

# Configuration Manual for Enhancing Cybersecurity through AI-Driven Threat Detection Systems

MSc Research Project Cyber Security

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#### **MSc Project Submission Sheet**

#### **School of Computing**

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Enhancing Cyber Security through AI- Driven Threat Detection

**Module:** Systems

**Lecturer:** Eugene Mclaughlin

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Enhancing Cyber Security through AI- Driven Threat Detection

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## Configuration Manual for Enhancing Cybersecurity through AI-Driven Threat Detection Systems

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#### 1. Introduction

This manual provides a comprehensive guide for implementing a machine learning-based threat detection system using the Network Intrusion Dataset. The goal of this research is to leverage various machine learning models to classify network traffic as either benign or malicious, specifically focusing on Distributed Denial of Service (DDoS) attacks.

## 2. System Hardware Requirements

- Processor (CPU):
  - Intel Core i7 or AMD Ryzen 7 (8 cores, 16 threads minimum)
  - Preferred: Intel Core i9 or AMD Ryzen 9 for better performance.
- Memory (RAM):
  - Minimum: 16 GB
  - Recommended: 32 GB or more for faster model training, especially for deep learning tasks.
- Storage:
  - Minimum: 500 GB SSD for storing datasets, model outputs, and logs.
  - Recommended: 1 TB SSD or higher for extensive datasets and efficient I/O performance.
- GPU (for deep learning models):
  - Minimum: NVIDIA GTX 1060 / AMD equivalent for basic model training.
  - Recommended: NVIDIA RTX 3060 or higher (e.g., RTX 3080/3090) for faster neural network training.
- Operating System: Windows 10/11, macOS, or Linux (Ubuntu 20.04 or newer preferred).

## 3. Software Requirements:

- Python 3.7 or newer
- pandas (for data handling), numpy (for numerical operations).
- matplotlib, seaborn (for data visualization and plotting).
- scikit-learn (for model building, classification, evaluation).
- tensorflow and keras (for deep learning model development).
- sklearn.metrics (for performance metrics such as accuracy, confusion matrix).
- warnings (for ignoring warnings), LabelEncoder, SimpleImputer, MinMaxScaler, StandardScaler, SelectKBest.
- Jupyter Notebook, Visual Studio Code, or PyCharm (for better debugging and development experience).
- Anaconda or Miniconda (for environment management and package installation).

## 4. Dataset Details

#### **Dataset Source:**

The dataset used in this project is from Kaggle, specifically the "Network Intrusion Dataset". It contains network traffic data for different types of attacks (e.g., DDoS, PortScan, and more) labeled as either BENIGN or DDoS. The dataset is useful for training machine learning models for intrusion detection and cybersecurity analysis.

Dataset Link: Network Intrusion Dataset on Kaggle

#### **Dataset Description:**

- The dataset consists of various network traffic features like flow duration, packet length, packet count, flags, and other network attributes, making it suitable for detecting different attack types.
- The data is collected in different scenarios and reflects real-time network traffic patterns, which includes both normal (BENIGN) and malicious (DDoS) behavior.

**File Format:** CSV file: Friday-WorkingHours-Afternoon-DDos.pcap\_ISCX.csv **Features:** Includes features such as flow duration, packet length, flow bytes/s, total forward packets, total backward packets, active time, idle time, and TCP flags.

## 5. Execution of the Code Implementation

#### **Import Required Libraries**

Start by importing the essential libraries required for data manipulation, model building, and visualization. The following libraries are used:

```
#import the necessary libaries
import pandas as pd # For data manipulation and analysis
import numpy as np # For numerical operations
import matplotlib.pyplot as plt # For basic data visualizationn
import seaborn as sns # For enhanced data visualization
from sklearn.preprocessing import LabelEncoder #For label encoding categorical variable
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.impute import SimpleImputer
from sklearn.model selection import train test split #For splitting the data into train and test
from sklearn.neighbors import KNeighborsClassifier #KNN Classifier
from sklearn.ensemble import RandomForestClassifier # Random forest Classifier
from sklearn.linear_model import LogisticRegression #Logistic Regression Classifier
from sklearn.tree import DecisionTreeClassifier #Decision Tree classifier
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.metrics import accuracy_score,classification_report,confusion_matrix # For model evaluation
from sklearn.metrics import roc_curve, auc #roc_curve plot
import warnings
warnings.filterwarnings('ignore')
```

