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Hybrid Approaches in Network Traffic Classification: Enhancing Model Performance Using Bagging Techniques

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ABSTRACT: The rapid growth of internet technologies and multimedia applications has led to a significant increase in network traffic, creating a demand for accurate and efficient traffic classification systems. Traditional methods like port-based and deep packet inspection (DPI) are often limited, especially with encrypted traffic. This study investigates the effectiveness of machine learning algorithms – Naïve Bayes, Decision Tree, and Random Forest – in classifying network traffic into video, audio, and web categories. To improve model stability and accuracy, Bagging ensemble techniques are applied. Experimental results show that Bagging combined with Random Forest provides the highest classification accuracy across all traffic types. The findings suggest that hybrid models enhance classification performance, making them suitable for real-time network management systems.

KEY WORDS: Network Traffic Classification, Machine Learning, Ensemble Methods, Naïve Bayes, Decision Tree, Random Forest, Bagging.

I. INTRODUCTION

In recent years, the rapid development of internet technologies and the widespread use of multimedia applications have led to a sharp increase in global network traffic. The growing number of services and the need to deliver them with high quality and minimal delay have intensified the demand for efficient network management systems. This, in turn, has created the necessity for accurate network traffic classification and prioritization of critical traffic types [1].

Network traffic classification, especially in the presence of encrypted traffic, has become more complex due to the limitations of traditional methods such as port-based identification or deep packet inspection (DPI) [2-3]. Therefore, machine learning (ML) based approaches are considered a relevant solution. ML algorithms, by analyzing statistical features of network traffic, enable the accurate differentiation of traffic types such as video, audio, and web flows.

This paper analyzes the performance of machine learning algorithms, including Naïve Bayes, Decision Tree, and Random Forest, in network traffic classification. Furthermore, these models are enhanced with the Bagging ensemble approach to improve their stability and accuracy, and their results are comparatively evaluated. Throughout the paper, Precision, Recall, and F1-score metrics are used to assess the models, leading to the identification of the most optimal approach for real-world system implementation.

II. RESEARCH METHODOLOGY

In this study, three types of machine learning algorithms were used for network traffic classification: Naïve Bayes, Decision Tree (DT), and Random Forest (RF). The results of each algorithm were compared, and their effectiveness was evaluated. Additionally, to improve classification accuracy and ensure model stability, the Bagging (Bootstrap Aggregating) ensemble method was also applied. For model evaluation, 70% of the dataset was used for training and the remaining 30% for testing.

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The performance of the models was assessed using the following three key metrics:

Precision: the proportion of correctly identified instances among all instances classified as a given class.
Recall: the proportion of correctly identified instances among all actual instances of a given class.
F1-score: the harmonic mean of Precision and Recall, providing a balanced measure of accuracy [4].

These metrics not only evaluate the accuracy of the model but also provide insights into its overall performance and applicability in real-world systems.

Description of the Algorithms Used

Naïve Bayes is a classifier based on probability theory, relying on the assumption of independence between attributes. This algorithm is well-known for its simplicity, fast processing, and low resource requirements [5]. In this study, the model was trained in 0.12 seconds. However, due to its inability to account for dependencies between attributes, Naïve Bayes showed low accuracy, particularly in classifying complex network traffic.

The Decision Tree algorithm operates based on a tree-like structure, where data is split across different attributes. Each internal node represents a decision point based on an attribute, while leaf nodes represent class labels. The main advantages of this algorithm are its interpretability, fast training, and efficiency with smaller datasets.

Random Forest is an ensemble classifier composed of multiple decision trees, each built on randomly selected subsets of data and attributes. This method aims to improve accuracy and reduce overfitting by combining the outputs of individual trees [6].

Bagging (Bootstrap Aggregating) is an ensemble technique that improves model performance by combining various models (or different versions of the same model). In this study, Bagging was applied to the Naïve Bayes, DT, and RF models, which led to noticeable improvements in their effectiveness.

- Each model was independently trained on randomly sampled smaller subsets (bootstrapped datasets).
- Final results were evaluated based on the average of multiple model outputs.

