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CLASSIFICATION OF SOFTWARE DEFINED NETWORK TRAFFIC TO PROVIDE QUALITY OF SERVICE

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ABSTRACT

Accurate traffic classification is of fundamental importance to numerous network activities, from security monitoring to accounting, and from Quality of Service to providing operators with useful forecasts for long-term provisioning. The initial stage in analysing and classifying the various types of applications running via a network is network traffic classification. This method allows network operators or internet service providers to control the overall performance of a network. We apply machine learning models to categorize traffic by application. This can be done by extracting the features of the traffic. This classified data can be used to stop unnecessary traffic and allow only user required traffic. Basically we prioritize the network traffic based on the features extracted during the classification. Features related to OTT are identified and we try to restrict them in the network for reducing the traffic in the network for providing better quality of service. We intend to stop traffic from Over-the-top(OTT) platforms like Netflix, Prime Videos, etc. Hence, by this the quality of service can be improved for user required applications.

1. INTRODUCTION

Network traffic is categorized in a variety of ways of extreme interest for both internet service providers and also network operators. It helps to classify the types of data flowing and link each one to the apps that produce it. This information is crucial for many purposes, including network monitoring,

applications behavior and network security, and to improve Quality of Service(QoS). The term "Software-defined networking" (SDN) refers to a method of networking where traffic on a network is controlled by application programming interfaces (APIs) or software-based controllers that communicate with the underlying hardware infrastructure. This architecture is distinct from traditional networks, which employ specialized hardware to regulate network traffic (such as switches and routers). SDN can manage traditional hardware or create and manage virtual networks through software. Although software-defined networking provides a fresh way to control how data packets are routed through a single server, network virtualization enables organizations to segment different virtual networks within a single physical network or to connect devices on different physical networks to create a single virtual network. Compared to traditional networking, SDN is far more versatile since the control plane is software-based. Without adding extra hardware, it enables administrators to manage the network, alter configuration options, supply resources, and boost network capacity from a single user interface. By providing a knowledge basis for identifying the performance levels required by applications, classification is a critical mechanism for traffic treatment. Deep Packet Inspection (DPI) and port-based classification are the two most used approaches for traffic classification. As more communication is encrypted and more apps use dynamic ports and ports for other well-known applications, these techniques are becoming outdated [1]. Machine Learning (ML), an alternate approach for traffic classification, employs the statistical characteristics of network traffic flows to address the basic issues with DPI and port-based categorization for encrypted flows. Network traffic classification is a crucial component for managing infrastructure and ensuring the QoS for various applications. In reality, a thorough traffic classification process enables the effective management of already available network resources, enabling more precise and reliable resource allocation systems [2]. The classification of network traffic can be carried out using the features related to the OTT platforms. The feature extraction is a process of recognising features and attributes that often represent video streaming platforms or OTT platforms.

II.LITERATURE SURVEY

Gianni D'Angelo et al. suggested a model that begins with statistical characteristics (basic features), taken from traffic flows over a predetermined time period, and creates

additional features that explain the correlations between the features (spatial features), as well as changes in those features over time (temporal features). They suggested a deep architecture made up of neural networks based on autoencoders (AEs). The autoencoders encode-decode function contain various combinations of recurrent and convolutional network layers in order to extract such information. The following combinations were looked into: CNN, LSTM, ConvLSTM, CNN-LSTM, and Stacked-CNN-LSTM. The LSTM recurrent network was used to extract temporal features, while the convolutional network was utilised to extract spatial features.

III.EXISTING SYSTEM

Traditional network management relies on static rules and predefined policies to classify traffic and manage quality of service (QoS). These systems typically use packet headers and fixed attributes such as IP addresses, ports, and protocols to categorize network traffic. Network devices like routers and switches apply these static rules to enforce QoS policies, including traffic shaping, prioritization, and bandwidth allocation. However, this approach has several limitations. Static classification lacks flexibility, often failing to adapt to changing traffic patterns or dynamic network conditions, which can result in inefficient QoS management. Additionally, it provides limited contextual awareness, as it does not consider application-layer data or deeper packet inspection, leading to suboptimal handling of different types of traffic. Scalability is also an issue, as managing and updating static rules becomes increasingly cumbersome with growing and diverse network traffic. Finally, static systems are typically not capable of real-time adaptation to network anomalies or performance issues, delaying responses and potentially leading to degraded QoS during peak times or attacks.