#### **Load the Dataset**

The dataset can be downloaded from Kaggle and loaded into a pandas DataFrame. This will allow you to explore and preprocess the data.

```
#fetch the dataset
   dataFrame = pd.read_csv('Friday-WorkingHours-Afternoon-DDos.pcap_ISCX.csv')
   #columns in the dataset
   dataFrame.columns
Index([' Destination Port', ' Flow Duration', ' Total Fwd Packets',
        ' Total Backward Packets', 'Total Length of Fwd Packets',
       ' Total Length of Bwd Packets', ' Fwd Packet Length Max',
       ' Fwd Packet Length Min', ' Fwd Packet Length Mean',
       ' Fwd Packet Length Std', 'Bwd Packet Length Max',
       ' Bwd Packet Length Min', ' Bwd Packet Length Mean',
        ' Bwd Packet Length Std', 'Flow Bytes/s', ' Flow Packets/s',
        ' Flow IAT Mean', ' Flow IAT Std', ' Flow IAT Max', ' Flow IAT Min',
       'Fwd IAT Total', 'Fwd IAT Mean', 'Fwd IAT Std', 'Fwd IAT Max', 'Fwd IAT Min', 'Bwd IAT Total', 'Bwd IAT Mean', 'Bwd IAT Std', 'Bwd IAT Std', 'Bwd IAT Max', 'Bwd IAT Min', 'Fwd PSH Flags', 'Bwd PSH Flags',
        ' Fwd URG Flags', ' Bwd URG Flags', ' Fwd Header Length',
        ' Bwd Header Length', 'Fwd Packets/s', ' Bwd Packets/s',
       ' Min Packet Length', ' Max Packet Length', ' Packet Length Mean',
       ' Packet Length Std', ' Packet Length Variance', 'FIN Flag Count',
       ' SYN Flag Count', ' RST Flag Count', ' PSH Flag Count',
       ' ACK Flag Count', ' URG Flag Count', ' CWE Flag Count',
       ' ECE Flag Count', ' Down/Up Ratio', ' Average Packet Size',
       ' Avg Fwd Segment Size', ' Avg Bwd Segment Size',
       ' Fwd Header Length.1', 'Fwd Avg Bytes/Bulk', ' Fwd Avg Packets/Bulk',
       ' Fwd Avg Bulk Rate', ' Bwd Avg Bytes/Bulk', ' Bwd Avg Packets/Bulk',
       'Bwd Avg Bulk Rate', 'Subflow Fwd Packets', ' Subflow Fwd Bytes',
       ' Subflow Bwd Packets', ' Subflow Bwd Bytes', 'Init_Win_bytes_forward',
       ' Init_Win_bytes_backward', ' act_data_pkt_fwd',
       ' min_seg_size_forward', 'Active Mean', ' Active Std', ' Active Max',
        ' Active Min', 'Idle Mean', ' Idle Std', ' Idle Max', ' Idle Min',
       ' Label'],
      dtype='object')
```

#### **Explore the Dataset**

Before performing any preprocessing, understand the dataset by inspecting the first and last few rows, dataset info, and basic statistics:

	Pytho											
	Destination Port	Flow Duration	Total Fwd Packets	Total Backward Packets	Total Length of Fwd Packets	Total Length of Bwd Packets	Fwd Packet Length Max	Fwd Packet Length Min	Fwd Packet Length Mean	Fwd Packet Length Std		min_seg_size_fo
0	54865	3	2	0	12	0	6	6	6.0	0.0		
1	55054	109	1	1	6	6	6	6	6.0	0.0		
2	55055	52	1	1	6	6	6	6	6.0	0.0		
3	46236	34	1	1	6	6	6	6	6.0	0.0		
4	54863	3	2	0	12	0	6	6	6.0	0.0		

