III.B.Tech - I Sem Application Development – Machine Learning Explore

BATCH NO-152

CYBER SENTINAL:(Threat Intelligence and Analytics)

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2024-2025

MALLA REDDY UNIVERSITY

(As per Telangana State Private Universities Act No.11 of 2018 and G.O.Ms.No.14, Higher Education (UE) Department)

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the App Development report entitled "CYBER SENTINAL:(Threat Intelligence and Analytics)" by **CH.ThirmalRaju (2211CS010112) ,E.CherishmaDevi (2211CS010157), G.Srinath (2211CS010174) , Ch.Meghana (2211CS010114)** , B.Tech III year I semester , Department of CSE, duringthe year 2024-2025.The results embodied in this report have not been submitted to any other university or institute for the award of any degree or diploma.

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DECLARATION

I declare that this project **"CYBER SENTINAL:(Threat Intelligence and Analytics)"** submitted in partial fulfillment of the degree of B. Tech in CSE is a record oforiginal work carriedout by me under the supervision of **Mr.k.Sreekanth,** and has not formed the basis for the awardof any other degree or diploma,in this or any other Institution or University. In keeping with the ethical practice in reporting scientific information, due acknowledgements have been made whenever the findings of others have been cited.

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Acknowledgment

We have been truly blessed to have a wonderful internal guide **Mr.k.Sreekanth,** Department of CSE, Malla Reddy University for guiding us to explore the ramification of our work and we express oursincere gratitude towards him for leading me through the completion of Project.

We would like to say our sincere thanks to **Mr.G.Mohan Ram,** Department of CSE, App Development Coordinator, for providingseamless support and right suggestions are given in the development of the App.

We would like to say our sincere thanksto **Dr.Meeravali,** HOD, Department of CSE III. B.Tech, Malla Reddy University for providing seamless support and right suggestions are given in the development of the App.

We wish to expressour sincere thanks to **DR.V.S.K.Reddy** sirand The Management of Malla Reddy University for providing excellentinfrastructure and their visionary thoughts to prepareourselves industry ready by focusingon new technologies.

Finally, we would like to thank our family members and friends for their moral support and encouragement to achieve goals.

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Abstract

Abstract :This project focuses on analyzing and classifying network traffic data, specifically distinguishing between benign and malicious requests in the context of a Software-Defined Networking (SDN) dataset. The data includes various features such as source and destination IP addresses, protocols, and labels indicating whether the request is benign (0) or malicious (1). The analysis begins by exploring the dataset with visualization techniques, including bar charts and pie charts, to identify patterns and imbalances in the distribution of benign and malicious traffic. Notably, the dataset contains a significant proportion of malicious requests, which are essential for detecting attacks such as DDoS (Distributed Denial of Service). Various methods, including Logistic Regression and K-Nearest Neighbors (KNN), are applied to classify the traffic into benign and malicious categories.

In the preprocessing phase, the data is cleaned by handling missing values and encoding categorical features. The dataset is then split into training and testing sets, with standardized scaling applied to the feature set. Several machine learning algorithms are tested for their classification performance. Logistic Regression, with different solvers, is used to predict the class labels, and the best-performing solver is identified. K-Nearest Neighbors (KNN) is also explored, and the optimal number of neighbors and distance metrics are determined using cross-validation and GridSearchCV. The accuracy of both models is evaluated using classification metrics like accuracy score, precision, recall, and F1-score. These models are then compared to assess their effectiveness in detecting malicious requests.

The analysis further extends to removing malicious users (i.e., DDoS attacks) from the dataset to observe how this affects the distribution of benign and malicious requests. After filtering out the malicious requests, the dataset shows a shift in the balance, with an increased proportion of genuine users. The results are visualized in a pie chart, highlighting the changes in the number of malicious users before and after removal. This approach demonstrates the impact of removing DDoS attacks on network traffic analysis and provides insights into refining detection systems for SDN environments. The models and techniques employed in this study contribute to enhancing the ability to detect and mitigate malicious activities in network traffic.

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CHAPTER-1

1.1 INTROUCTION TO THE APP

Introduction.: In recent years, the rise of malicious activities, such as Distributed Denial-of-Service (DDoS) attacks, has posed a significant threat to network security. The need for automated systems that can detect and classify these threats in real-time has become paramount. In this context, machine learning techniques have shown immense potential in identifying malicious and benign traffic. The dataset used in this analysis provides a glimpse into this problem by categorizing network requests as either "Malicious" or "Genuine," with each request carrying several features like source IP address, destination, protocol type, and other network characteristics. The goal is to build a predictive model that can accurately classify network requests based on these features and distinguish between normal and malicious behavior.

The analysis begins by exploring and visualizing the data to understand its structure and any patterns present within it. Initial steps include the handling of missing values, identifying numeric and categorical features, and visualizing the distribution of the target variable, which contains labels for either benign or malicious traffic. By utilizing various plotting techniques, such as count plots, pie charts, and bar plots, we gain insights into the class imbalance between malicious and genuine users. It is crucial to understand these imbalances as they can significantly affect model performance, especially in scenarios like DDoS attacks, where malicious traffic often outnumbers benign requests. The feature selection process also includes transforming categorical variables into numerical ones through one-hot encoding, ensuring that all inputs are suitable for machine learning algorithms.

Following data preprocessing, several machine learning models are applied, including Logistic Regression and K-Nearest Neighbors (KNN). These models are trained on the dataset and evaluated using accuracy metrics, confusion matrices, and classification reports to assess their performance. The analysis also incorporates hyperparameter tuning to optimize the KNN model and determine the best settings for classification tasks. The effectiveness of the models is evaluated by comparing their performance on different types of traffic and understanding the challenges in detecting malicious behavior, particularly in the presence of attack patterns like DDoS

1.2 Problem Statement

In the context of cybersecurity and network monitoring, detecting malicious activities such as Distributed Denial of Service (DDoS) attacks is of paramount importance. The goal of this project is to analyze and classify network traffic data in order to identify malicious requests (such as DDoS attacks) and separate them from legitimate (benign) users. By doing so, we can develop machine learning models to enhance the ability to identify and mitigate threats in real-time network traffic data. The dataset provided contains labeled network traffic information, with features such as source IP, destination IP, protocol type, and the number of requests made by each source IP. The labels indicate whether the traffic is benign (0) or malicious (1).

The primary challenge in this dataset is to properly preprocess the data, handle missing values, and select the relevant features for building accurate predictive models. Given the imbalanced nature of the dataset—where the number of malicious requests may be significantly smaller than the number of legitimate requests—the project focuses on implementing and evaluating machine learning algorithms to detect DDoS attacks and other malicious behaviors. Techniques like Logistic Regression, K-Nearest Neighbors (KNN), and GridSearchCV for hyperparameter tuning are applied to train models and assess their performance. The performance of each model is evaluated using accuracy, classification reports, and confusion matrices to identify the most effective approach for malicious traffic detection.

Additionally, the project also addresses the challenge of improving model performance by removing malicious users from the dataset. The analysis includes exploring the distribution of malicious and benign requests, followed by filtering out DDoS attacks (or malicious users) from the data, allowing us to understand the impact of malicious activity on model performance and classification. The visualizations in the form of pie charts and bar plots are used to illustrate the proportion of malicious and legitimate users before and after filtering out DDoS attacks. This approach not only helps in improving the model's accuracy but also provides insights into the behavior of malicious users within the network.

1.3 Objective

Threat Detection in SDN Networks: Detect and classify network traffic as malicious or benign using machine learning models.
Data Preprocessing and Feature Engineering: Clean and structure the raw data, handle missing values, and encode categorical variables for model compatibility.
Machine Learning Model Implementation:
Implement Logistic Regression and K-Nearest Neighbors (KNN) to classify traffic as benign or malicious.
Performance Evaluation and Comparison: Evaluate models using metrics such as accuracy, precision, recall, and F1-score for performance comparison.
Visual Analysis and Interpretation of Network Traffic: Visualize the distribution of benign vs. malicious traffic and key features like source IPs and protocols used in attacks.
Removal of DDoS Attack Data and Impact Analysis: Remove DDoS attack data to analyze the impact on model performance and the distribution of malicious traffic.
Dataset Exploration and Preprocessing
Explore the dataset to identify missing values, data types, and feature characteristics.
Visualize the label distribution to understand class imbalances.
Handle missing data and convert categorical variables to numeric representations.
Feature Engineering
Analyze feature correlations to identify relationships useful for classification.
Normalize the dataset to standardize feature values for model compatibility.
Determine feature importance to identify key factors in detecting malicious activities.
3. Exploration of Malicious and Genuine Traffic Patterns
Analyze traffic patterns, focusing on source IP addresses, protocols, and attack types.
Examine the distribution of malicious vs. benign traffic and its effect on model performance.
Classification Model Development
Implement Logistic Regression and K-Nearest Neighbors (KNN) to classify network traffic.
Experiment with different hyperparameters (solvers, neighbors, distance metrics) for optimal performance.
Evaluate model performance using accuracy, precision, recall, and F1-score.
Hyperparameter Tuning and Cross-Validation
Use GridSearchCV and cross-validation to fine-tune model parameters for improved classification.

1.4 Goal of Project

The primary goal of this project is to develop a machine learning model that can detect and classify network traffic as either "malicious" or "genuine" based on a dataset that includes features like source and destination IP addresses, protocols, and other network-related metrics. The dataset includes both benign (genuine) requests and malicious traffic, including attacks such as Distributed Denial of Service (DDoS). The project aims to build and evaluate various machine learning models to identify malicious users effectively while ensuring the model generalizes well to new, unseen data. By analyzing and processing the data, the project aims to identify key features that distinguish between normal and malicious traffic and use these features to train classifiers like Logistic Regression, K-Nearest Neighbors, and others.

