the best features and enhance data quality. Finally, **Data Splitting** divides the dataset into training and testing sets to prepare for model training and evaluation. The DFD Level 1 visually represents how data flows through each process and how these processes interconnect to facilitate accurate prediction.

3.3.3 Level 2:



The Data Flow Diagram (DFD) Level 2 provides a detailed view of the anomaly prediction system. It starts with **Data Selection** of the CSV dataset, followed by **Data Preprocessing** to handle missing values and apply label encoding. **Feature Extraction** using PCA reduces dimensionality, and **Data Splitting** divides the data into training and testing sets. **Classification** involves training models like different DL. **Result Generation** assesses model accuracy, and **Prediction** determines if an individual is anomaly or notbased on the model outputs.

3.4 UML DIAGRAMS:

UML stands for Unified Modelling Language. UML is a standardized general-purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group.

The goal is for UML to become a common language for creating models of object oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modelling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful in the modelling of large and complex systems. The UML is a very important part of developing objects oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

GOALS:

The Primary goals in the design of the UML are as follows:

1. Provide users a ready-to-use, expressive visual modeling Language so that they can develop and exchange meaningful models.

2. Provide extendibility and specialization mechanisms to extend the core concepts.

3. Be independent of particular programming languages and development process.

4. Provide a formal basis for understanding the modeling language.

5. Encourage the growth of OO tools market.

3.4.1 USE CASE DIAGRAM:

Use-case diagrams describe the high-level functions and scope of a system. These diagrams also identify the interactions between the system and its actors. The use cases and actors in use-case diagrams describe what the system does and how the actors use it, but not how the system operates internally.

A use case is a list of actions or event steps typically defining the interactions between a role (known in the Unified Modelling Language (UML) as an actor) and a system to achieve a goal. The actor can be a human or other external system.

UML use case diagrams are ideal for:

- Representing the goals of system-user interactions
- Defining and organizing functional requirements in a system
- Specifying the context and requirements of a system
- Modelling the basic flow of events in a use case

Notations:

- **Use cases**: Horizontally shaped ovals that represent the different uses that a user might have.
- **Actors**: Stick figures that represent the people actually employing the use cases.
- **Associations**: A line between actors and use cases. In complex diagrams, it is important to know which actors are associated with which use cases.
- **System boundary boxes**: A box that sets a system scope to use cases. All use cases outside the box would be considered outside the scope of that system. For example, Psycho Killer is outside the scope of occupations in the chainsaw example found below.

- **Packages**: A UML shape that allows you to put different elements into groups. Just as with component diagrams, these groupings are represented as file folders.

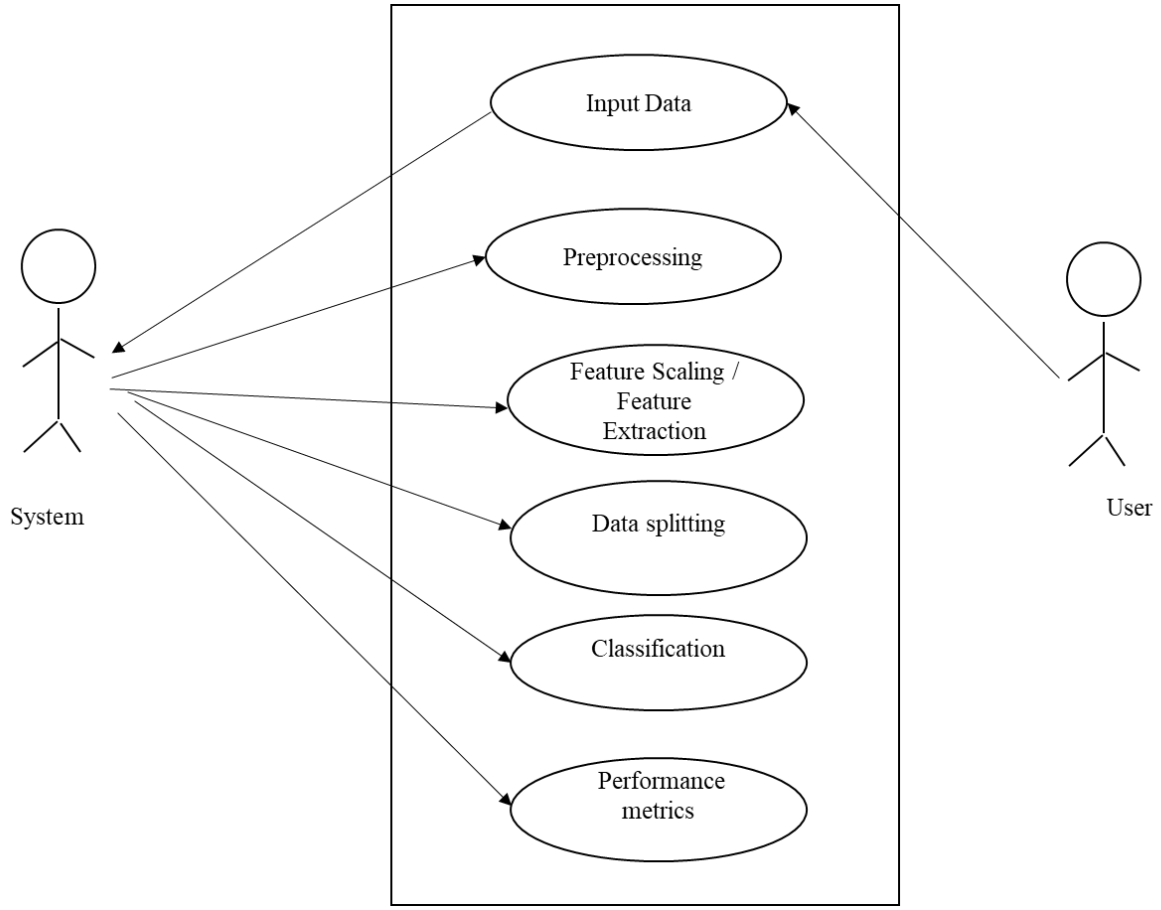


FIGURE 3.4.1: USE CASE DIAGRAM

3.4.2 ACTIVITY DIAGRAM:

This shows the flow of events within the system. The activities that occur within a use case or within an objects behaviour typically occur in a sequence. An activity diagram is designed to be simplified look at what happens during an operations or a process. Each activity is represented by a rounded rectangle the processing within an activity goes to compilation and then an automatic transmission to the next activity occurs. An arrow represents the transition from one activity to the next. An activity diagram describes a system in terms of activities. Activities are the state that represents the execution of a set of operations.

These are similar to flow chart diagram and dataflow.

Initial state: which state is starting the process?

Action State: An action state represents the execution of an atomic action, typically the invocation of an operation. An action state is a simple state with an entry action whose only exit transition is triggered by the implicit event of completing the execution of the entry action.

Transition: A transition is a directed relationship between a source state vertex and a target state vertex. It may be part of a compound transition, which takes the static machine from one static configuration to another, representing the complete response of the static machine to a particular event instance.

Final state: A final state represents the last or "final" state of the enclosing composite state. There may be more than one final state at any level signifying that the composite state can end in different ways or conditions.

When a final state is reached and there are no other enclosing states it means that the entire state machine has completed its transitions and no more transitions can occur.

Decision: A state diagram (and by derivation an activity diagram) expresses decision when guard conditions are used to indicate different possible transitions that depend on Boolean conditions of the owning object.