III. RESULTS AND ANAYSIS

This section presents the performance analysis of the Naïve Bayes, Decision Tree (DT), and Random Forest (RF) algorithms, along with their Bagging-enhanced versions, in the task of network traffic classification. The evaluation metrics used include Precision, Recall, and F1-score, which are analyzed separately for each traffic class: Audio, Video, and Web.

The results obtained using the Naïve Bayes algorithm are as follows:

Table1. Results of Naïve Bayes

class	Precision	Recall	F1-score
Audio	0.36	0.03	0.06
Video	0.36	0.99	0.53
Web	0.67	0.02	0.03

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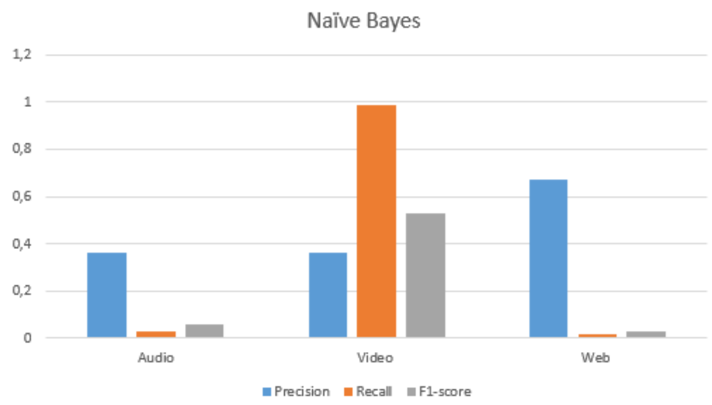

Fig.1. Naive Bayes Performance: Precision, Recall, and F1-score

As observed, the Naïve Bayes model demonstrated low classification performance for Audio and Web traffic, with extremely low Recall and F1-score values. However, for Video traffic, the model achieved high Recall (0.99), meaning it correctly identified most of the actual video flows. Despite this, its Precision remained low (0.36), indicating a high number of false positives. This reflects the algorithm's inability to accurately model complex traffic features due to the assumption of attribute independence.
The Decision Tree (DT) algorithm demonstrated relatively high accuracy for video traffic, although lower results were recorded for the audio and web classes. This outcome highlights the DT algorithm's tendency towards overfitting in certain cases. The model was trained in an average of 1.35 seconds and produced the following results:

Table2. Results of DT

class	Precision	Recall	F1-score
Audio	0.82	0.78	0.80
Video	0.91	0.91	0.91
Web	0.80	0.84	0.82

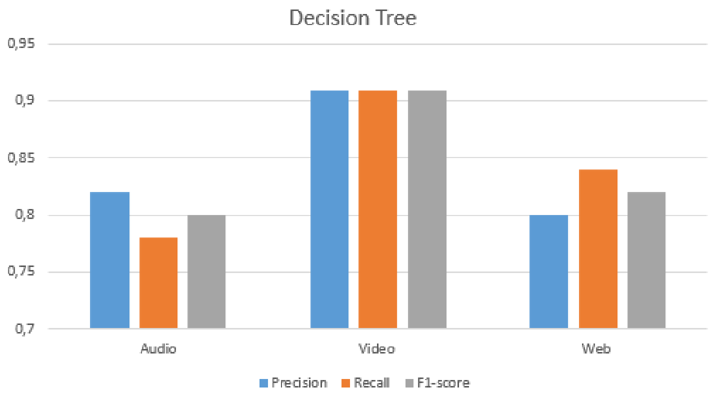

Fig.2. Decision Tree Performance: Precision, Recall, and F1-score

For the video class, the DT algorithm achieved balanced Precision and Recall, both at 0.91.
For the audio class, the results were satisfactory, with an F1-score of 0.80, indicating that the model performs reliably for this class.