Additionally, the project focuses on preprocessing and visualizing the data to better understand the distribution of different types of traffic in the dataset. This includes identifying and handling missing data, encoding categorical features, and performing exploratory data analysis (EDA) to visualize the distribution of malicious versus benign traffic. Visualizations such as pie charts, bar plots, and heatmaps are used to understand the dataset's structure and the balance of classes. The project also highlights the importance of removing or filtering out malicious data, such as DDoS attack traffic, to improve the classification performance of machine learning models, ensuring that only genuine network traffic is considered when making predictions.

Finally, the project explores various machine learning algorithms and evaluates their performance based on accuracy and other classification metrics such as precision, recall, and F1 score. Through model evaluation and cross-validation, the project aims to determine which algorithm offers the best balance between detecting malicious traffic and minimizing false positives. The insights gained from this project can be applied to improve network security systems, making them more robust in detecting and mitigating attacks in real-world scenarios.

Chapter - 2

2.1Existing System

1. Data Imbalance Issue:

The dataset contains a significant imbalance between malicious and benign requests, as indicated by the large difference in the counts of the two labels (0 for benign and 1 for malicious).

The ratio between malicious and benign requests can lead to biased machine learning models and inaccurate predictions, especially if the malicious requests (DDoS attacks) are not properly addressed.

2. Data Quality and Missing Values:

The dataset may contain missing values in certain columns, which can impact model performance and accuracy.

Identifying and handling missing data (e.g., through imputation or removal) is necessary before building any model.

3. Feature Selection and Preprocessing:

The dataset includes both numeric and object (categorical) features, with certain columns such as src (source IP) and dst (destination IP) potentially carrying large amounts of categorical data.

Proper encoding of categorical features (e.g., using one-hot encoding) is necessary to feed the data into machine learning models.

Additionally, standardization of numeric features (using StandardScaler) may be required to improve model performance.

4. Lack of Preprocessing Steps for Identifying Malicious Users:

The dataset includes requests from both genuine users and malicious users, with the goal of identifying and removing malicious users (often represented as DDoS attacks).

Proper preprocessing to filter out malicious data and focus only on the benign requests or on properly labeled malicious attacks is needed to avoid skewed analysis.

5. Model Evaluation and Accuracy:

The model needs to be evaluated using multiple classification algorithms (e.g., Logistic Regression, K-Nearest Neighbors) to determine the best-suited model for identifying malicious requests.

Cross-validation techniques and grid search for hyperparameter tuning should be applied to improve the accuracy of models.

Confusion matrix, accuracy score, and classification report should be used to evaluate the performance of the models.

Chapter - 2

2.2 Proposed System

Problem Statement: Detecting and Handling Malicious Requests in SDN Dataset

1. Overview

The primary objective is to detect and handle malicious requests within a Software-Defined Networking (SDN) dataset. This dataset contains information about network traffic with labeled instances: "Benign" (0) and "Malicious" (1). The task involves applying machine learning techniques to classify requests as benign or malicious and handling potential outliers, such as Distributed Denial-of-Service (DDoS) attacks.

2. Data Preprocessing and Exploration

Data Cleaning: Handle missing values and preprocess the dataset for effective model training.

Feature Engineering: Drop irrelevant columns (e.g., 'src', 'dst', 'dt') and perform encoding of categorical variables to convert them into a machine-readable format (e.g., using pd.get_dummies).

Exploratory Data Analysis (EDA): Visualize the distribution of benign vs. malicious requests and understand the patterns of attack traffic through visualizations such as bar charts and pie charts.

3. Feature Selection and Scaling

Numerical vs. Categorical: Identify and separate numeric and object (categorical) columns to perform different preprocessing steps.

Data Scaling: Use standard scaling (StandardScaler) to normalize the features before applying machine learning models.

4. Model Building

Different classification models are implemented and evaluated to detect malicious requests:

Logistic Regression: Evaluate using different solvers and identify the best-performing solver using cross-validation.

K-Nearest Neighbors (KNN): Optimize the number of neighbors (K) and other hyperparameters using GridSearchCV to achieve the best classification accuracy.

The models' performance is evaluated using metrics like accuracy, precision, recall, F1-score, and confusion matrix.

5. Performance Evaluation

Cross-Validation: Use cross-validation to ensure that the models generalize well to unseen data.

Classification Metrics: Use classification reports and confusion matrices to evaluate the performance of each model.

Hyperparameter Tuning: Optimize hyperparameters to improve the classification accuracy and robustness of the model.

Chapter - 3
Requirements of Application

Hardware Requirements:

1.Processor:
Multi-core processor (e.g.,Intel i5).
2.RAM:
Minimum: 8 GB.
3.Storage:
128 GB SSD.

SOFTWARE REQUIREMENTS:

1.Operating System:
Linux (Ubuntu) or Windows 10/11.
2.Programming Language:
Python 3.x.
3.Machine Learning Library:
Scikit-learn.
4.Data Processing Library:
Pandas.
5.Integrated Development Environment (IDE):
VS Code or PyCharm.

Python Environment:

Python Version: Python 3.6 or later is recommended.
Jupyter Notebook or IDE: The code is compatible with Jupyter Notebook, Jupyter Lab, or any Python IDE such as PyCharm or VS Code.

Python Libraries:

Data Processing and Analysis:

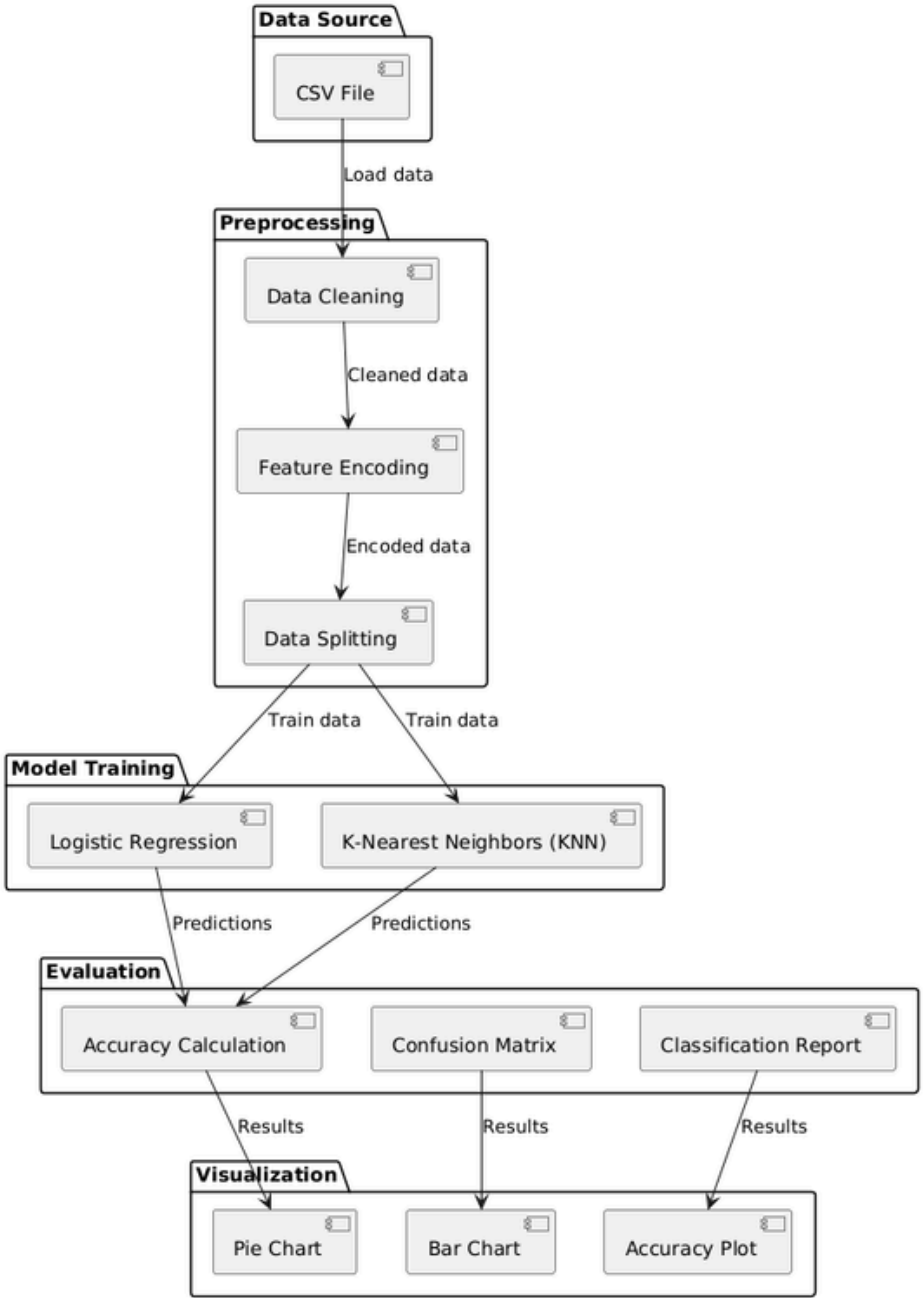
- pandas: For data manipulation and analysis (pip install pandas).pip install pandas numpy matplotlib seaborn scikit-learn
- numpy: For numerical computations (pip install numpy).