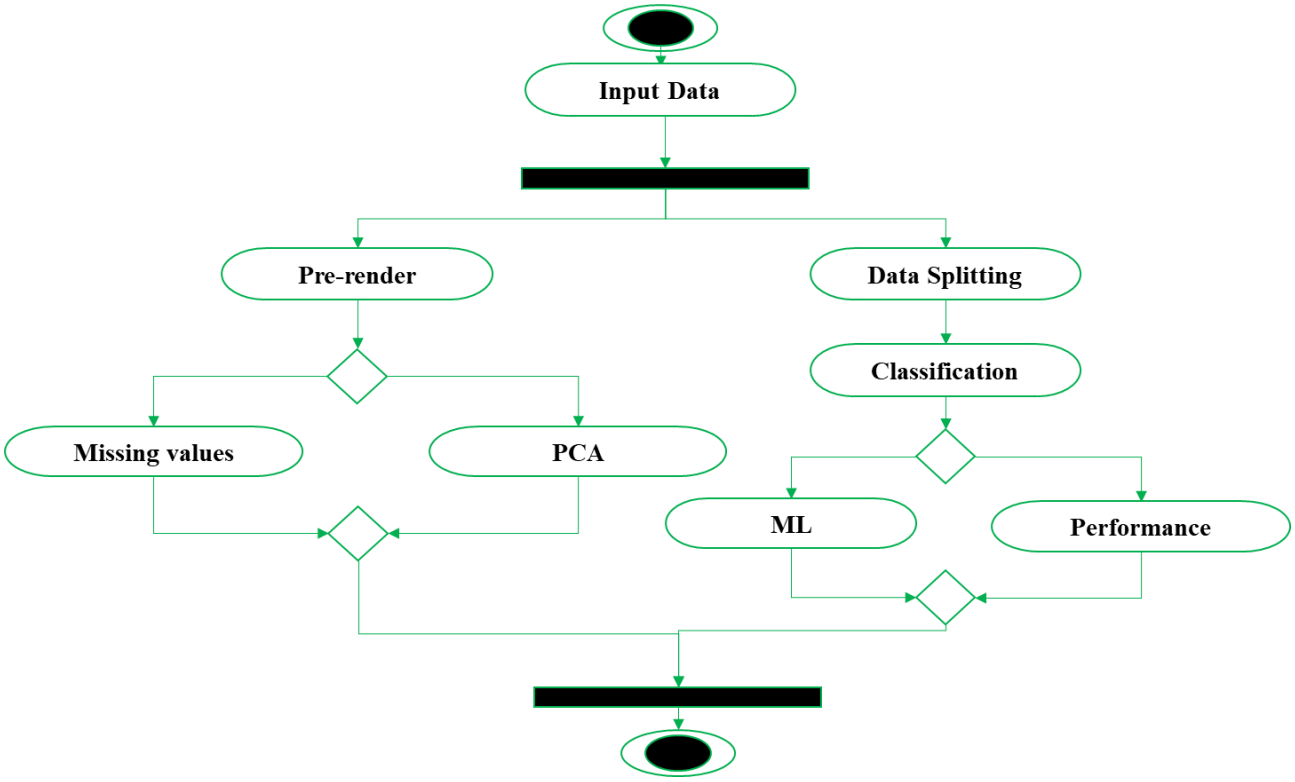


FIGURE 3.4.2: ACTIVITY DIAGRAM

The activity diagram outlines the sequential steps involved in the diabetes prediction process. It starts with Data Collection, where the dataset is imported and prepared. The next phase, Data Preprocessing, addresses missing values and applies label encoding. Following this, Feature selection using PCA is performed to reduce data complexity. The dataset is then Split into training and testing sets. Model Training occurs with different DL algorithms followed by Model Evaluation to measure performance through accuracy metrics. Finally, Prediction generates outcomes, determining if an individual is anomaly or not based on the processed data and trained models. Each step ensures a systematic approach to achieving accurate predictions.

3.4.3 SEQUENCE DIAGRAM:

Sequence diagrams document the interactions between classes to achieve a result, such as a use case. Because UML is designed for object-oriented programming, these communications between classes are known as messages. The Sequence diagram lists objects horizontally, and time vertically, and models these messages over time.

Graphical Notation: In a Sequence diagram, classes and actors are listed as columns, with vertical lifelines indicating the lifetime of the object over time.

Object: Objects are instances of classes, and are arranged horizontally. The pictorial representation for an Object is a class (a rectangle) with the name prefixed by the object.

Lifeline The Lifeline identifies the existence of the object over time. The notation 2for a Lifeline is a vertical dotted line extending from an object.

Activation: Activations, modelled as rectangular boxes on the lifeline, indicate when the object is performing an action.

Message: Messages, modelled as horizontal arrows between Activations.

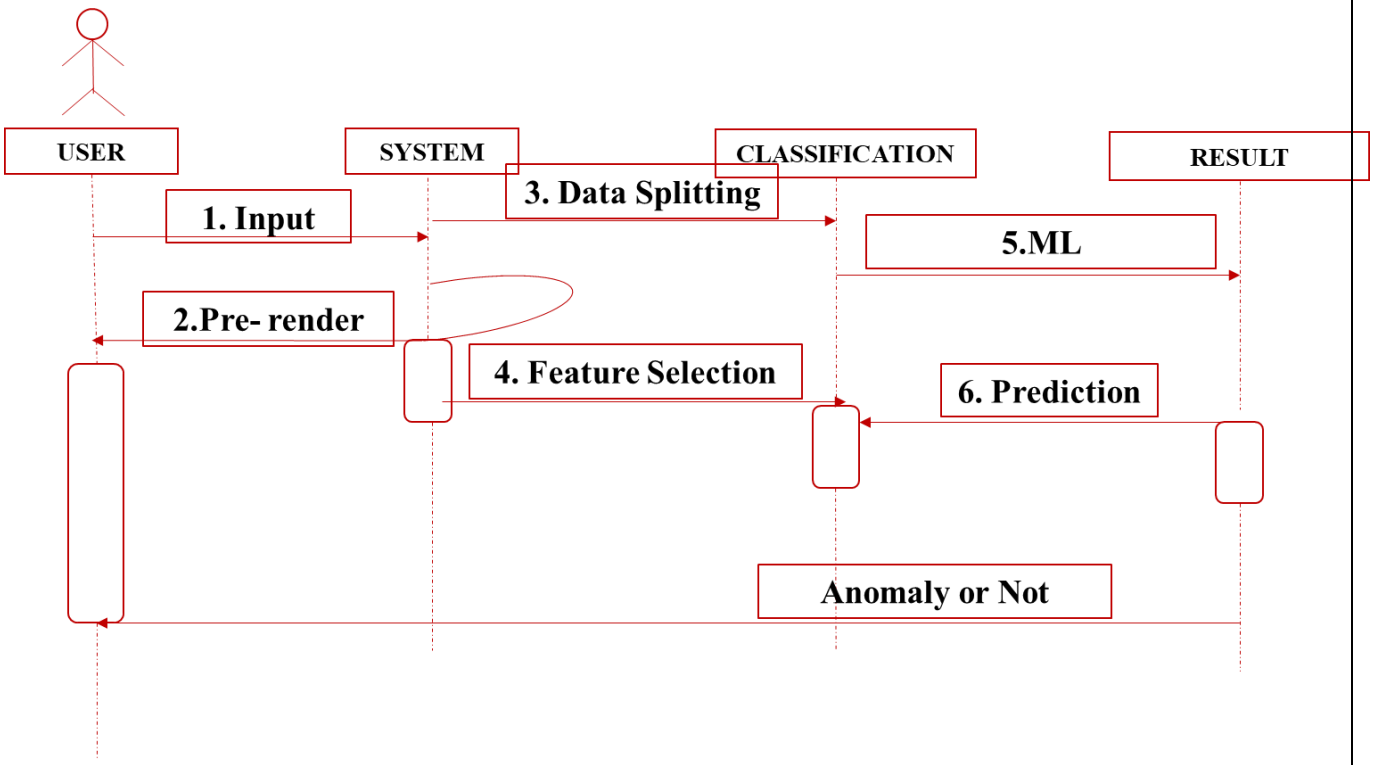


FIGURE 3.4.3: SEQUENCE DIAGRAM

The sequence diagram illustrates the step-by-step interactions between different components of the diabetes prediction system. It begins with the User initiating the process by uploading the autism dataset. The system first performs Data Preprocessing, including handling missing values and applying label encoding. Next, Feature selection is executed using chi-square to optimize data for analysis. The data is then split into Training and Testing sets. The Model Training phase follows, where algorithms like different DL models are employed. After training, the Model Evaluation component assesses performance metrics. Finally, the Prediction step generates the outcome, indicating whether an individual is affected by autism. Each interaction ensures that data flows seamlessly through the system for accurate predictions.

3.4.4 ER DIAGRAM:

An Entity Relationship (ER) Diagram is a type of flowchart that illustrates how "entities" such as people, objects or concepts relate to each other within a system.

ER Diagrams are most often used to design or debug relational databases in the fields of software engineering, business information systems, education and research.

Also known as ERDs or ER Models, they use a defined set of symbols such as rectangles, diamonds, ovals and connecting lines to depict the interconnectedness of entities, relationships and their attributes.

They mirror grammatical structure, with entities as nouns and relationships as verbs.

Notation:

Entity

A definable thing—such as a person, object, concept or event—that can have data stored about it. Think of entities as nouns. Examples: a customer, student, car or product. Typically shown as a rectangle.

Entity type: A group of definable things, such as students or athletes, whereas the entity would be the specific student or athlete. Other examples: customers, cars or products.

Entity set: Same as an entity type, but defined at a particular point in time, such as students enrolled in a class on the first day.

Other examples: Customers who purchased last month, cars currently registered in Florida. A related term is instance, in which the specific person or car would be an instance of the entity set.

Entity categories: Entities are categorized as strong, weak or associative. A **strong entity** can be defined solely by its own attributes, while a **weak entity** cannot. An associative entity associates entities (or elements) within an entity set.

Entity keys: Refers to an attribute that uniquely defines an entity in an entity set. Entity keys can be super, candidate or primary. **Super key:** A set of attributes (one or more) that together define an entity in an entity set.

Candidate key: A minimal super key, meaning it has the least possible number of attributes to still be a super key. An entity set may have more than one candidate key. **Primary key:** A candidate key chosen by the database designer to uniquely identify the entity set. **Foreign key:** Identifies the relationship between entities.

Relationship

How entities act upon each other or are associated with each other. Think of relationships as verbs.

For example, the named student might register for a course.

The two entities would be the student and the course, and the relationship depicted is the act of enrolling, connecting the two entities in that way.

Relationships are typically shown as diamonds or labels directly on the connecting lines.