#### **Data Cleaning and Preprocessing**

- Handle missing values: Replace NaN with zeros or use imputation techniques.
- Handle infinities: Replace any infinite values with NaN, then impute or drop.

```
# Replace infinities with NaN
dataFrame.replace([np.inf, -np.inf], np.nan, inplace=True)
# Replace NaNs with 0
dataFrame.fillna(0, inplace=True)
```

• Remove duplicates: Drop duplicate rows to prevent skewing the analysis.

```
print('Number of duplicates are : ', dataFrame.duplicated().sum())

Number of duplicates are : 2633

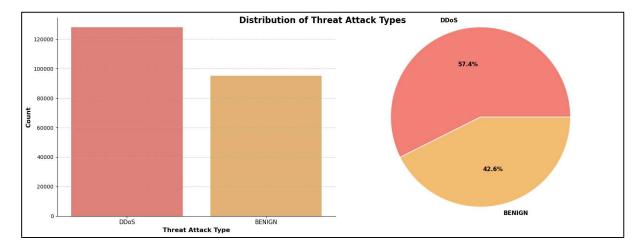
# Remove duplicates from the DataFrame
  dataFrame = dataFrame.drop_duplicates()

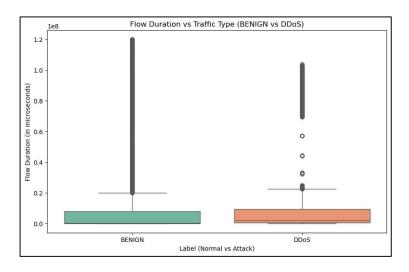
# Check the number of duplicates after removal
  print('Number of duplicates are : ', dataFrame.duplicated().sum())

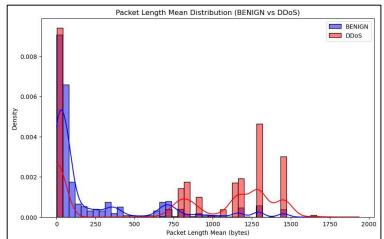
Number of duplicates are : 0
```

## **Exploratory Data Analysis (EDA)**

Perform an exploratory analysis to gain insights into the dataset. This includes visualizations of attack types, flow duration, packet length distribution, and more.







#### **Feature Engineering**

• Label Encoding: Convert categorical labels into numerical values.

```
#encode the string objects to the categorical values to numerical values
encoder = {}
for i in dataFrame.select_dtypes('object').columns:
    encoder[i] = LabelEncoder()
    dataFrame[i] = encoder[i].fit_transform(dataFrame[i])
```

• Feature Selection: Use SelectKBest to select the top features.

```
# Impute missing values (replace NaNs with the mean)
imputer = SimpleImputer(strategy='mean')
X_imputed = imputer.fit_transform(x)

# Determine the number of columns (features) in your DataFrame
num_columns = dataFrame.shape[1]

# Set an appropriate value for k (less than or equal to the number of columns)
k = min(10, num_columns)

# Initialize SelectKBest with the scoring function
k_best = SelectKBest(score_func=f_classif, k=k)

# Fit and transform the imputed data to select the top 10 features
X_new = k_best.fit_transform(X_imputed, y)
```

#### **Split the Data**

Split the dataset into training and testing sets (80% training, 20% testing).

```
# Split the data into features (X) and labels (y)
X = dataFrame[selected_feature_names].values
y= dataFrame[' Label'].values

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.20,random_state=0)

print('Training Features Shape:', X_train.shape)
print('Training Labels Shape:', y_train.shape)
print('Testing Features Shape:', X_test.shape)
print('Testing Labels Shape:', y_test.shape)

Training Features Shape: (178489, 10)
Training Labels Shape: (178489,)
Testing Features Shape: (44623, 10)
Testing Labels Shape: (44623,)
```