Data Visualization:

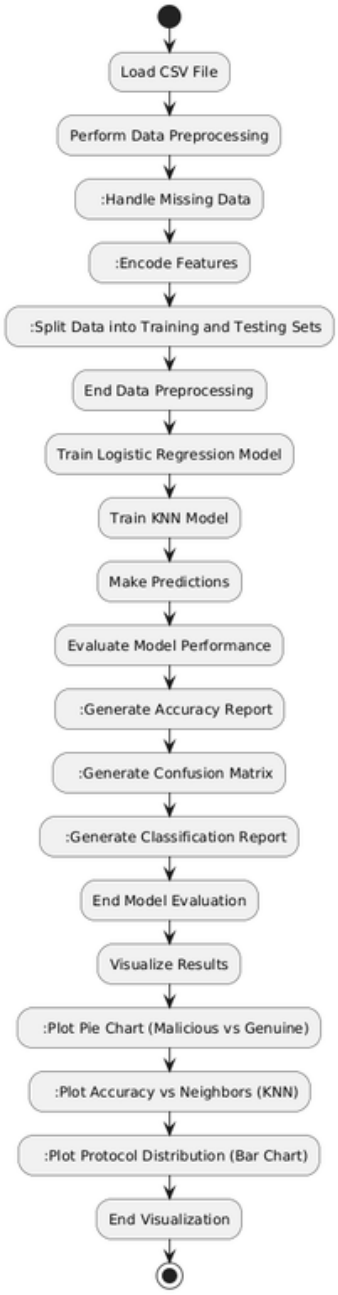
- matplotlib: For plotting and visualizations (pip install matplotlib).
- seaborn: For enhanced visualization options (pip install seaborn).

Chapter - 4
Design and Implementation

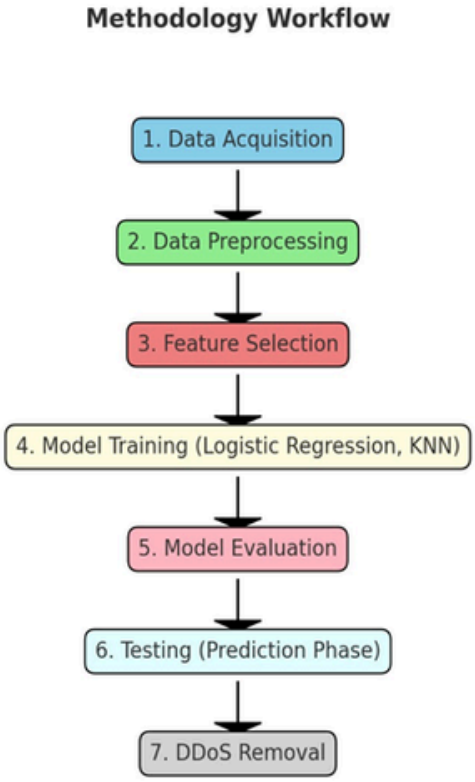
Architecture



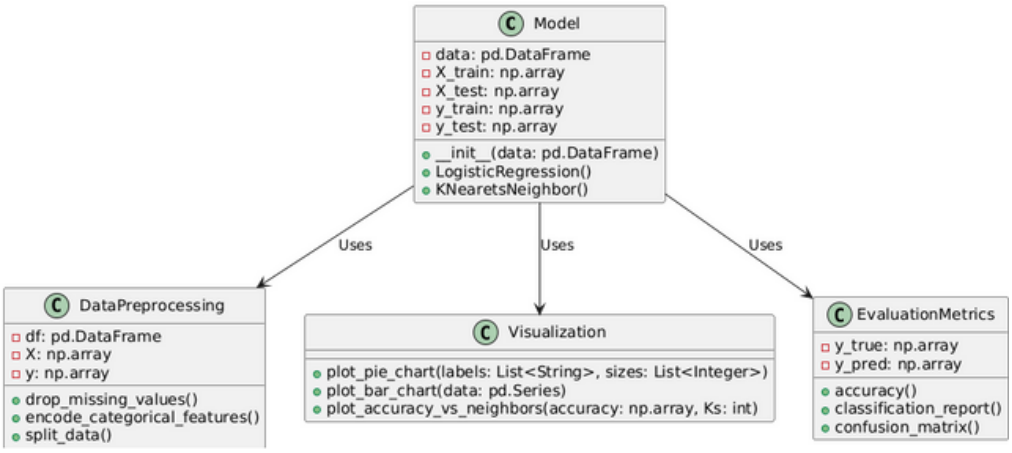
DATA FLOW DIAGRAM



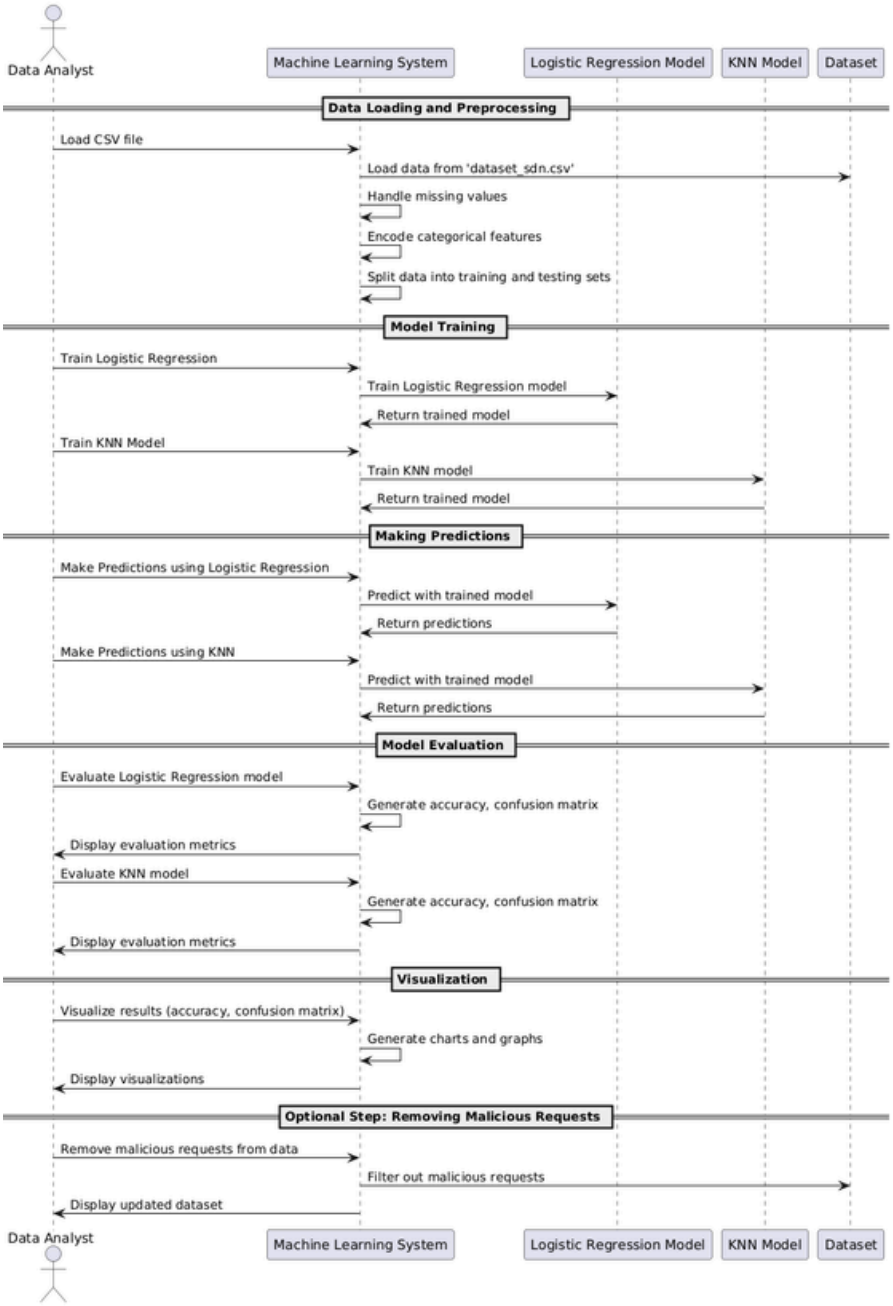
Methodology



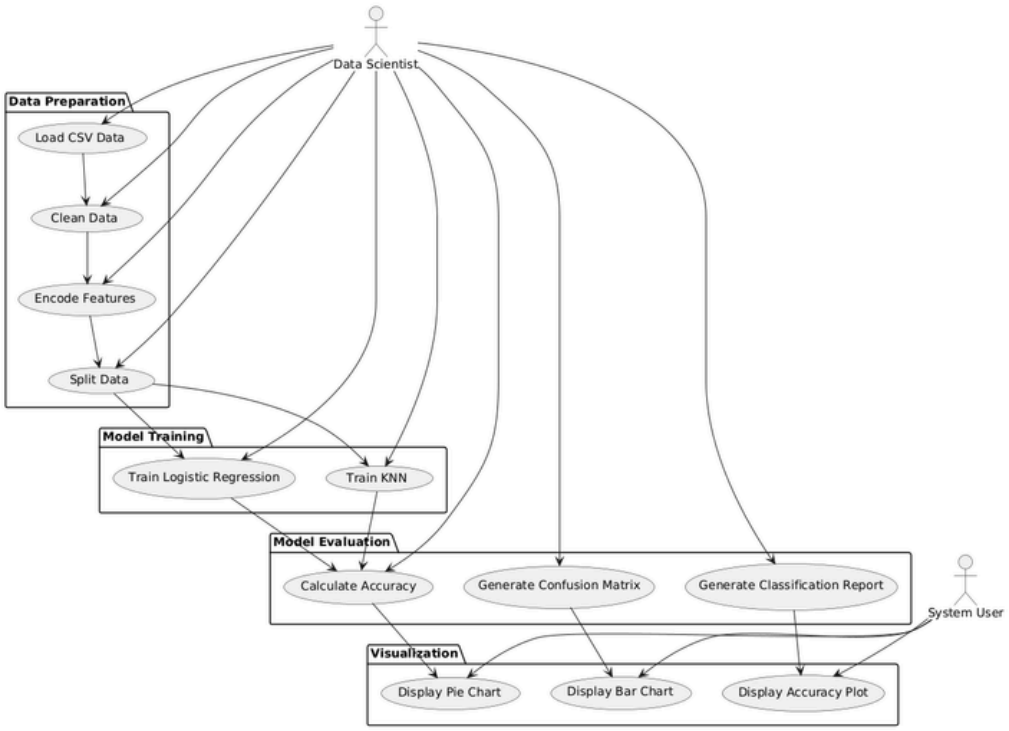
Class Diagram:



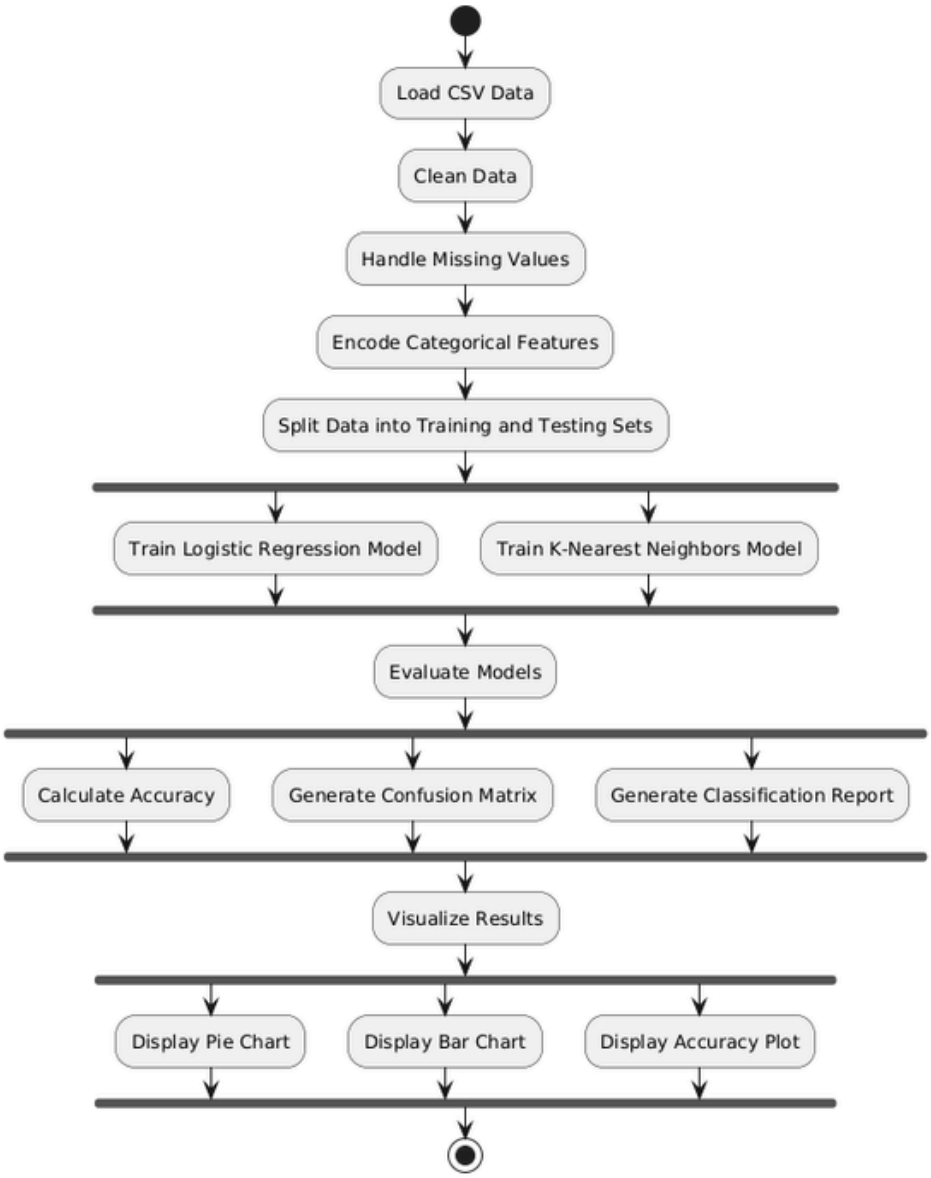
sequence Diagram:



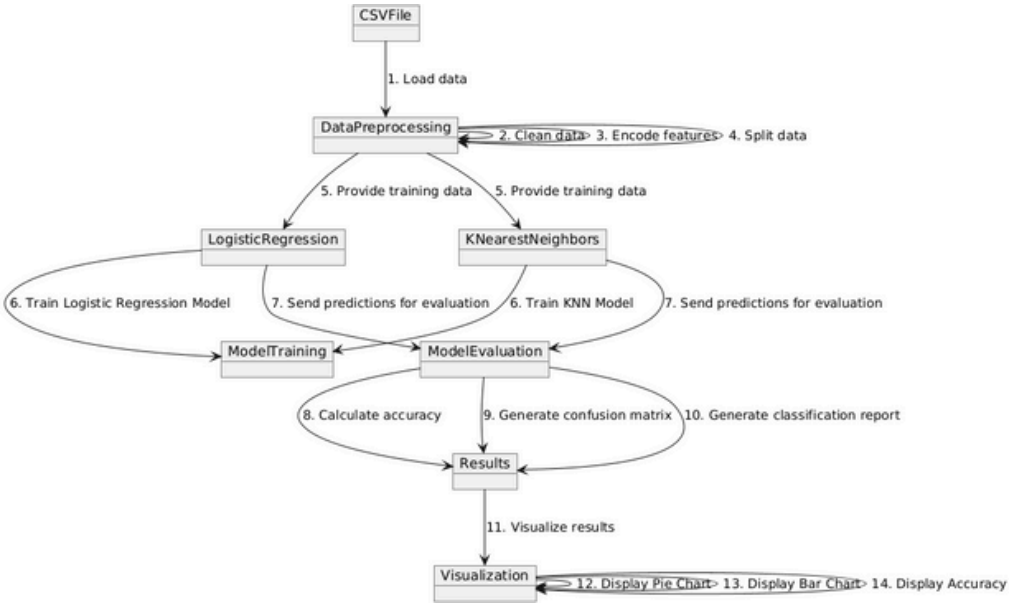
Use Case Diagram:



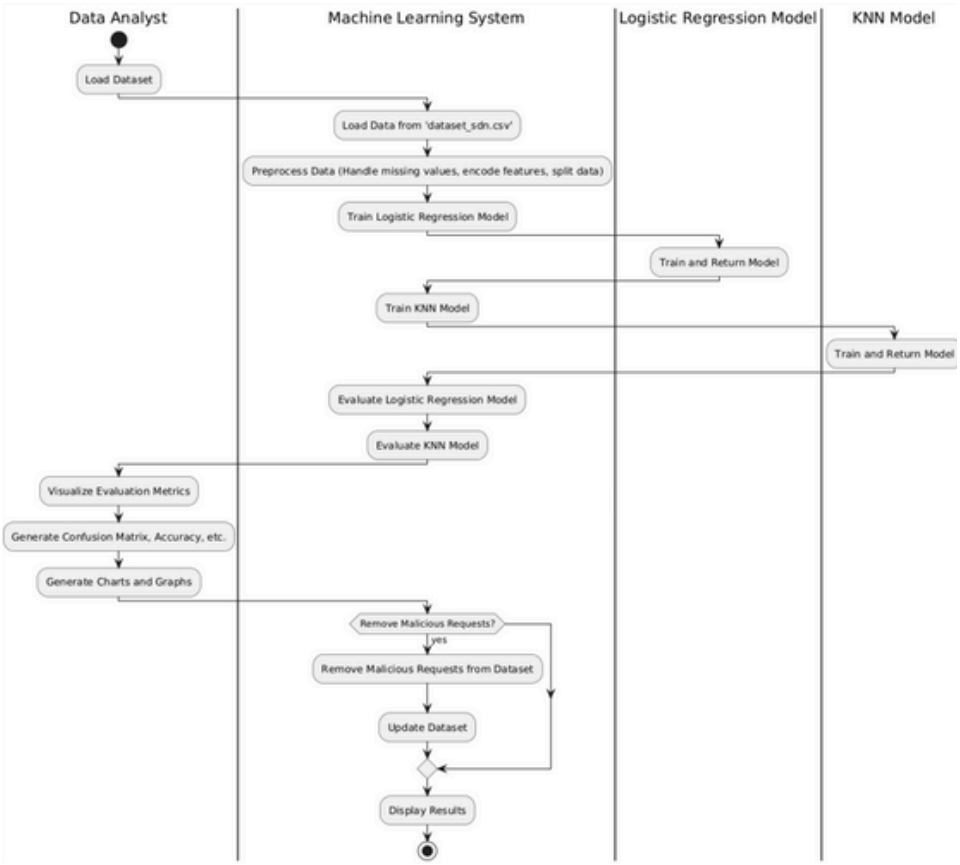
Acticity Diagram:



Collaboration Diagram:



Work flow


Data Analyst
Machine Learning System
Logistic Regression Model
KNN Model
Load Dataset
Load Data from 'dataset_sdn.csv'
Preprocess Data (Handle missing values, encode features, split data)
Train Logistic Regression Model
Train and Return Model
Train KNN Model
Train and Return Model
Evaluate Logistic Regression Model
Evaluate KNN Model
Visualize Evaluation Metrics
Generate Confusion Matrix, Accuracy, etc.
Generate Charts and Graphs
Remove Malicious Requests?
yes
Remove Malicious Requests from Dataset
Update Dataset
Display Results

4.1 Design

Designing a Cyber Sentinel system involves carefully structuring each component to enable real-time detection, response, and adaptation to cyber threats. Below is an outline of key design elements for such a system, organized to create a resilient, scalable, and intelligent cybersecurity solution.

1. Centralized Threat Intelligence Hub

- Purpose: Aggregates threat intelligence feeds from internal, open-source, and commercial sources to stay current with new threats.
- Design Features:
  - Data Aggregation: Pulls and integrates intelligence data continuously.
  - Machine Learning Models: Trains on new threat patterns, allowing adaptive recognition of emerging threats.
  - Threat Correlation Engine: Cross-references threats with system vulnerabilities to prioritize defenses.