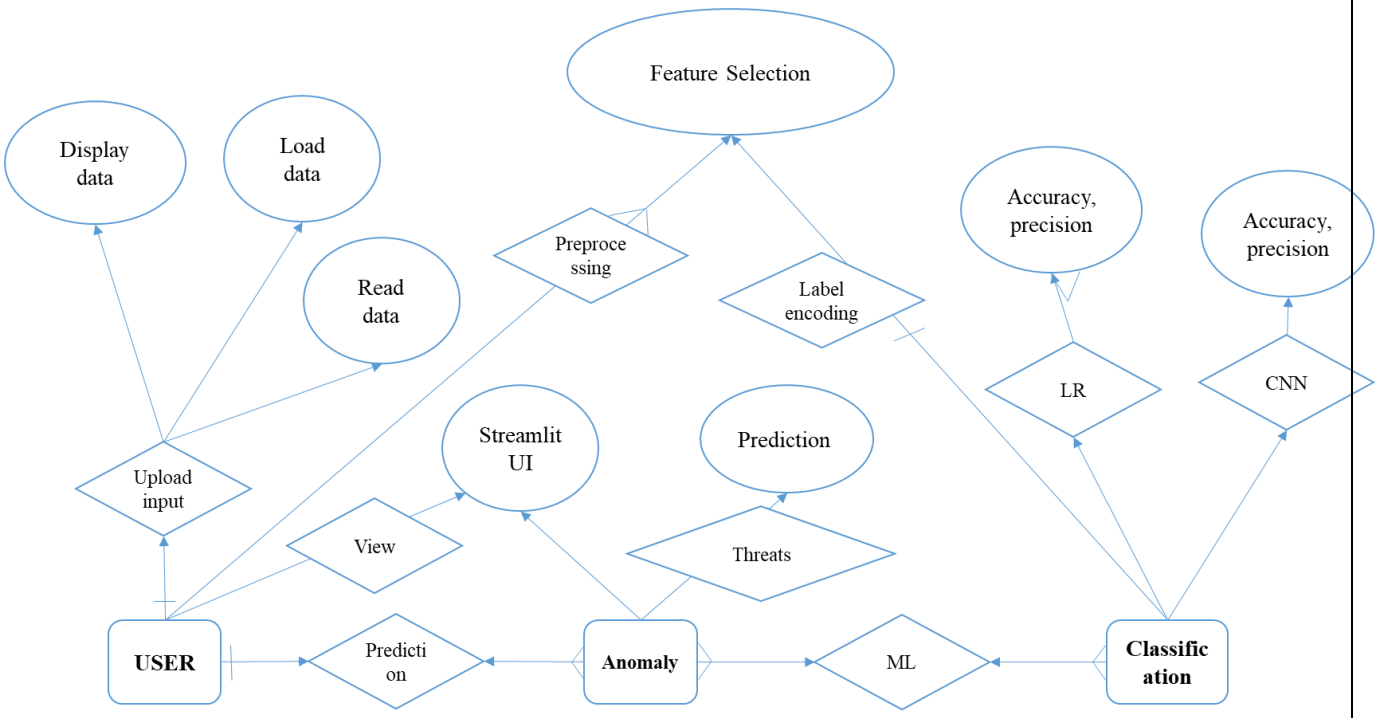


FIGURE 3.4.4: ER DIAGRAM

3.3.5 CLASS DIAGRAM:

Class diagrams identify the class structure of a system, including the properties and methods of each class. Also depicted are the various relationships that can exist between classes, such as an inheritance relationship.

Part of the popularity of Class diagrams stems from the fact that many CASE tools, such as Rational XDE, will auto-generate code in a variety of languages, these tools can synchronize models and code, reducing the workload, and can also generate Class diagrams from object-oriented code.

Graphical Notation: The elements on a Class diagram are classes and the relationships between them.

Class: Classes are building blocks in object-oriented programming. A class is depicted using a rectangle divided into three section.

The top section is name of class; the middle section defines the properties of class. The bottom section list the methods of the class.

Association: An Association is a generic relationship between two classes, and is modelled by a line connecting the two classes.

This line can be qualified with the type of relationship, and can also feature multiplicity rule (e.g. one-to-one, one-to-many, many-to-many) for the relationship.

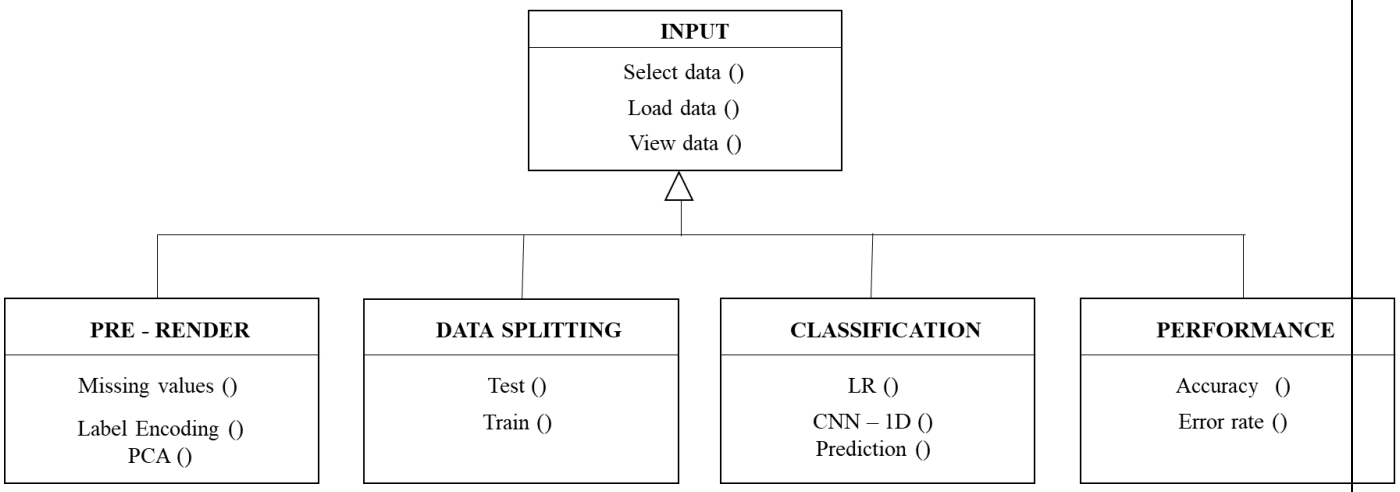


FIGURE 3.4.5: CLASS DIAGRAM

The class diagram represents the structure of the anomaly prediction system by defining the key classes and their relationships. Central classes include Dataset, which handles data import and preprocessing, and Model, which encompasses different deep learning algorithms. The Pre-processor class manages tasks such as handling missing values and applying label encoding, while the Feature selector class is responsible for techniques like PCA. The Evaluator class assesses model performance through metrics like accuracy. Relationships between these classes illustrate how data is processed and utilized, from initial collection and preparation to training and evaluation, ensuring a cohesive approach to predicting anomaly outcomes.

CHAPTER 4
IMPLEMENTATION

4.1 MODULES:

- Data Acquisition
- Data Preprocessing
- Feature Extraction
- Data Splitting
- Model Classification
- Result Generation
- Prediction

4.2 MODULES DESCRIPTION:

4.2.1 DATA ACQUISITION

- The first step in the methodology involves acquiring the anomaly datasets from a reliable data repository.
- The process begins with data acquisition, where relevant datasets are sourced from repositories that specialize in anomaly detection and cybersecurity, ensuring a comprehensive representation of network traffic and attack patterns
- These datasets are usually available in formats such as `.csv` or `.xlsx`, which are compatible with data processing tools and machine learning frameworks.
- It is crucial to ensure that the datasets are obtained from reputable sources to maintain data quality and reliability.

4.2.2 DATA PRE-PROCESSING:

1. **Handling Missing Data:**
    - **Imputation Techniques:** Missing data can be addressed using imputation techniques such as mean imputation, median imputation, or more advanced methods like k-nearest neighbors (KNN) imputation. Imputation helps in filling in missing values based on the statistical properties or patterns observed in the existing data.
    - **Removal Strategies:** Alternatively, rows with missing values can be removed if the proportion of missing data is minimal and does not significantly affect the dataset's integrity. This approach is straightforward but may lead to loss of valuable information if many rows are affected.
2. **Label Encoding:**
    - Categorical variables in the dataset may need to be converted into numerical format to be suitable for machine learning algorithms. Label encoding assigns a unique integer to each category. For instance, if a feature "Gender" has values "Male" and "Female," these might be encoded as 0 and 1, respectively. This transformation is necessary for models that require numerical input but can be supplemented with one-hot encoding for models needing binary representation.
    -

4.2.4 FEATURE EXTRACTION:

Principal Component Analysis (PCA) is a statistical technique used for dimensionality reduction while preserving as much variability as possible. Here's a brief overview of its key concepts and steps:

Key Concepts:

1. **Dimensionality Reduction**: PCA helps reduce the number of variables in a dataset while retaining its essential features, making it easier to visualize and analyze.
2. **Variance**: PCA identifies the directions (principal components) along which the variance of the data is maximized.
3. **Eigenvalues and Eigenvectors**: The principal components are derived from the eigenvectors of the covariance matrix of the data. Eigenvalues indicate the amount of variance captured by each principal component.