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For the web class, the DT algorithm produced moderately high results, particularly in Recall, which reached 0.84, showing that the model correctly identified web traffic in most cases.
According to the research findings, the Random Forest (RF) algorithm showed slightly higher accuracy compared to DT. The RF model was trained in an average of 4.80 seconds and produced the following high-performance results:

Table3. Results of RF

class	Precision	Recall	F1-score
Audio	0.82	0.85	0.84
Video	0.92	0.90	0.91
Web	0.83	0.82	0.83

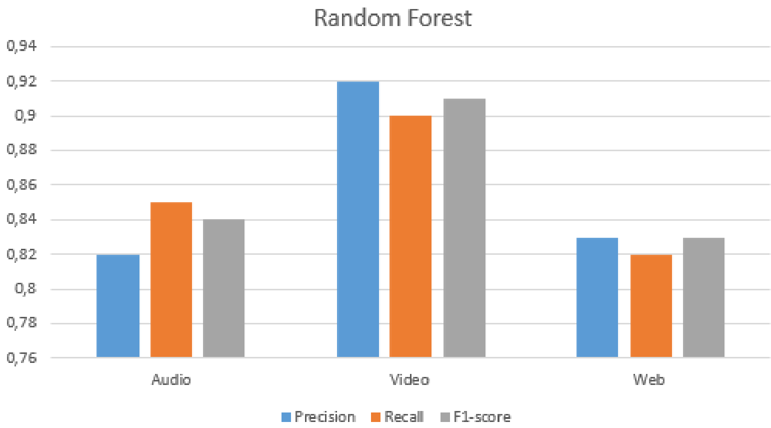

Fig.3. Random Forest Performance: Precision, Recall, and F1-score

For the video class, the RF algorithm delivered the highest precision (Precision - 0.92) and Recall - 0.90, indicating that the model classified video traffic with very high effectiveness.
In the audio class, RF provided a better Recall (0.85) compared to DT, with an F1-score of 0.84, confirming the model's strong performance in this category.
For the web class, RF produced stable and balanced results (Precision - 0.83, Recall -0.82).
The Random Forest algorithm demonstrated high and balanced performance across all classes. It recorded the best precision and F1-score for video traffic in particular. The main advantage of RF is its ability to reduce overfitting and ensure stable classification by combining multiple decision trees. Based on the research findings, RF was evaluated as the most reliable algorithm for network traffic classification.

After evaluating the DT, RF, and Naïve Bayes models in this study, we explored a hybrid approach to improve model accuracy. Specifically, each algorithm was combined with Bagging, which significantly enhanced their stability and overall performance.

During the research, the integration of Bagging with Decision Tree, Random Forest, and Naïve Bayes models resulted in a noticeable improvement in their effectiveness. Through Bagging:

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Table4. ML algorithms with Bagging

Naïve Bayes with Bagging

class	Precision	Recall	F1-score
Audio	0.48	0.12	0.18
Video	0.32	0.82	0.46
Web	0.62	0.26	0.13

Decision Tree with Bagging

class	Precision	Recall	F1-score
Audio	0.94	0.94	0.95
Video	0.97	0.96	0.96
Web	0.93	0.93	0.92

Random Forest with Bagging

class	Precision	Recall	F1-score
Audio	0.98	0.93	0.96
Video	0.96	0.95	0.95
Web	0.94	0.95	0.95

Although each model showed specific results for individual classes, the application of Bagging improved their overall performance. This led to higher accuracy and stability in network traffic classification.

VI. CONCLUSION AND FUTURE WORK

The application of the Bagging method in this study was found to significantly enhance the classification accuracy of the algorithms. The Bagging with Decision Tree combination achieved F1-scores ranging from 0.92 to 0.96 across all traffic classes. The highest performance was observed with the Bagging with Random Forest combination, which enabled precise classification of complex and diverse network traffic. Conversely, adding Bagging to the Naïve Bayes model did not yield substantial improvements due to the model's high bias, which limited the effectiveness of Bagging. Therefore, ensemble-based Random Forest and Decision Tree models are recommended as the most suitable solutions for efficient network traffic classification.

Future research could explore the application of other ensemble techniques such as Boosting or Stacking to further improve classification performance. Additionally, investigating deep learning approaches for encrypted traffic classification, as well as real-time deployment of these models in dynamic network environments, would be valuable extensions of this work.

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