IV.PROPOSED SYSTEM

The proposed system aims to overcome these limitations by leveraging the dynamic and adaptive capabilities of Software-Defined Networking (SDN). SDN introduces a centralized controller that enables more flexible and intelligent traffic management. This system utilizes machine learning algorithms to classify traffic dynamically based on various attributes, including application-level data and contextual information, rather than relying solely on static rules. This dynamic classification approach improves the accuracy and adaptability of traffic management, allowing for more precise QoS

allocation. The system integrates deep packet inspection and application-layer insights to gain a comprehensive understanding of traffic requirements, ensuring that high-priority applications receive the necessary resources. Real-time adaptability is another key feature, as the SDN controller allows for continuous monitoring and immediate adjustment to changing network conditions and traffic patterns. This capability helps in promptly addressing performance variations and anomalies. Additionally, the SDN architecture supports scalable and flexible traffic management by centralizing control and automating policy updates, which simplifies rule management and enhances efficiency. Overall, this approach provides improved security and performance optimization, ensuring a higher quality of service by effectively managing and responding to evolving network demands.

The screenshot shows a network traffic analysis tool interface. The main window displays a list of traffic records. Each record consists of a numerical ID, a source IP address, a destination IP address, and a classification label. The labels include 'Non-Tor.Chat', 'Non-Tor.Email', and 'Non-Tor.Browsing'. The IP addresses are in standard dotted-decimal notation or scientific notation (e.g., 15.1.4364E+15). The interface includes a search bar at the top, a list of columns, and a table of data.

ID	Source IP	Destination IP	Classification
33206	15.1.4364E+15	15.1.4364E+15	Non-Tor.Chat
33207	15.1.4364E+15	15.1.4364E+15	Non-Tor.Chat
33208	15.1.4364E+15	15.1.4364E+15	Non-Tor.Chat
33209	14.1.4364E+15	15.1.4364E+15	Non-Tor.Chat
33210	3623019.03.1.4364E+15	15.1.4364E+15	Non-Tor.Chat
33211	19500717.27.1.4364E+15	15.1.4364E+15	Non-Tor.Chat
33212			
33213			
33214			
33215			
33216			
33217			mail
33218			
33219	0.0.0.0.1.43681E+15	2.508672.84.1.43681E+15	15.1.43681E+15 Non-Tor.Email
33220			
33221	3.0.0.1.43681E+15	2119216.818.1.43681E+15	15.1.43681E+15 Non-Tor.Email
33222			
33223	0.0.1.43681E+15	2310563.251.1.43681E+15	15.1.43681E+15 Non-Tor.Email
33224			
33225	1.43681E+15	2271534.216.1.43681E+15	15.1.43681E+15 Non-Tor.Email
33226			
33227	43681E+15		Non-Tor.Email
33228	0.0.1.44E+15	1645271.661.1.43681E+15	15.1.43681E+15 Non-Tor.Email
33229			
33230	6.20.0.0.0.1.43681E+15	30549381.65.1.43682E+15	15.1.43681E+15 Non-Tor.Email

In above dataset each row contains one traffic data and in last column we have traffic classification labels as Email, Chat, Browsing and etc. so by using above dataset we will train Ensemble algorithm and calculate traffic classification accuracy.

To implement this project we have designed following modules

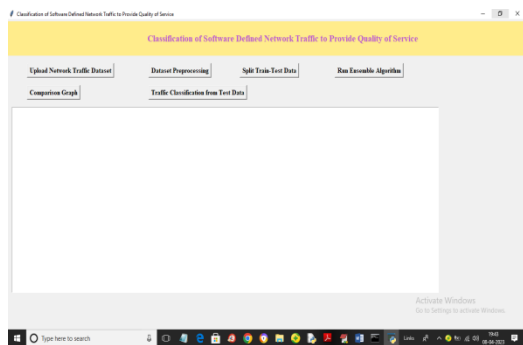
- 1) Upload Network Traffic Dataset: using this module we will upload dataset to application and then find and plot graph of different traffic found in dataset
- 2) Dataset Preprocessing: using this module we will process dataset to remove missing values, normalization and shuffling all dataset values. Dataset contains some non-numeric values but machine learning accept only numeric values so by employing Label encoding class we will convert all non-numeric data to numeric values
- 3) Split Train-Test Data: using this module we will split dataset into train and test where application using 80% dataset for training and 20% for testing
- 4) Run Ensemble Algorithm: 80% processed data will be input to a group of ensemble algorithms such as SVM, Random Forest and J48 trained a model and

this model will be applied on 20% test data to calculate classification accuracy.