Steps in PCA:

1. **Standardization**: If variables have different units or scales, standardize the data (subtract the mean and divide by the standard deviation).
2. **Covariance Matrix Computation**: Calculate the covariance matrix to understand how variables relate to one another.
3. **Eigenvalue and Eigenvector Calculation**: Compute the eigenvalues and eigenvectors of the covariance matrix.
4. **Principal Component Selection**: Sort the eigenvalues and choose the top kkk eigenvalues and their corresponding eigenvectors, which represent the principal components.
5. **Projection**: Project the original data onto the new subspace defined by the selected principal components.

Applications:

- **Data Visualization**: Reducing dimensions helps in visualizing high-dimensional data in 2D or 3D plots.
- **Noise Reduction**: By eliminating less significant components, PCA can help reduce noise in the data.

- **Feature Extraction**: It helps in identifying the most important features that explain the variability in the data.

4.2.5 DATA SPLITTING:

1. **Training and Testing Sets:**
    - The dataset is divided into training and testing subsets. Typically, a common split is 80% of the data for training and 20% for testing, though this can vary based on dataset size and requirements.
    - **Training Set:** Used to develop and train the machine learning models. This set allows the model to learn the underlying patterns and relationships in the data.
    - **Testing Set:** Used to evaluate the performance of the trained model. This set helps in assessing how well the model generalizes to unseen data and provides metrics for evaluating its accuracy and effectiveness.

4.2.6 MODEL CLASSIFICATION:

Logistic regression is a statistical method used for binary classification problems, where the goal is to predict the probability that a given input belongs to a particular category. It is a type of regression analysis used when the dependent variable is categorical.

Key Concepts:

1. **Binary Outcome**: Logistic regression predicts the probability of a binary outcome (e.g., yes/no, success/failure).

How It Works:

1. **Modeling**: Logistic regression estimates the relationship between the independent variables (features) and the log-odds of the dependent variable.
2. **Training**: The model is trained using maximum likelihood estimation (MLE), which finds the parameter values that maximize the likelihood of observing the given data.
3. **Thresholding**: To classify observations, a threshold (often 0.5) is applied to the predicted probabilities. If the predicted probability exceeds the threshold, the observation is classified into one category; otherwise, it falls into the other.

Advantages:

- **Simplicity**: Easy to implement and interpret, making it suitable for binary classification.
- **Efficiency**: Requires less computational power compared to more complex models.
- **Probabilistic Output**: Provides probabilities that can be useful for understanding confidence in predictions.

Random Forest

Random Forest is a versatile and powerful machine learning algorithm widely used for classification and regression tasks. It belongs to the ensemble learning family, which means it constructs a multitude of decision trees during training and outputs the mode of their predictions (for classification) or the mean prediction (for regression). This ensemble approach helps to improve the overall model accuracy and robustness while reducing the risk of overfitting.

Key Features:

1. **Ensemble Learning**: Random Forest operates by creating multiple decision trees, each trained on a random subset of the data. This randomness helps ensure that the model does not rely too heavily on any single feature or training instance, leading to greater generalization.
2. **Bootstrap Aggregating (Bagging)**: The algorithm uses a technique called bagging, where each tree is trained on a random sample of the dataset with replacement. This means some instances may be repeated in a training set while others may be left out, promoting diversity among the trees.
3. **Feature Randomness**: When splitting nodes in each decision tree, Random Forest selects a random subset of features rather than considering all features. This further enhances the diversity of the trees and reduces correlation among them.
4. **Robustness**: Due to its ensemble nature, Random Forest is less sensitive to noise and outliers compared to individual decision trees. It effectively handles both categorical and numerical data, making it applicable in various domains.
5. **Interpretability**: While individual decision trees are easy to interpret, Random Forest as a whole can be more complex. However, feature importance scores can still be derived from the model, indicating which features are most influential in making predictions.

Advantages:

- **High Accuracy**: Often achieves high classification accuracy due to its ensemble approach.
- **Versatile**: Can be used for both classification and regression tasks.
- **Handles Missing Values**: Capable of maintaining accuracy even when some data points are missing.
- **Scalability**: Performs well on large datasets with many features.

1D Convolutional Neural Networks (CNN-1D)

1D Convolutional Neural Networks (CNN-1D) are a specialized type of convolutional neural network designed to process sequential data, such as time series or one-dimensional signals. Unlike traditional 2D CNNs, which are commonly used for image data, CNN-1D focuses on capturing patterns and features from sequential information, making it particularly effective for tasks such as natural language processing, audio analysis, and anomaly detection in time series data.

Key Features:

1. **Convolutional Layers**: CNN-1D employs convolutional layers that slide over input sequences (e.g., a time series) using 1D filters or kernels. These filters help extract local patterns by performing convolution operations, where they compute the weighted sum of the input data within a specific window.
2. **Feature Extraction**: The architecture automatically learns hierarchical feature representations through multiple convolutional layers. Each layer can capture increasingly complex patterns, which are essential for tasks like anomaly detection and classification.
3. **Pooling Layers**: To reduce dimensionality and computational load, CNN-1D often includes pooling layers (typically max pooling or average pooling). These layers downsample the feature maps, retaining the most important information while discarding less relevant details.
4. **Activation Functions**: Non-linear activation functions, such as ReLU (Rectified Linear Unit), are applied after each convolutional layer to introduce non-linearity, allowing the network to learn more complex patterns.
5. **Fully Connected Layers**: After several convolutional and pooling layers, the high-level features are flattened and passed through fully connected layers for final classification or regression tasks.

Advantages:

- **Effective for Sequential Data**: CNN-1D is particularly adept at processing time-dependent data, making it ideal for applications like anomaly detection in network traffic or sensor data.
- **Parameter Sharing**: By using convolutional filters, CNN-1D reduces the number of parameters compared to fully connected networks, leading to more efficient training.
- **Local Feature Learning**: The architecture focuses on local patterns, which can be crucial for identifying anomalies or specific characteristics in sequential data.

4.2.7: RESULT GENERATION:

The Final Result will get generated based on the overall classification and prediction. The performance of this proposed approach is evaluated using some measures like,

- **Accuracy**

Accuracy of classifier refers to the ability of classifier. It predicts the class label correctly and the accuracy of the predictor refers to how well a given predictor can guess the value of predicted attribute for a new data.

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

- **Precision**

Precision is defined as the number of true positives divided by the number of true positives plus the number of false positives.

$$Precision=TP/ (TP+FP)$$

- **Recall**

Recall is the number of correct results divided by the number of results that should have been returned. In binary classification, recall is called sensitivity. It can be viewed as the probability that a relevant document is retrieved by the query.

$$Recall=TP/ (TP+FN)$$

4.2.8 Prediction:

- In the prediction phase of our machine learning model, the system is designed to classify and identify various types of threats or attacks, including Insider threats, DDoS attacks, Man-in-the-Middle (MitM) attacks, and port scanning activities.
- This process begins by feeding new, unseen data—specifically network traffic attributes—into the trained classification algorithms.
- The algorithms analyze the data based on the patterns learned during the training phase, leveraging features extracted from the dataset.

- Once the model processes the input, it generates predictions indicating whether a specific type of threat is present.

- Each classification algorithm, such as Random Forest or CNN-1D, utilizes the relevant dataset attributes to determine the likelihood of an attack occurring.

- The output is a predicted label for each instance of incoming data, which signifies whether it is benign or potentially harmful.

CHAPTER 5

SYSTEM REQUIREMENTS

5.1 HARDWARE REQUIREMENTS:

- System : Pentium IV 2.4 GHz
- Hard Disk : 200 GB
- Mouse : Logitech.
- Keyboard : 110 keys enhanced
- Ram : 4GB

5.2 SOFTWARE REQUIREMENTS:

- O/S : Windows 10.
- Language : Python
- Front End : Streamlit - Framework
- Software used :Anaconda Navigator – Spyder

5.3 SOFTWARE DESCRIPTION:

5.3.1 Python

Python is one of those rare languages which can claim to be both *simple* and powerful. You will find yourself pleasantly surprised to see how easy it is to concentrate on the solution to the problem rather than the syntax and structure of the language you are programming in. The official introduction to Python is Python is an easy to learn, powerful programming language. It has efficient high-level data structures and a simple but effective approach to object-oriented programming.

Python's elegant syntax and dynamic typing, together with its interpreted nature, make it an ideal language for scripting and rapid application development in many areas on most platforms. I will discuss most of these features in more detail in the next section.

5.3.2 Features of Python

- **Simple**

Python is a simple and minimalistic language. Reading a good Python program feels almost like reading English, although very strict English! This pseudo-code nature of Python is one of its greatest strengths. It allows you to concentrate on the solution to the problem rather than the language itself.

- **Easy to Learn**

As you will see, Python is extremely easy to get started with. Python has an extraordinarily simple syntax, as already mentioned.

- **Free and Open Source**

Python is an example of a *FLOSS* (Free/Libré and Open Source Software). In simple terms, you can freely distribute copies of this software, read its source code, make changes to it, and use pieces of it in new free programs. FLOSS is based on the concept of a community which shares knowledge. This is one of the reasons why Python is so good - it has been created and is constantly improved by a community who just want to see a better Python.