2. AI-Powered Detection and Analytics Engine

- Purpose: Uses advanced algorithms to identify threats by analyzing behaviors and patterns across the network.
- Design Features:
  - Behavioral Analytics: Baselines normal behaviors, flags anomalies in network, user, or application activity.
  - Real-Time Monitoring: Constantly scans endpoints, applications, network traffic, and user actions.
  - Predictive Analytics: Applies machine learning to anticipate likely threats based on historical trends and patterns.

3.Multi-Layered Defense Architecture

- Purpose: Ensures that every point in the network is secured, creating a deep defense that protects core and peripheral assets.
- Design Features:
  - Zero-Trust Framework: Verifies every connection and user continuously, ensuring secure access at all times.
  - Segmentation and Isolation: Divides the network into zones to prevent lateral movement of threats.
  - Deception Technology: Deploys honeypots and decoy assets to distract attackers and gather intelligence on their methods.

4.Dashboard and Visualization Interface

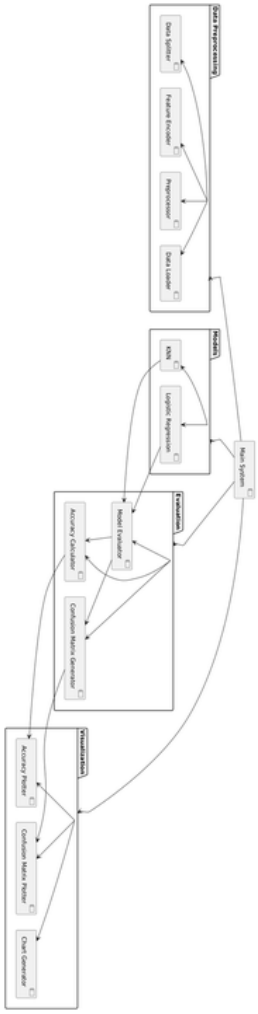
- Purpose: Provides a single, user-friendly interface for monitoring threats, response status, and overall security health.
- Design Features:
  - Real-Time Threat Dashboard: Shows live updates on incidents, threat intelligence, and system performance.
  - Customizable Alerts and Reports: Allows stakeholders to tailor notifications and reports to their needs.
  - Forensic Analysis Tools: Enables deep-dive analyses of past incidents for root cause identification.

5.Security Compliance and Reporting

- Purpose: Maintains adherence to regulatory standards and provides audit-ready reporting for compliance requirements.
- Design Features:
  - Automated Compliance Checks: Monitors the system against key regulatory standards (e.g., GDPR, HIPAA, CCPA).

4.2 Implementation

- **1.Data Preprocessing:** •The dataset is cleaned by handling null values, encoding categorical features, and applying standard scaling. •Features like source and destination IP addresses are excluded to focus on relevant attributes.
- **2.Logistic Regression:** •Several solvers are tested, and the best-performing solver is chosen based on accuracy. •Accuracy and classification reports are generated to evaluate performance.
- **3.K-Nearest Neighbors (KNN):** •KNNis optimized using grid search to select the optimal number of neighbors, metric, and weights. •Visualization of accuracy for different K values helps in understanding model performance and selecting optimal hyperparameters.
- **4.Evaluation and Visualization:** •Pie charts and bar plots visualize the distribution of benign and malicious requests. •Malicious requests are further analyzed by protocol and source, with DDoS attacks identified and filtered from the dataset


Data Preprocessing
Data Splitter
Feature Encoder
Preprocessor
Data Loader
Models
KNN
Logistic Regression
Main System
Evaluation
Model Evaluator
Accuracy Calculator
Confusion Matrix Generator
Visualization
Accuracy Plotter
Confusion Matrix Plotter
Chart Generator