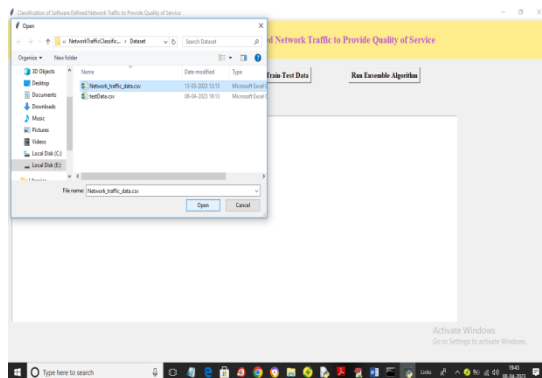
In an ensemble group one classifier with the best accuracy will be selected.

- 5) Comparison Graph: using this module we will plot accuracy, precision, recall and FSCORE comparison graph
- 6) Traffic Classification from Test Data: using this module we will input TEST data and then Ensemble model will classify test data into possible traffic types.

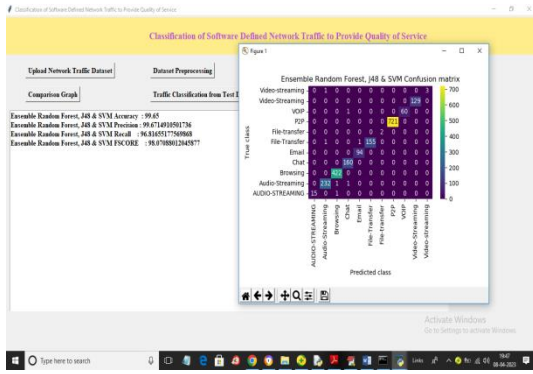
To run project double click on run.bat file to get below screen



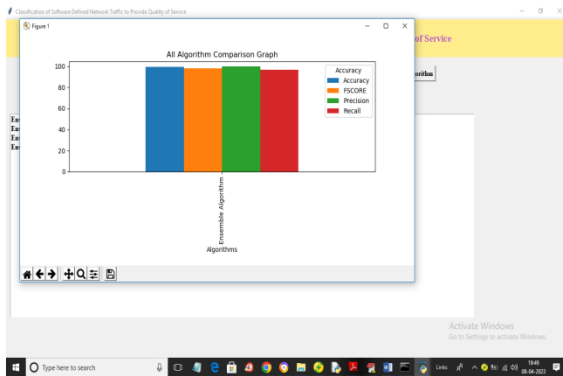
In above screen click on 'Upload Network Traffic Dataset' button to upload dataset and get below output



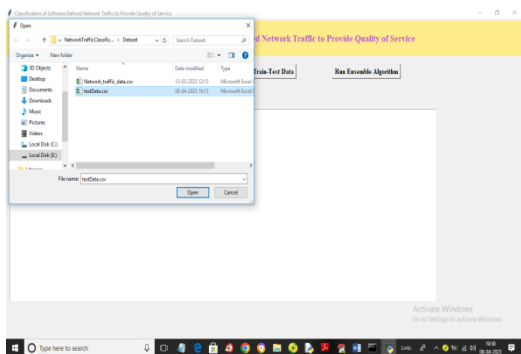
In above screen selecting and uploading dataset and then click on 'Open' button to load dataset and get below output



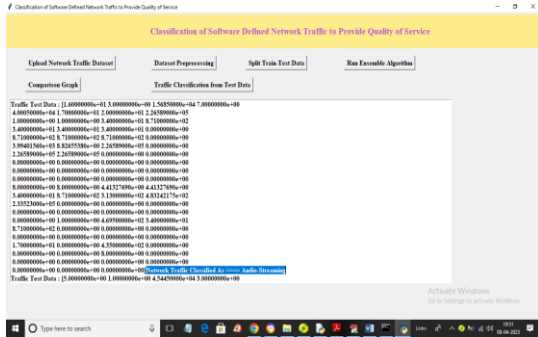
In above screen with Ensemble algorithm we got 99% accuracy and we can see other metrics also and in confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels and all blue boxes contains INCORRECT prediction count which are few and all different colour boxes contains CORRECT prediction count. Now close above graph and then click on ‘Comparison Graph’ button to get below graph