- **High-level Language**

When you write programs in Python, you never need to bother about the low-level details such as managing the memory used by your program, etc.

- **Portable**

Due to its open-source nature, Python has been ported to (i.e. changed to make it work on) many platforms. All your Python programs can work on any of these platforms without requiring any changes at all if you are careful enough to avoid any system-dependent features.

You can use Python on GNU/Linux, Windows, FreeBSD, Macintosh, Solaris, OS/2, Amiga, AROS, AS/400, BeOS, OS/390, z/OS, Palm OS, QNX, VMS, Psion, Acorn RISC OS, VxWorks, PlayStation, Sharp Zaurus, Windows CE and PocketPC!

You can even use a platform like Kivy to create games for your computer *and* for iPhone, iPad, and Android.

- **Interpreted**

This requires a bit of explanation.

A program written in a compiled language like C or C++ is converted from the source language i.e. C or C++ into a language that is spoken by your computer (binary code i.e. 0s and 1s) using a compiler with various flags and options. When you run the program, the linker/loader software copies the program from hard disk to memory and starts running it.

Python, on the other hand, does not need compilation to binary. You just *run* the program directly from the source code. Internally, Python converts the source code into an intermediate form called bytecodes and then translates this into the native language of your computer and then runs it. All this, actually, makes using Python much easier since you don't have to worry about compiling the program, making sure that the proper libraries are linked and loaded, etc. This also makes your Python programs much more portable, since you can just copy your Python program onto another computer and it just works!

- **Object Oriented**

Python supports procedure-oriented programming as well as object-oriented programming. In *procedure-oriented* languages, the program is built around procedures or functions which are nothing but reusable pieces of programs. In *object-oriented* languages, the program is built around objects which combine data and functionality. Python has a very powerful but simplistic way of doing OOP, especially when compared to big languages like C++ or Java.

- **Extensible**

If you need a critical piece of code to run very fast or want to have some piece of algorithm not to be open, you can code that part of your program in C or C++ and then use it from your Python program.

- **Embeddable**

You can embed Python within your C/C++ programs to give *scripting* capabilities for your program's users.

- **Extensive Libraries**

The Python Standard Library is huge indeed. It can help you do various things involving regular expressions, documentation generation, unit testing, threading, databases, web browsers, CGI, FTP, email, XML, XML-RPC, HTML, WAV files, cryptography, GUI (graphical user interfaces), and other system-dependent stuff. Remember, all this is always available wherever Python is installed. This is called the *Batteries Included* philosophy of Python.

Besides the standard library, there are various other high-quality libraries which you can find at the Python Package Index.

5.3.3 Streamlit framework:

Streamlit is an open-source Python library that makes it easy to create and share beautiful, custom web apps for machine learning and data science. It allows you to build interactive web applications straight from Python scripts. Here are some of the key features and concepts related to Streamlit:

Key Features

- Ease of Use: Streamlit enables you to create web applications by writing only Python code. You don't need any HTML, CSS, or JavaScript knowledge.
- Real-time Interactivity: Streamlit apps can automatically update as users interact with widgets like sliders, dropdowns, and text inputs.
- Data Visualization: It integrates seamlessly with popular data visualization libraries like Matplotlib, Plotly, and Altair.
- Widgets: Streamlit provides a variety of widgets to collect user input and make your apps interactive.
- Deployment: Streamlit apps can be deployed easily on the web through services like Streamlit Sharing, Heroku, or AWS.

Basic Concepts

- Script Execution: Streamlit runs your entire script from top to bottom each time you interact with a widget, which means the state of your app is reset each time unless you use caching.
- Widgets: Widgets like sliders, text inputs, buttons, and checkboxes allow users to provide input.
- Layout: You can organize the layout of your app using layout primitives like st.sidebar, st.columns, and st.expander.

5.4 TESTING PRODUCTS:

System testing is the stage of implementation, which aimed at ensuring that system works accurately and efficiently before the live operation commence. Testing is the process of executing a program with the intent of finding an error. A good test case is one that has a high probability of finding an error. A successful test is one that answers a yet undiscovered error.

Testing is vital to the success of the system. System testing makes a logical assumption that if all parts of the system are correct, the goal will be successfully achieved. . A series of tests are performed before the system is ready for the user acceptance testing. Any engineered product can be tested in one of the following ways. Knowing the specified function that a product has been designed to from, test can be conducted to demonstrate each function is fully operational. Knowing the internal working of a product, tests can be conducted to ensure that "al gears mesh", that is the internal operation of the product performs according to the specification and all internal components have been adequately exercised.

5.4.1 UNIT TESTING:

Unit testing is the testing of each module and the integration of the overall system is done. Unit testing becomes verification efforts on the smallest unit of software design in the module. This is also known as 'module testing'. The modules of the system are tested separately. This testing is carried out during the programming itself. In this testing step, each model is found to be working satisfactorily as regard to the expected output from the module. There are some validation checks for the fields. For example, the validation check is done for verifying the data given by the user where both format and validity of the data entered is included. It is very easy to find error and debug the system.

5.4.2 INTEGRATION TESTING:

Data can be lost across an interface, one module can have an adverse effect on the other sub function, when combined, may not produce the desired major function. Integrated testing is systematic testing that can be done with sample data. The need for the integrated test is to find the overall system performance. There are two types of integration testing. They are:

i) Top-down integration testing.

ii) Bottom-up integration testing.

5.4.3 TESTING TECHNIQUES/STRATEGIES:

- **WHITE BOX TESTING:**

White Box testing is a test case design method that uses the control structure of the procedural design to drive cases. Using the white box testing methods, we Derived test cases that guarantee that all independent paths within a module have been exercised at least once.

- **BLACK BOX TESTING:**

1. Black box testing is done to find incorrect or missing function
2. Interface error
3. Errors in external database access
4. Performance errors.
5. Initialization and termination errors

In ‘functional testing’, is performed to validate an application conforms to its specifications of correctly performs all its required functions. So this testing is also called ‘black box testing’. It tests the external behaviour of the system. Here the engineered product can be tested knowing the specified function that a product has been designed to perform, tests can be conducted to demonstrate that each function is fully operational.

5.4.4 SOFTWARE TESTING STRATEGIES

VALIDATION TESTING:

After the culmination of black box testing, software is completed assembly as a package, interfacing errors have been uncovered and corrected and final series of software validation tests begin validation testing can be defined as many, But a single definition is that validation succeeds when the software functions in a manner that can be reasonably expected by the customer.

USER ACCEPTANCE TESTING:

User acceptance of the system is the key factor for the success of the system. The system under consideration is tested for user acceptance by constantly keeping in touch with prospective system at the time of developing changes whenever required.

OUTPUT TESTING:

After performing the validation testing, the next step is output asking the user about the format required testing of the proposed system, since no system could be useful if it does not produce the required output in the specific format.

The output displayed or generated by the system under consideration. Here the output format is considered in two ways. One is screen and the other is printed format. The output format on the screen is found to be correct as the format was designed in the system phase according to the user needs. For the hard copy also output comes out as the specified requirements by the user. Hence the output testing does not result in any connection in the system.

5.5 TEST CASES:

Here are five test cases for the prediction functionality of a machine learning-based anomaly detection system. Each test case outlines the objective, input data, expected output, and a brief description of the scenario being tested.

Test Case 1: DDoS Attack Detection

- **Objective:** Validate the detection of a DDoS attack.
- **Input Data:**
  - Source IP: 192.168.1.100
  - Destination IP: 192.168.1.200
  - Packet Size: 1500 bytes
  - Request Rate: 1000 requests/min
- **Expected Output:**
  - Prediction: DDoS Attack
  - Alert: DDoS attack detected from 192.168.1.100 to 192.168.1.200.
- **Description:** This test case simulates a high request rate from a single source IP to a target, characteristic of a DDoS attack. The system should correctly identify this pattern and trigger an alert.

Test Case 2: Insider Threat Detection

- **Objective:** Validate the detection of an insider threat.
- **Input Data:**
  - Source IP: 10.0.0.5
  - Destination IP: 10.0.0.50
  - Data Accessed: Sensitive Data
  - Access Frequency: 5 times in 1 hour
- **Expected Output:**
  - Prediction: Insider Threat
  - Alert: Insider threat detected from 10.0.0.5 accessing sensitive data.
- **Description:** This test case checks for unusual access patterns to sensitive data by an internal user. The model should flag this activity as a potential insider threat.

Test Case 3: Man-in-the-Middle Attack Detection

- **Objective:** Validate the detection of a Man-in-the-Middle (MitM) attack.
- **Input Data:**
  - Source IP: 192.168.1.150
  - Destination IP: 192.168.1.250
  - Anomalies Detected: Unusual packet routing
  - SSL Certificate Status: Invalid
- **Expected Output:**
  - Prediction: Man-in-the-Middle Attack
  - Alert: MitM attack detected between 192.168.1.150 and 192.168.1.250.

- **Description:** This test case simulates traffic where the SSL certificate is invalid and routing anomalies are present, indicating a possible MitM attack. The system should recognize these signs and raise an alert.