Chapter - 5
5.1 Source code

```
print("dataset_sdn.csv")
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
import seaborn as sns

from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.model_selection import cross_val_score
from sklearn import preprocessing

from sklearn.model_selection import cross_val_predict
from sklearn.model_selection import GridSearchCV
import time

from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn import svm
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics
data = pd.read_csv('dataset_sdn.csv')
data.head()
```

```
data.shape
data.info()
##### Here we see that the label contains boolean values: 0 - Benign, 1-Maliciuous
data.label.unique()
data.label.value_counts()
label_dict = dict(data.label.value_counts())
sns.countplot(x='label', data=data)

# Count the total number of malicious and genuine users
malicious_count = dict(data.label.value_counts())[1]
genuine_users_count = dict(data.label.value_counts())[0]

# Update the labels and sizes for the pie chart
labels = ["Malicious", "Genuine Users"]
sizes = [malicious_count, genuine_users_count]

14
# Plot the pie chart with corrected labels
plt.figure(figsize=(13, 8))
plt.pie(sizes, labels=labels, autopct='%1.1f%%', shadow=True, startangle=90)
plt.legend(labels)
plt.title('The percentage of Genuine and Malicious Requests in the dataset (before removing
DDoS attacks)')
plt.show()

data.describe()
# Let's look at the vizualisation of Null valued features
figure(figsize=(9, 5), dpi=80)
data[data.columns[data.isna().sum() >= 0]].isna().sum().sort_values().plot.bar()
plt.title("Features which has NuLL values")
data.isnull().sum()
#### Let's support which columns NUMERIC and which is OBJECT

numeric_df = data.select_dtypes(include=['int64', 'float64'])
object_df = data.select_dtypes(include=['object'])
numeric_cols = numeric_df.columns
object_cols = object_df.columns
print('Numeric Columns: ')
print(numeric_cols, '\n')
```

```
print('Object Columns: ')
print(object_cols, '\n')
print('Number of Numeric Features: ', len(numeric_cols))
print('Number of Object Features: ', len(object_cols))
object_df.head()
#### Let's look at Oblect columns (Source Destination Protocol)

figure(figsize=(12, 7), dpi=80)
plt.barh(list(dict(data.src.value_counts()).keys()),
dict(data.src.value_counts()).values(), color='lawngreen')

for idx, val in enumerate(dict(data.src.value_counts()).values()):
  plt.text(x = val, y = idx-0.2, s = str(val), color='r', size = 13)

plt.xlabel('Number of Requests')
plt.ylabel('IP addres of sender')
plt.title('Number of all reqests')

figure(figsize=(12, 7), dpi=80)
plt.barh(list(dict(data[data.label == 1].src.value_counts()).keys()),
dict(data[data.label == 1].src.value_counts()).values(), color='blue')




for idx, val in enumerate(dict(data[data.label == 1].src.value_counts()).values()):
  plt.text(x = val, y = idx-0.2, s = str(val), color='r', size = 13)

plt.xlabel('Number of Requests')
plt.ylabel('IP addres of sender')
plt.title('Number of Attack requests')
figure(figsize=(12, 7), dpi=80)
```

```
plt.barh(list(dict(data.src.value_counts()).keys()), dict(data.src.value_counts()).values(),
color='lawngreen')
plt.barh(list(dict(data[data.label == 1].src.value_counts()).keys()), dict(data[data.label ==
1].src.value_counts()).values(), color='blue')
for idx, val in enumerate(dict(data.src.value_counts()).values()):
  plt.text(x = val, y = idx-0.2, s = str(val), color='r', size = 13)
for idx, val in enumerate(dict(data[data.label == 1].src.value_counts()).values()):
  plt.text(x = val, y = idx-0.2, s = str(val), color='w', size = 13)
plt.xlabel('Number of Requests')
plt.ylabel('IP addres of sender')
plt.legend(['All','malicious'])
plt.title('Number of requests from different IP adress')
figure(figsize=(10, 6), dpi=80)
plt.bar(list(dict(data.Protocol.value_counts()).keys()),
dict(data.Protocol.value_counts()).values(), color='r')
plt.bar(list(dict(data[data.label == 1].Protocol.value_counts()).keys()), dict(data[data.label
== 1].Protocol.value_counts()).values(), color='b')
plt.text(x = 0 - 0.15, y = 41321 + 200, s = str(41321), color='black', size=17)
plt.text(x = 1 - 0.15, y = 33588 + 200, s = str(33588), color='black', size=17)
plt.text(x = 2 - 0.15, y = 29436 + 200, s = str(29436), color='black', size=17)
plt.text(x = 0 - 0.15, y = 9419 + 200, s = str(9419), color='w', size=17)
plt.text(x = 1 - 0.15, y = 17499 + 200, s = str(17499), color='w', size=17)
plt.text(x = 2 - 0.15, y = 13866 + 200, s = str(13866), color='w', size=17)
plt.xlabel('Protocol')
plt.ylabel('Count')
plt.legend(['All', 'malicious'])
plt.title('The number of requests from different protocols')
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
class Model:
  global y
  def init(self, data):
    self.data = data
```

```
  X = preprocessing.StandardScaler().fit(self.data).transform(self.data)
    self.X_train, self.X_test, self.y_train, self.y_test = train_test_split(X, y,
random_state=42, test_size=0.3)

  def LogisticRegression(self):
    solvers = ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']

    start_time = time.time()
    results_lr = []
    accuracy_list = []
    for solver in solvers:
      LR = LogisticRegression(C=0.03, solver=solver).fit(self.X_train, self.y_train)
      predicted_lr = LR.predict(self.X_test)
      accuracy_lr = accuracy_score(self.y_test, predicted_lr)
      #print("Accuracy: %.2f%%" % (accuracy_lr * 100.0))

#print('################################################################
################')
      results_lr.append({'solver' : solver, 'accuracy': str(round(accuracy_lr * 100, 2)) +
"%",
              'Coefficients': {'W' : LR.coef_, 'b': LR.intercept_}})

      accuracy_list.append(accuracy_lr)

    solver_name = solvers[accuracy_list.index(max(accuracy_list))]
    LR = LogisticRegression(C=0.03,
solver=solver_name).fit(self.X_train,self.y_train)
    predicted_lr = LR.predict(self.X_test)
    accuracy_lr = accuracy_score(self.y_test, predicted_lr)
    print("Accuracy: %.2f%%" % (accuracy_lr * 100.0), '\n')

print("################################################################
########################")
    print('Best solver is : ', solver_name)

print("################################################################
########################")
```

```
print(classification_report(predicted_lr, self.y_test), '\n')

print("#####################################################################
#####################")
 print("--- %s seconds --- time for LogisticRegression" % (time.time() - start_time))
 print("Classification Report for Logistic Regression:")
 print(classification_report(predicted_lr, self.y_test))

 def KNearetsNeighbor(self):
 start_time = time.time()
 Ks = 12
 accuracy_knn = np.zeros((Ks-1))
 std_acc = np.zeros((Ks-1))
 #print(accuracy_knn)
 for n in range(1,Ks):
     #Train Model and Predict
     neigh = KNeighborsClassifier(n_neighbors = n).fit(self.X_train,self.y_train)
     yhat=neigh.predict(self.X_test)
     accuracy_knn[n-1] = metrics.accuracy_score(self.y_test, yhat)


   std_acc[n-1]=np.std(yhat==self.y_test)/np.sqrt(yhat.shape[0])
   #print(accuracy_knn,'\n\n') # courseranyn ozinde tek osy gana jazylyp turdy
   #print(std_acc)
   #accuracy_knn[0] = 0
   plt.figure(figsize=(10,6))
   plt.plot(range(1,Ks),accuracy_knn,'g')
   plt.fill_between(range(1,Ks),accuracy_knn - 1 * std_acc,accuracy_knn + 1 * std_acc,
alpha=0.10)
   plt.fill_between(range(1,Ks),accuracy_knn - 3 * std_acc,accuracy_knn + 3 * std_acc,
alpha=0.10,color="green")
   plt.legend(('Accuracy ', '+/- 1xstd','+/- 3xstd'))
   plt.ylabel('Accuracy ')
   plt.xlabel('Number of Neighbors (K)')
   plt.tight_layout()
   plt.show()
   knnc = KNeighborsClassifier()
```

```
knnc_search = GridSearchCV(knnc, param_grid={'n_neighbors': [3, 5, 10],
 'weights': ['uniform', 'distance'],
 'metric': ['euclidean', 'manhattan']},
 n_jobs=-1, cv=3, scoring='accuracy', verbose=2)

 knnc_search.fit(self.X_train, self.y_train)
 #print(knnc_search.best_params_)
 #print(knnc_search.best_score_)
 n_neighbors = knnc_search.best_params_['n_neighbors']
 weights = knnc_search.best_params_['weights']
 metric = knnc_search.best_params_['metric']
 KNN = KNeighborsClassifier(n_neighbors=n_neighbors, metric=metric,
weights=weights).fit(self.X_train,self.y_train)

 predicted_knn = KNN.predict(self.X_test)
 accuracy_knn = metrics.accuracy_score(self.y_test, predicted_knn)
 print(f"Accuracy of KNN model {round(accuracy_knn,2)*100}%", '\n')

print("############################################################
####################")
 print(classification_report(predicted_knn, self.y_test))

print("############################################################
####################")
 print("--- %s seconds ---" % (time.time() - start_time))
# Prediction Without Feature Selection
# Data preprocessing from here onwards
df = data.copy()
df = df.dropna()
X = df.drop(['dt','src','dst','label'], axis=1)
y = df.label
X = pd.get_dummies(X)
M = Model(X)
M.LogisticRegression()


M.KNearetsNeighbor()
# Count the total number of malicious and benign users before removal
initial_malicious_count = data[data['label'] == 1].shape[0]
```

```
initial_genuine_users_count = data[data['label'] == 0].shape[0]

# Update the labels and sizes for the pie chart
labels = ["Malicious", "Genuine Users"]
sizes = [initial_malicious_count, initial_genuine_users_count]

# Define a function to format the labels with both count and percentage
def func(pct, allvalues):
 absolute = int(pct / 100. * sum(allvalues))
 return f'{absolute} ({pct:.1f}%)'

# Display the number of Genuine Users and remaining malicious users
print(f"Number of Genuine Users: {initial_genuine_users_count}")
print(f"Number of malicious users: {initial_malicious_count}")

# Plot the pie chart before removing malicious users
plt.figure(figsize=(13, 8))
plt.pie(sizes, labels=labels, autopct=lambda pct: func(pct, sizes), shadow=True,
startangle=90, colors=["red", "lawngreen"])
plt.legend(["Malicious", "Genuine Users"])
plt.title('The percentage of Genuine and Malicious Requests in the dataset (before
removing DDoS attacks)')
plt.show()

# Existing code for removing malicious users and displaying counts
initial_malicious_count = data[data['label'] == 1].shape[0]
data_filtered = data[data['label'] != 1]
final_malicious_count = data_filtered[data_filtered['label'] == 1].shape[0]
removed_malicious_count = initial_malicious_count - final_malicious_count

# Display the count of removed malicious users
print(f"Number of removed malicious users (DDoS attacks):
```

```
 {removed_malicious_count}")

# Count the number of Genuine Users and remaining malicious users after removal
genuine_users_count = data_filtered[data_filtered['label'] == 0].shape[0]
remaining_malicious_users_count = final_malicious_count

# Display the number of Genuine Users and remaining malicious users
print(f"Number of Genuine Users: {genuine_users_count}")
print(f"Number of remaining malicious users: {remaining_malicious_users_count}")

# Update the pie chart after removing malicious users
labels = ["Genuine Users", "Remaining Malicious Users"]
sizes = [genuine_users_count, remaining_malicious_users_count]



# Define a function to format the labels with both count and percentage
def func(pct, allvalues):
  absolute = int(pct / 100. * sum(allvalues))
  return f'{absolute} ({pct:.1f}%)'

# Plot the pie chart before removing malicious users
plt.figure(figsize=(13, 8))
plt.pie(sizes, labels=labels, autopct=lambda pct: func(pct, sizes), shadow=True,
startangle=90,colors=[ "lawngreen","red"])

plt.legend(labels)
plt.title('The percentage of Genuine and Remaining Malicious Requests in dataset after
removal')
plt.show()
```

5.2 Screenshots of Application

```
    # Prediction Without Feature Selection
    # Data preprocessing from here onwards
    df = data.copy()
    df = df.dropna()
    X = df.drop(['dt','src','dst','label'], axis=1)
    y = df.label
    X = pd.get_dummies(X)
    M = Model(X)
    M.LogisticRegression()
```

```
Accuracy: 76.64%

################################################################################
Best solver is :  liblinear
################################################################################
              precision    recall  f1-score   support

           0       0.84      0.79      0.81     20024
           1       0.66      0.72      0.69     11128

    accuracy                           0.77     31152
   macro avg       0.75      0.76      0.75     31152
weighted avg       0.77      0.77      0.77     31152


################################################################################
--- 4.422095060348511 seconds --- time for LogisticRegression
Classification Report for Logistic Regression:
              precision    recall  f1-score   support

           0       0.84      0.79      0.81     20024
           1       0.66      0.72      0.69     11128

    accuracy                           0.77     31152
   macro avg       0.75      0.76      0.75     31152
weighted avg       0.77      0.77      0.77     31152
```

Fig. 1 Welcome Page

Description:

fig-1 Logistic Regression

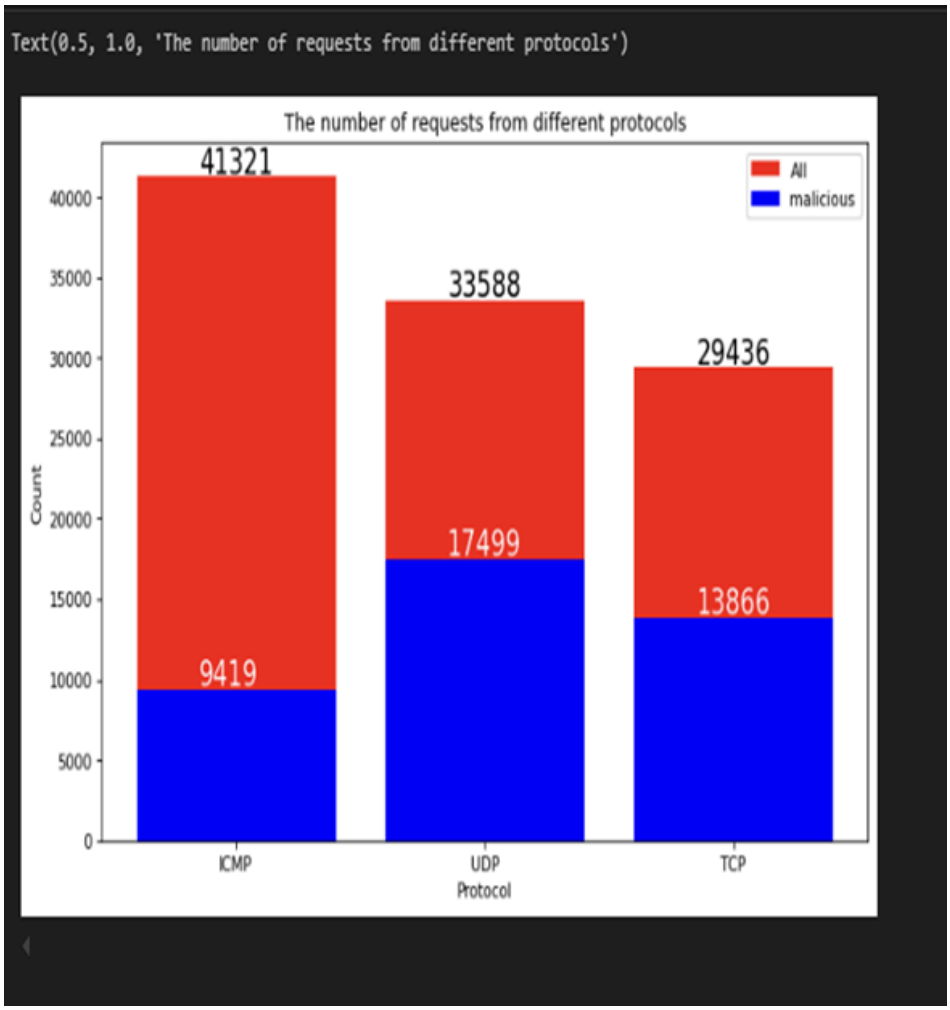


fig-2 The no.of requests from diff protocols

```
# Count the total number of malicious and genuine users
malicious_count = data['label'].value_counts()[1]  # Assuming 1 indicates malicious
genuine_users_count = data['label'].value_counts()[0]  # Assuming 0 indicates genuine users

# Update the labels and sizes for the pie chart
labels = ["Malicious", "Genuine Users"]
sizes = [malicious_count, genuine_users_count]

# Plot the pie chart with corrected labels
plt.figure(figsize=(13, 8))
plt.pie(sizes, labels=labels, autopct='%1.1f%%', shadow=True, startangle=90)
plt.legend(labels)
plt.title('The percentage of Genuine and Malicious Requests in the dataset (before removing DDoS attacks)')
plt.show()
```