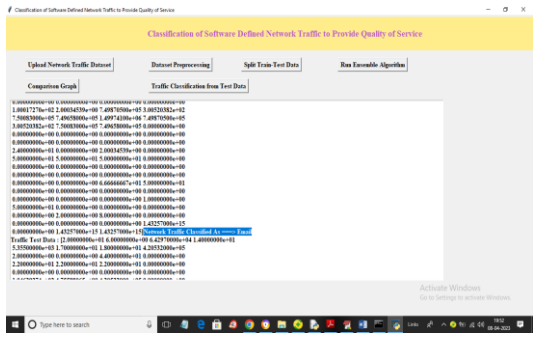
In above graph x-axis represents algorithm name and y-axis represents accuracy, precision and other metrics in different colour bars and all metrics got performance values greater than 98%. Now click on ‘Traffic Classification from Test Data’ button to upload test and then Ensemble model will classify traffic



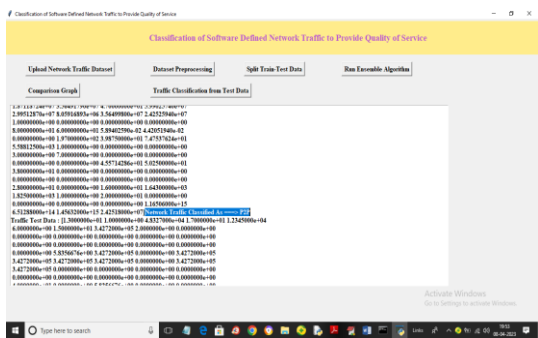
In above screen selecting and uploading Test Data file and this file will not have traffic classification label and Ensemble model will analyse above file and classify network traffic type and get below output



In above screen in square bracket we can see test data and then in blue colour text we can see classified traffic as 'Audio Streaming' and scroll down above screen to view all predicted output

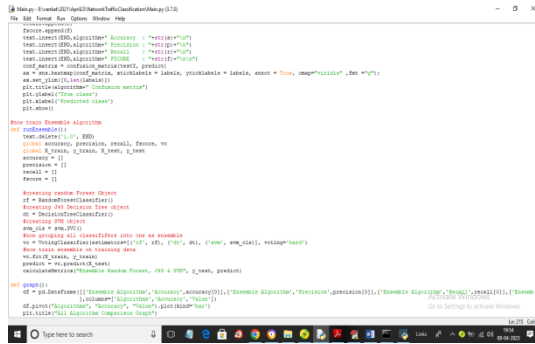


In above screen traffic classified as Email



In above screen traffic classified as 'P2P'. Similarly by following above screens you can run code

In below screen showing code for Ensemble Model by combining 3 algorithms



```

# Import necessary libraries
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, AdaBoostClassifier, VotingClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import numpy as np

# Load the dataset
X_train, X_test, y_train, y_test = load_data()

# Create ensemble models
rf = RandomForestClassifier(n_estimators=100, max_depth=10, min_samples_split=10, min_samples_leaf=5)
gb = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, max_depth=10)
adaboost = AdaBoostClassifier(n_estimators=100)

# Create a Voting Classifier
ensemble = VotingClassifier(estimators=[('rf', rf), ('gb', gb), ('adaboost', adaboost)])

# Train the ensemble model
ensemble.fit(X_train, y_train)

# Predict on test data
y_pred = ensemble.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
confusion = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred)

# Print results
print(f"Accuracy: {accuracy}")
print(confusion)
print(report)

# Red comments in the original image:
# ensemble = VotingClassifier(estimators=[('rf', rf), ('gb', gb), ('adaboost', adaboost)])
# ensemble.fit(X_train, y_train)
# y_pred = ensemble.predict(X_test)
# ensemble = VotingClassifier(estimators=[('rf', rf), ('gb', gb), ('adaboost', adaboost)])
# ensemble.fit(X_train, y_train)
# y_pred = ensemble.predict(X_test)

```

In above screen read red colour comments to know about ensemble algorithms grouping and classifying from one best algorithm

V. CONCLUSION

In this study, we conducted extensive research on network classification and examined numerous research papers on various classification models. Many papers presented feature extraction algorithms for classifying network traffic to its application. A significant amount of work is required to extract specific features of OTT platforms. We intend to restrict network traffic from OTT platforms. This lessens traffic and raises quality of service as a result.

VI. REFERENCES

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