Test Case 4: Port Scanning Detection

- **Objective:** Validate the detection of a port scanning activity.
- **Input Data:**
  - Source IP: 172.16.0.1
  - Destination IP: 172.16.0.100
  - Ports Scanned: 20-25
  - Scan Frequency: 50 scans in 10 seconds
- **Expected Output:**
  - Prediction: Port Scanning
  - Alert: Port scanning activity detected from 172.16.0.1 targeting 172.16.0.100.
- **Description:** This test case simulates rapid scanning of multiple ports from a single source IP. The system should correctly identify this as a port scanning attempt and notify administrators.

Test Case 5: Normal Traffic Classification

- **Objective:** Validate the classification of normal network traffic.
- **Input Data:**
  - Source IP: 192.168.1.10
  - Destination IP: 192.168.1.20
  - Packet Size: 500 bytes
  - Request Rate: 10 requests/min
-

- **Expected Output:**
    - Prediction: Normal Traffic
    - Alert: No threat detected for traffic from 192.168.1.10 to 192.168.1.20.
- **Description:** This test case simulates regular network activity with a typical request rate and packet size. The system should classify this traffic as normal, confirming its ability to distinguish between benign and malicious activity.

CHAPTER 6

CONCLUSION

In conclusion, the proposed anomaly detection system leveraging machine learning techniques represents a significant advancement in the fight against cyber threats, particularly DDoS attacks. By integrating a hybrid classification approach that combines Logistic Regression and 1D Convolutional Neural Networks, the system enhances detection accuracy and reliability. The meticulous preprocessing of data, coupled with effective feature extraction using Principal Component Analysis, ensures that the model operates on high-quality inputs, optimizing its predictive capabilities. Additionally, the user-friendly interface and automated notification system empower organizations to respond swiftly to potential threats, thereby minimizing the impact of attacks. The comprehensive performance evaluation metrics further enable continuous refinement of the system, ensuring it remains effective in the face of evolving cyber threats. This adaptability not only increases its longevity but also makes it suitable for a wide range of applications across different sectors. By harnessing the power of machine learning, organizations can significantly bolster their cybersecurity defenses, transforming how they protect their digital assets. Ultimately, this project not only addresses the pressing need for robust cybersecurity solutions but also lays the groundwork for future advancements in anomaly detection, ultimately contributing to a safer digital environment for all users. The ongoing evolution of cyber threats necessitates continuous innovation, and this system stands as a proactive response to these challenges.

CHAPTER 7

FUTURE ENHANCEMENT

Looking ahead, several enhancements could be made to further improve the anomaly detection system for DDoS attacks and other cyber threats. One significant area for development is the incorporation of advanced deep learning techniques, such as recurrent neural networks (RNNs) or transformers, which can better capture temporal dependencies in network traffic data. This could lead to improved detection of sophisticated attack patterns that evolve over time. Additionally, integrating real-time threat intelligence feeds would enable the system to stay updated with the latest attack vectors and techniques used by cybercriminals, enhancing its responsiveness to emerging threats. Moreover, expanding the dataset to include diverse traffic patterns from various environments can help train more robust models that generalize well across different organizational contexts. Implementing anomaly detection techniques that leverage unsupervised learning could also prove beneficial, as they can identify previously unseen attack patterns without requiring labeled data. Finally, developing a more comprehensive visualization dashboard for administrators could facilitate better monitoring and analysis of potential threats, making it easier to understand system performance and take informed actions. By pursuing these enhancements, the system can evolve into a more powerful tool, providing organizations with an even greater level of protection against the ever-changing landscape of cyber threats.

CHAPTER 8

SAMPLE CODING

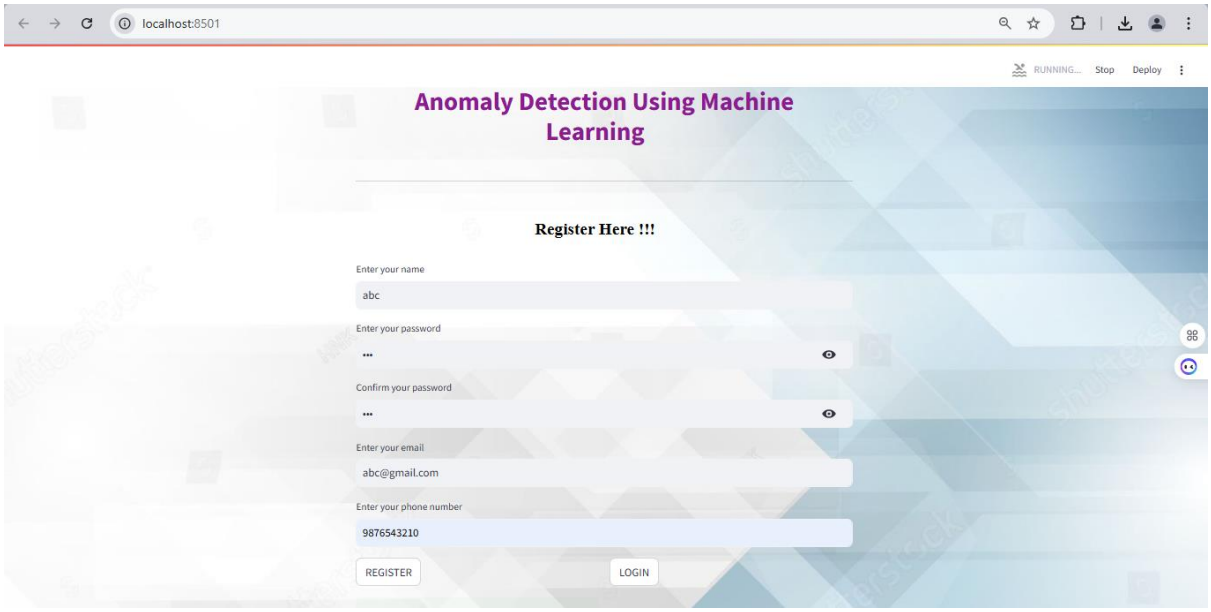
```
# ======================== IMPORT PACKAGES ==============
import pandas as pd
import time
from sklearn.model_selection import train_test_split
from sklearn import metrics
import matplotlib.pyplot as plt
import numpy as np
import warnings
warnings.filterwarnings("ignore")
from sklearn import preprocessing
# ===------------------------= INPUT DATA ------------------------------
dataframe=pd.read_csv("Dataset.csv")


print("-------------------------------")
print("Data Selection")
print("-------------------------------")
print()
print(dataframe.head(15))
```

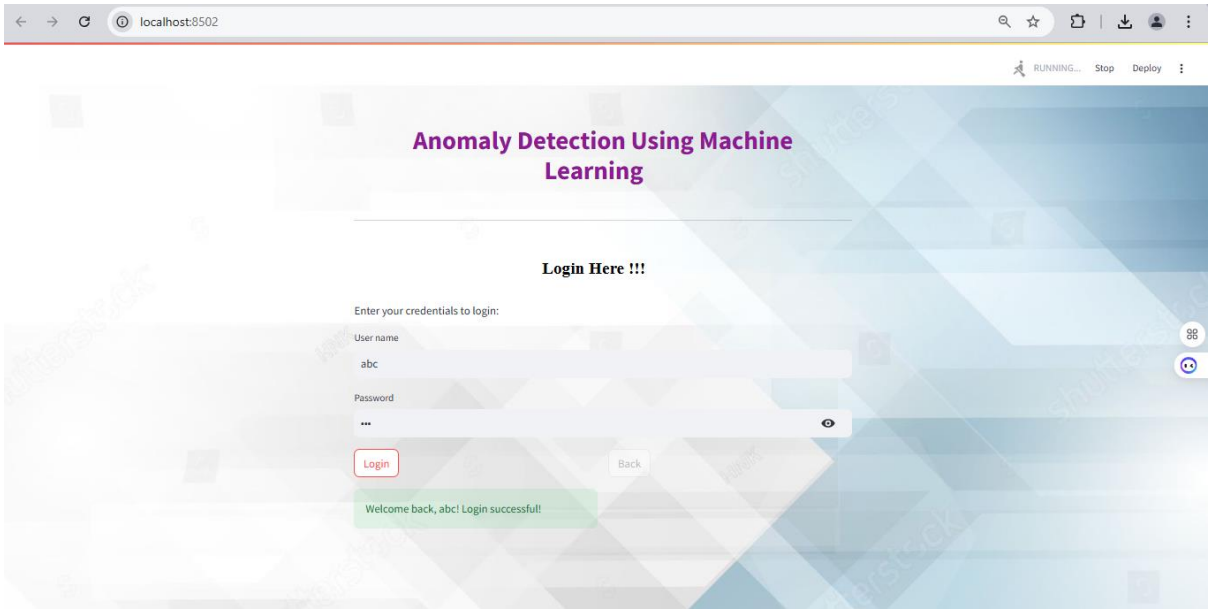
```
#------------------------- PRE PROCESSING -------------------------------
  #------ checking missing values --------
  print("--------------------------------------------------")
print("              Handling Missing values              ")
print("--------------------------------------------------")
print()
print(dataframe.isnull().sum())
res = dataframe.isnull().sum().any()
if res == False:
    print("------------------------------------------")
    print("  There is no Missing values in our dataset ")
    print("------------------------------------------")
    print()
else:
    print("------------------------------------------")
    print(" Missing values is present in our dataset   ")
    print("------------------------------------------")
    print()



    dataframe = dataframe.fillna(0)
    resultt = dataframe.isnull().sum().any()
```