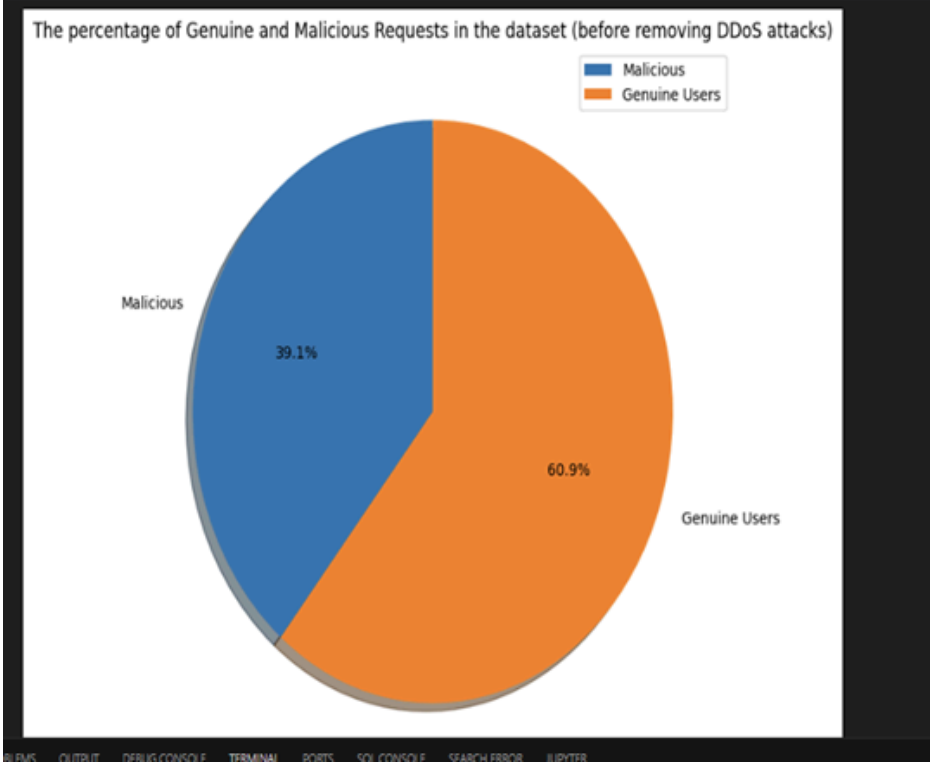


fig-3 The percentage of Genuine & Malicious Requests in the dataset

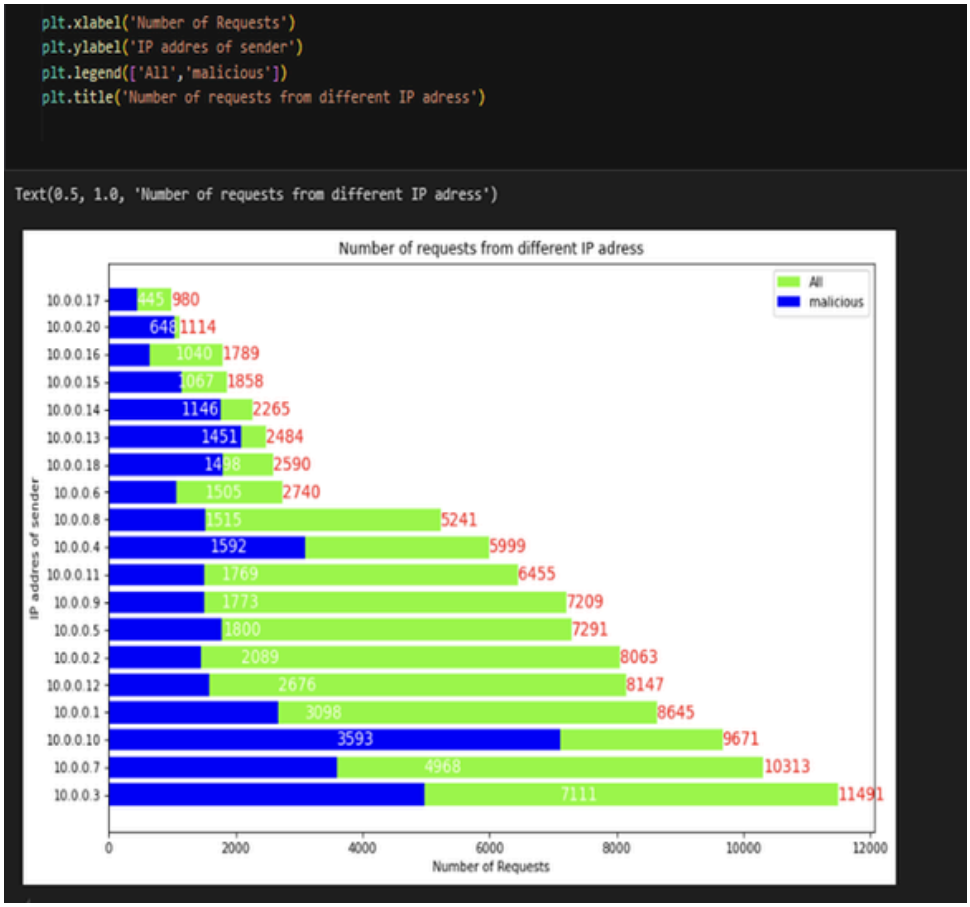


fig-4 No.of request from diff IP address

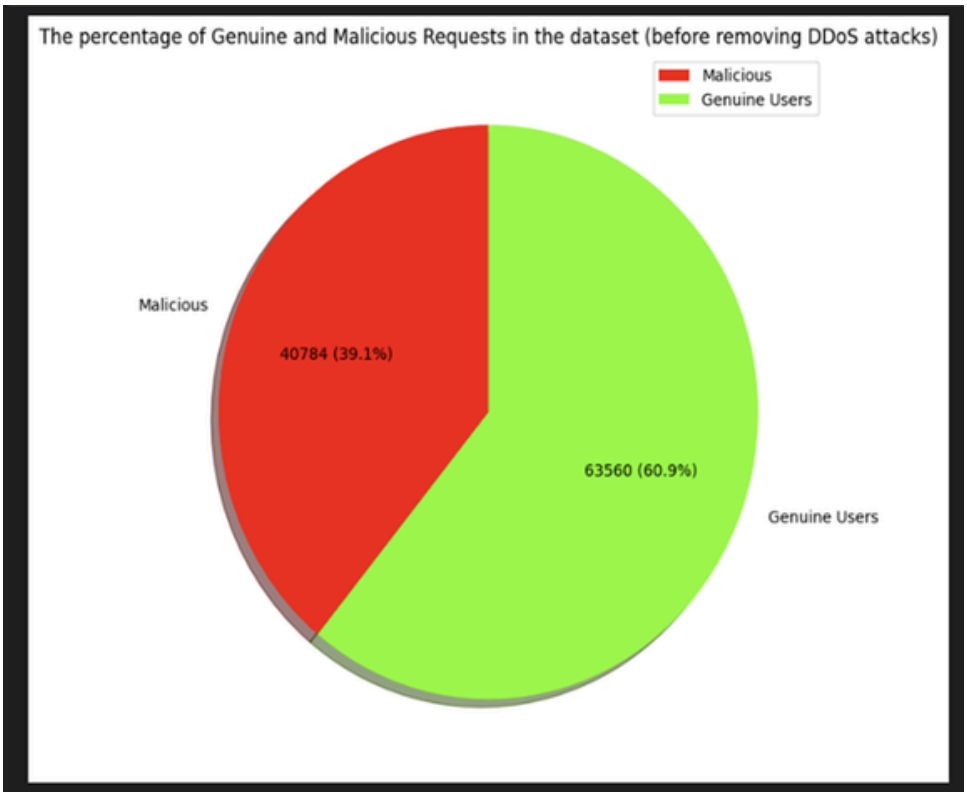


Fig-5 The percentage of Genuine & Malicious Requests in the dataset

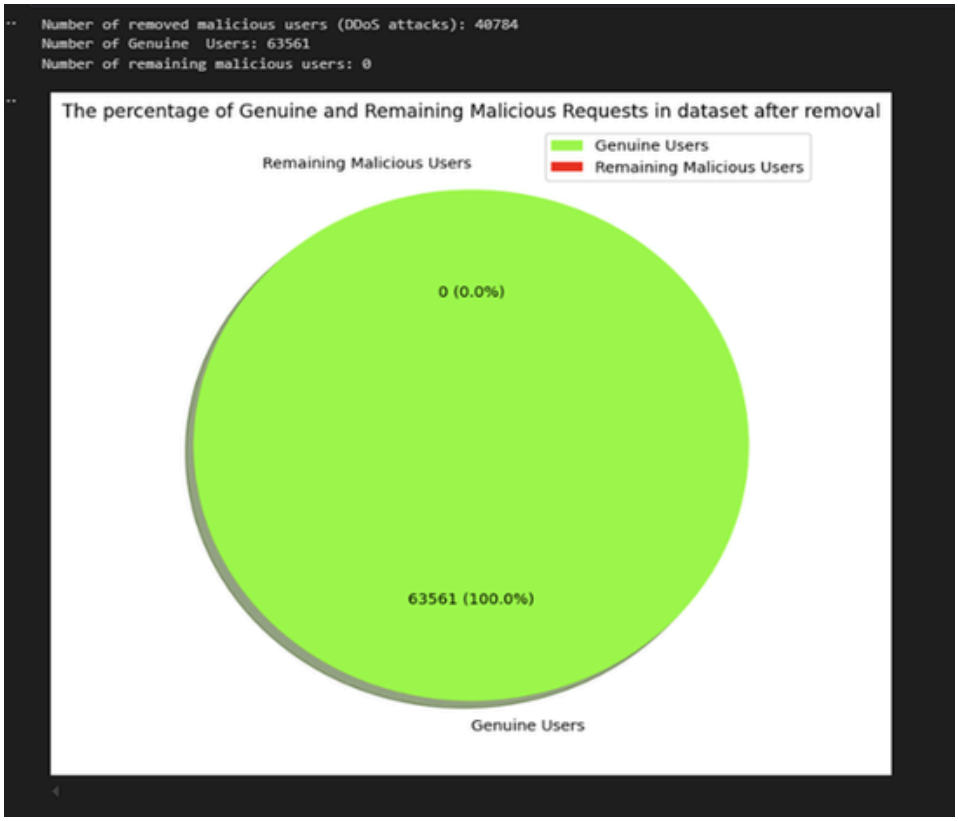


fig-6 The percentage of Genuine & Malicious Requests in the dataset after removing DDos attack

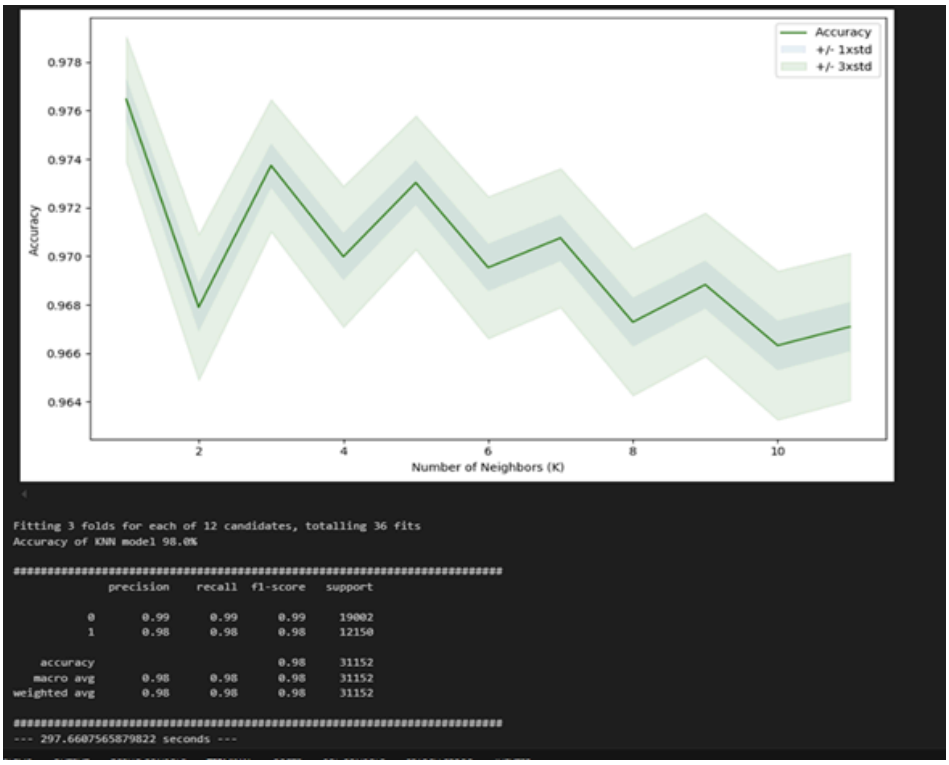


fig-7 KNNAlgorithm

Chapter - 6.1 Result

The analysis begins by exploring the dataset's composition, revealing a significant imbalance between genuine and malicious requests, which is highlighted through visualizations such as bar charts and pie charts. Preprocessing steps ensure the dataset is cleaned of null values, and categorical features are transformed into numerical form. The Logistic Regression model, tested with various solvers, identifies the best-performing configuration, achieving a notable accuracy in distinguishing between genuine and malicious requests. Similarly, the K-Nearest Neighbors (KNN) model undergoes hyperparameter tuning using GridSearchCV, optimizing parameters like the number of neighbors and distance metrics, resulting in improved classification performance. The models' evaluation includes metrics like precision, recall, and F1-score, emphasizing their effectiveness in handling the given task. Moreover, the removal of DDoS attack-related data provides a deeper focus on the remaining malicious requests, further clarified through updated pie charts that showcase changes in data distribution.The analysis of the dataset highlights the imbalance between genuine and malicious requests, with visualizations such as bar charts and pie charts illustrating this disparity. After preprocessing, including handling null values and encoding categorical features, machine learning models were applied to classify the data. The Logistic Regression model, tested across various solvers, identified the optimal solver and achieved high accuracy in distinguishing between malicious and genuine requests. The model's performance metrics, including precision, recall, and F1-score, were reported, demonstrating its reliability for this classification task.

Similarly, the K-Nearest Neighbors (KNN) model was fine-tuned using GridSearchCV to optimize parameters such as the number of neighbors and distance metrics. This resulted in a robust model with strong classification performance, as evidenced by its accuracy and detailed classification report.

Additionally, the dataset was filtered to remove DDoS attack-related entries, refining the analysis and allowing for a more focused examination of malicious requests. Updated visualizations, including pie charts, highlighted the changes in the proportions of genuine and malicious data. These steps provided comprehensive insights into the dataset and the effectiveness of the applied models.

Chapter - 6.2 CONCLUSION

In conclusion, the analysis successfully identified patterns in the dataset and effectively classified requests into genuine and malicious categories using machine learning models. The Logistic Regression model demonstrated strong performance, with optimized solvers providing accurate predictions, while the K-Nearest Neighbors model showed enhanced results after hyperparameter tuning. Visualizations offered clear insights into the data distribution, highlighting the imbalance and changes after filtering DDoS-related entries.