#### **Model Initialization & Training**

Train several machine learning models and evaluate their performance:

K-Nearest Neighbors Classifier (KNN):

```
#Initialize and train one of the K-Nearest Neighbors Model for Classification of Threat attack
knn_classifier = KNeighborsClassifier(n_neighbors=10000)
knn_classifier.fit(X_train,y_train)

* KNeighborsClassifier * **O**
KNeighborsClassifier(n_neighbors=10000)
```

Decision Tree Classifier:

Logistic Regression Classifier:

```
#Initialize and train one of the (Logistic Regression Model) for Classification of threat attack logistic_regression_model = LogisticRegression(n_jobs=61) logistic_regression_model.fit(X_train,y_train)

* LogisticRegression ** ** ** LogisticRegression** (n_jobs=61)
```

#### • Random Forest Classifier:

#### • Deep Neural Network (DNN):

```
#Initialize and train one of the (Deep Neural Network Model) for Classification of Threat attack

dnn_model = Sequential()

dnn_model.add(Dense(128, input_dim=X_train.shape[1], activation='relu'))

dnn_model.add(Dense(64, activation='relu'))

dnn_model.add(Dense(32, activation='relu'))

dnn_model.add(Dense(32, activation='sigmoid')) # For binary classification; use 'softmax' for multiclass

Python

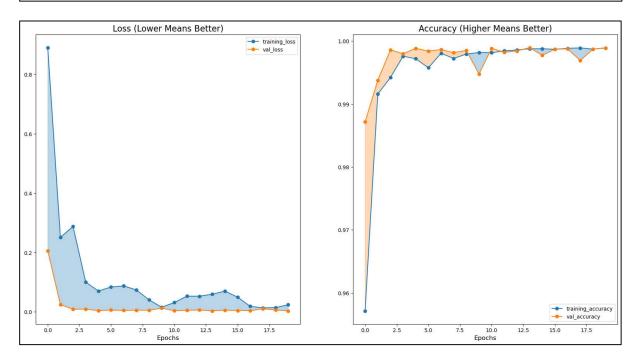
# Compile the model

dnn_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Train the model

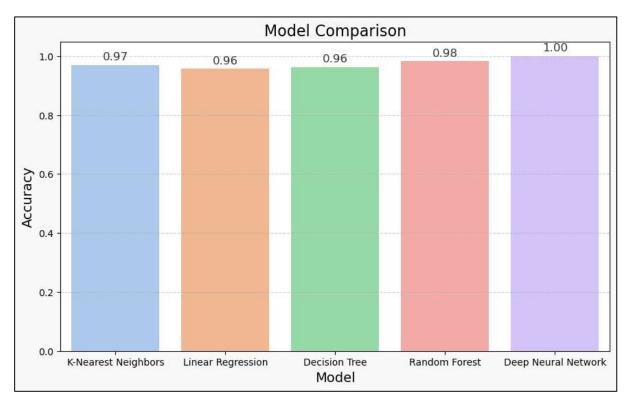
history = dnn_model.fit(X_train, y_train, epochs=20, batch_size=32, validation_split=0.2, verbose=1)

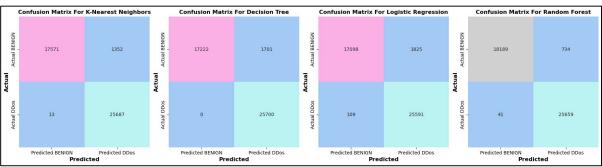
Python
```



#### **Model Comparison**

After training all the models, compare their performance metrics (accuracy, precision, recall, F1 score, etc.) to determine which model performs the best for detecting DDoS attacks.





This manual provides the necessary steps to load, preprocess, analyze, and model the Network Intrusion Dataset using machine learning techniques. By following these steps, you can run the code implementation for a robust threat detection system to classify network traffic as benign or DDos.

#### References

Python: https://www.python.org

Dataset Source: Network Intrusion Dataset on Kaggle