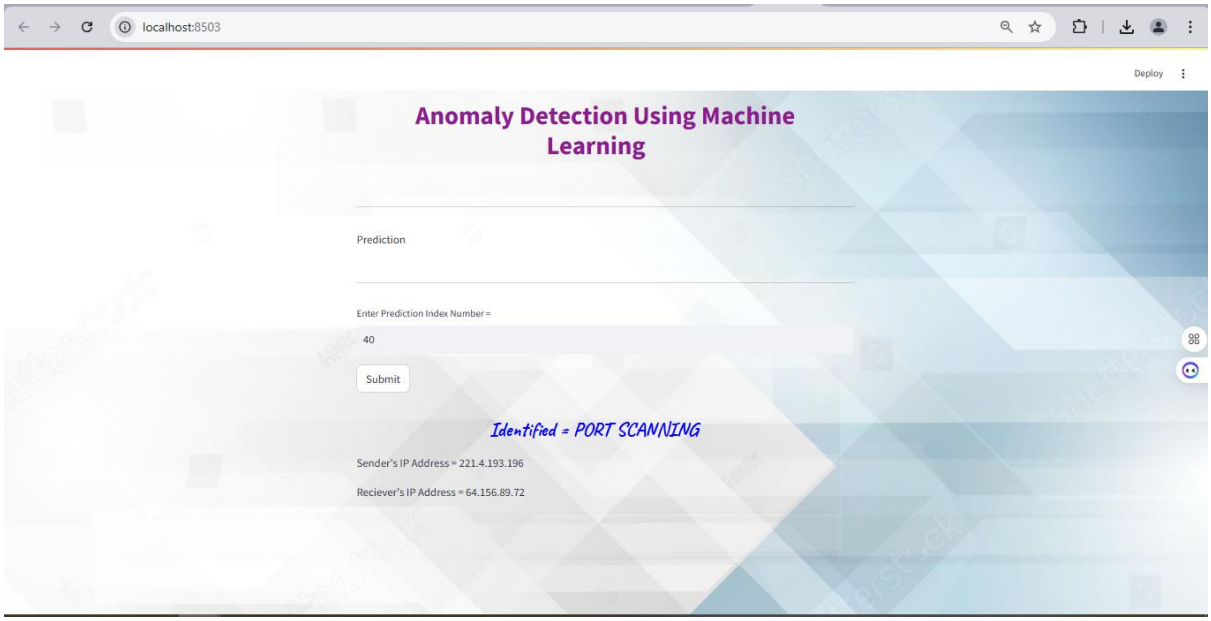
```
    if resultt == False:
        print("-----------------------------------------")
        print(" Data Cleaned !!!   ")
        print("-----------------------------------------")
        print()
        print(dataframe.isnull().sum())
# ---- LABEL ENCODING
print("--------------------------------")
print("Before Label Encoding")
print("--------------------------------")
df_class=dataframe['Label']
print(dataframe['Label'].head(15))
print("--------------------------------")
print("After Label Encoding")
print("--------------------------------")
label_encoder = preprocessing.LabelEncoder()
dataframe['Label']=label_encoder.fit_transform(dataframe['Label'])
```

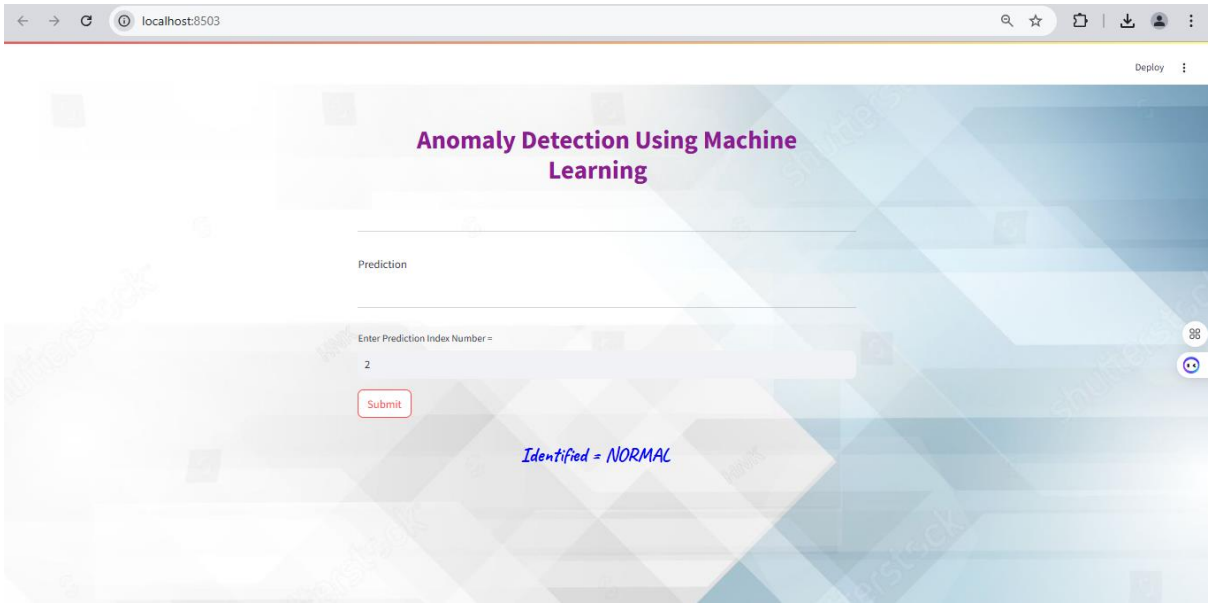
CHAPTER 9

SCREENSHOTS






localhost:8503
Deploy
Anomaly Detection Using Machine Learning
Prediction
Enter Prediction Index Number =
40
Submit
Identified = PORT SCANNING
Sender's IP Address = 221.4.193.196
Reciever's IP Address = 64.156.89.72


localhost:8503
Deploy
Anomaly Detection Using Machine Learning
Prediction
Enter Prediction Index Number =
2
Submit
Identified = NORMAL

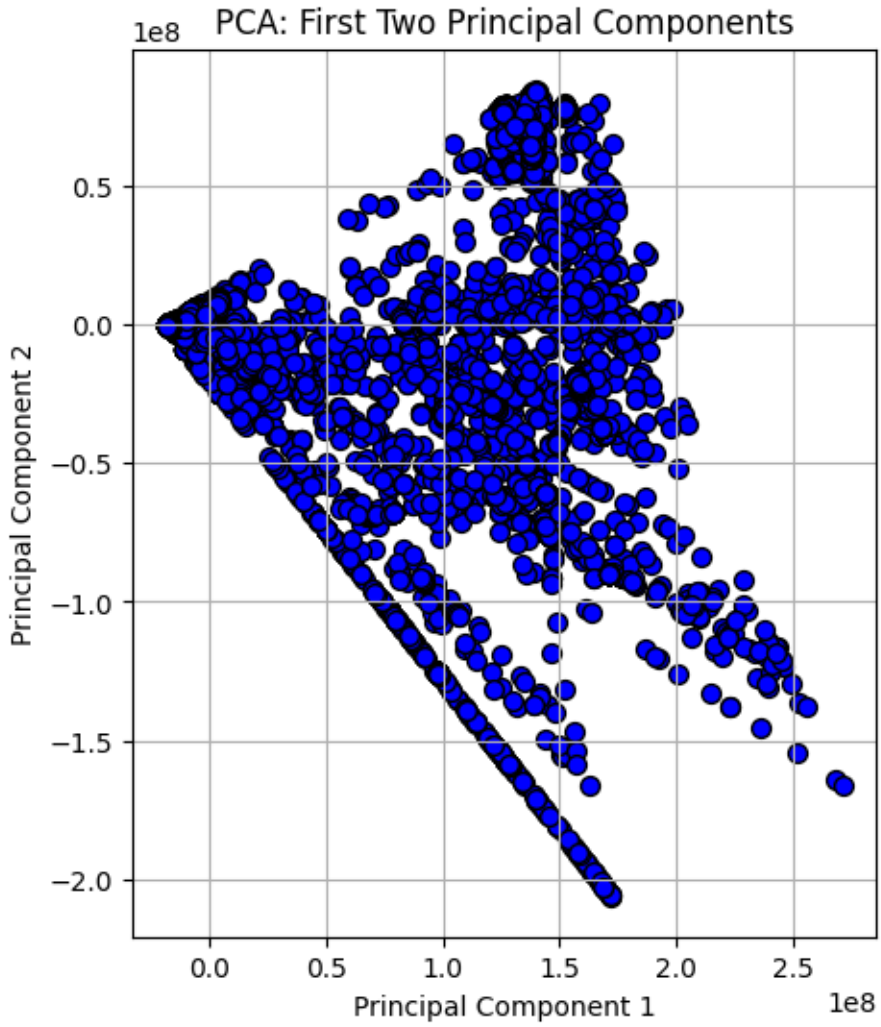
```
--------------------------------
Data Selection
--------------------------------

    'Flow Duration'  'Tot Fwd Pkts'  ...  'Idle Min'        Label
0              1518               2  ...           0  Brute_Force
1              5894               4  ...           0  Brute_Force
2               272               1  ...           0  Brute_Force
3              2611               4  ...           0  Brute_Force
4               294               1  ...           0  Brute_Force
5              4529               4  ...           0  Brute_Force
6              6111               4  ...           0  Brute_Force
7              8165               4  ...           0  Brute_Force
8             10106               4  ...           0  Brute_Force
9             11917               4  ...           0  Brute_Force
10             9016               1  ...           0  Brute_Force
11             1849               1  ...           0  Brute_Force
12             3876               1  ...           0  Brute_Force
13             6059               1  ...           0  Brute_Force
14             8300               1  ...           0  Brute_Force

[15 rows x 67 columns]
```

```
-----------------------------------------------------
              Handling Missing values
-----------------------------------------------------

'Flow Duration'      0
'Tot Fwd Pkts'       0
'Tot Bwd Pkts'       0
'TotLen Fwd Pkts'    0
'TotLen Bwd Pkts'    0
                    ..
'Idle Mean'          0
'Idle Std'           0
'Idle Max'           0
'Idle Min'           0
Label                0
Length: 67, dtype: int64
-------------------------------------------
  There is no Missing values in our dataset
-------------------------------------------
```

```
--------------------------------
Before Label Encoding
--------------------------------
0     Brute_Force
1     Brute_Force
2     Brute_Force
3     Brute_Force
4     Brute_Force
5     Brute_Force
6     Brute_Force
7     Brute_Force
8     Brute_Force
9     Brute_Force
10    Brute_Force
11    Brute_Force
12    Brute_Force
13    Brute_Force
14    Brute_Force
Name: Label, dtype: object
```

```
--------------------------------
After Label Encoding
--------------------------------
0     0
1     0
2     0
3     0
4     0
5     0
6     0
7     0
8     0
9     0
10    0
11    0
12    0
13    0
14    0
Name: Label, dtype: int32
```

```
-------------------------------------------
            Data Splitting
-------------------------------------------

Total no of input data   : 128799
Total no of test data    : 38640
Total no of train data   : 90159
-------------------------------------------
   Feature Extraction ---> PCA
-------------------------------------------

 Original Features     : 67
 Reduced Features      : 15
```