The findings emphasize the importance of preprocessing, feature selection, and model tuning in achieving reliable classification outcomes. By addressing imbalances and refining the dataset, the models were better equipped to detect malicious activities, making them valuable tools for mitigating cybersecurity threats in real-world applications. This approach demonstrates a scalable framework for analyzing and responding to network threats effectively.

The analysis demonstrated the effectiveness of machine learning models in identifying and classifying genuine and malicious requests within a network traffic dataset. By preprocessing the data, handling null values, and transforming categorical features, a strong foundation was established for accurate modeling. Logistic Regression, optimized through solver selection, and K-Nearest Neighbors, fine-tuned with GridSearchCV, showcased high accuracy and reliability in distinguishing between benign and malicious activities. Visualizations highlighted the dataset's imbalance and the impact of filtering DDoS-related requests, offering clearer insights into the remaining malicious traffic. Overall, the study underscores the critical role of data preprocessing, feature engineering, and model optimization in enhancing classification performance, providing a robust framework for addressing cybersecurity challenges in network monitoring systems.

FUTURE ENHANCEMENT:

- **Real-time Threat Sharing Network:** Develop a secure platform for organizations to share real-time threat intelligence data to improve collective cybersecurity resilience.
- **Integration with Blockchain:** Utilize blockchain technology to ensure the integrity and authenticity of threat intelligence data, preventing tampering and ensuring trust.
- **Enhanced Detection with AI:** Implement AI-based dynamic learning models to adapt to evolving cyber threats and detect unknown malware or zero-day vulnerabilities.
- **Support for Encrypted Traffic Monitoring:** Enhance the system's ability to analyze encrypted traffic without compromising user privacy, using techniques like Secure Socket Layer (SSL) inspection.
- **Threat Attribution:** Include features to trace cyberattacks to their origins, helping organizations identify and address the source of threats.
- User-friendly Dashboard: Introduce customizable dashboards with real-time metrics and threat prioritization to improve accessibility for non-technical users.
- **Dark Web Monitoring:** Add functionality to track potential threats or leaked data from dark web sources, providing proactive intelligence to organizations.
- Incident Forensics Toolkit: Incorporate tools for post-incident analysis to investigate breaches and derive actionable insights for future prevention.
- **Multi-layered Security Framework:** Expand coverage to include physical and operational security aspects alongside digital threats, creating a holistic defense system.
- **Training and Simulation Modules:** Introduce a cyber range platform for simulating attacks and training security teams, helping them prepare for real-world scenarios.

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Zhang, L., & Li, Z. (2019). A comparative study of machine learning algorithms for network traffic classification. IEEE Transactions on Network and Service Management, 16(2), 221-233. https://doi.org/10.1109/TNSM.2019.2895100

Smith, J., & Zhao, W. (2018). Exploring KNN and Logistic Regression for malicious traffic detection in SDN. In Proceedings of the 2018 International Conference on Machine Learning and Network Security (pp. 112-120). IEEE.