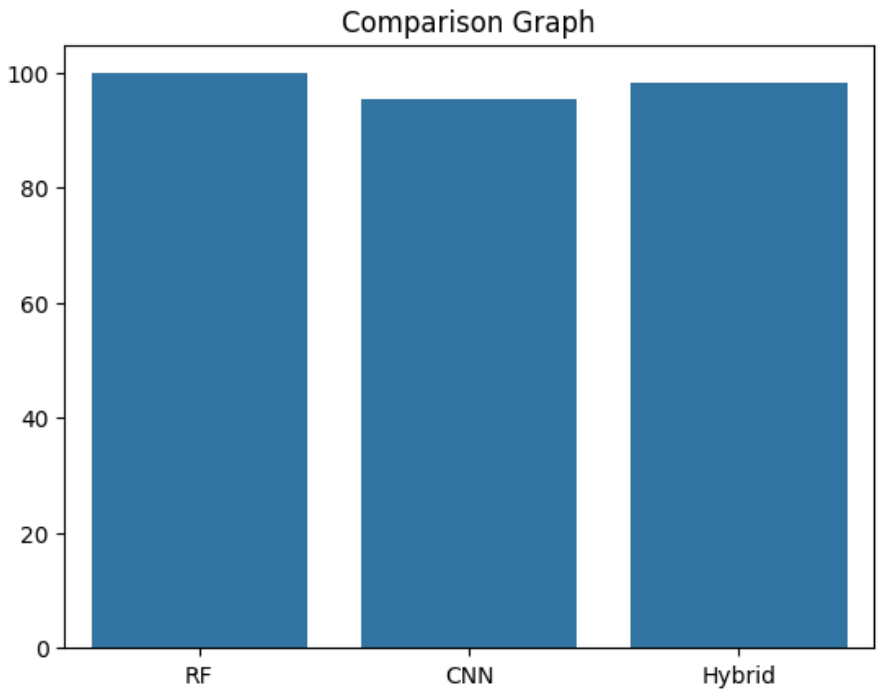


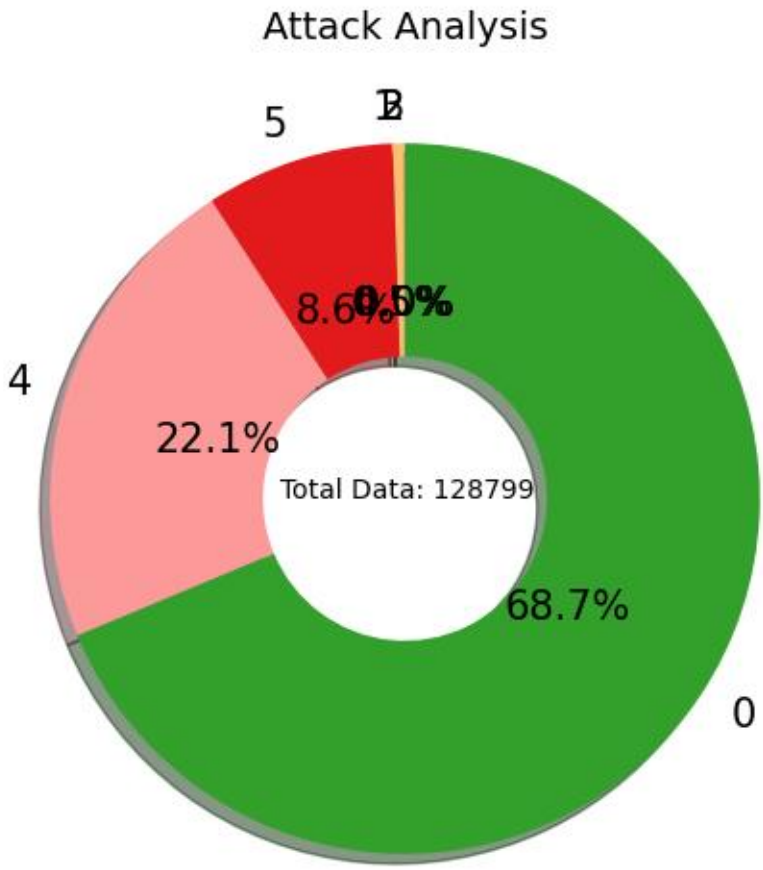

```
-------------------------------------------
  Performance Analysis - Random Forest
-------------------------------------------

1) Accuracy =  99.80590062111801

2) Loss     =  0.1940993788819867

3) Classification Report

              precision    recall  f1-score   support

           0       1.00      1.00      1.00     26480
           1       0.97      0.96      0.96       195
           2       0.82      0.64      0.72        14
           3       0.67      0.15      0.25        13
           4       1.00      1.00      1.00      8626
           5       1.00      0.99      0.99      3312

    accuracy                           1.00     38640
   macro avg       0.91      0.79      0.82     38640
weighted avg       1.00      1.00      1.00     38640

-------------------------------------------
```

```
-----------------------------------------------
   Convlotional Neural Network - CNN
-----------------------------------------------
Epoch 1/10
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 7s 2ms/step - loss: 5.6975 - val_loss: 5.7139
Epoch 2/10
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 10s 2ms/step - loss: 5.6561 - val_loss: 5.7139
Epoch 3/10
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 10s 2ms/step - loss: 5.6446 - val_loss: 5.7139
Epoch 4/10
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 7s 3ms/step - loss: 5.7134 - val_loss: 5.9961
Epoch 5/10
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 6s 2ms/step - loss: 4.9772 - val_loss: 4.7813
Epoch 6/10
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 6s 2ms/step - loss: 4.7811 - val_loss: 4.7813
Epoch 7/10
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 6s 2ms/step - loss: 4.7244 - val_loss: 4.7813
Epoch 8/10
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 6s 2ms/step - loss: 4.7817 - val_loss: 4.7813
Epoch 9/10
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 4.7531 - val_loss: 4.7813
Epoch 10/10
2818/2818 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 4.7240 - val_loss: 4.7813
1208/1208 ━━━━━━━━━━━━━━━━━━━━ 1s 937us/step - loss: 4.7288
-----------------------------------------------
```

```
-----------------------------------------------
  Performance Analysis - CNN
-----------------------------------------------

1208/1208 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step
1) Accuracy =  95.21873712539673

2) Loss     =  4.7812628746032715

-----------------------------------------------
```

```
-----------------------------------------------
  Performance Analysis - Hybrid CNN + LR
-----------------------------------------------

1208/1208 ━━━━━━━━━━━━━━━━━━━━ 1s 990us/step
1) Accuracy =  98.30108690261841

2) Loss     =  1.6989130973815918
```


Comparison Graph
100
80
60
40
20
0
RF
CNN
Hybrid


Attack Analysis
5
2
8.6%
0.5%
4
22.1%
Total Data: 128799
68.7%
0

CHAPTER 10

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CHAPTER 11

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