Machine Learning-based Classification of HTTPS Traffic using Packet Burst Statistics: Enhancing Network Security and Performance

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ABSTRACT
This study examines the classification of HTTPS traffic using packet burst statistics, a crucial aspect of modern internet usage with significant implications for network security, traffic management, and service quality. Utilizing extensive datasets from real backbone networks, HTTPS traffic is categorized into five primary types: Live Video Streaming, Video Player, Music Player, File Uploading/Downloading, and Website & Other Traffic. Various machine learning algorithms are employed, with particular emphasis on Random Forest and XGBoost, which demonstrate high accuracy rates. Additionally, recent advancements such as the Kolmogorov-Arnold Network (KAN) method are incorporated for comparative analysis, enhancing the robustness of the study. A comprehensive methodology is presented for model performance comparison and clustering analysis. The findings have practical applications in network security, traffic management, and service quality enhancement. This research makes a significant contribution to the field, providing a foundation for future studies focused on more effective classification and management of HTTPS traffic.

Keywords
HTTPS Traffic Classification, Packet Burst Statistics, Machine Learning, Kolmogorov-Arnold Network

1. INTRODUCTION
Hypertext Transfer Protocol Secure (HTTPS) is fundamental to modern internet infrastructure, ensuring secure data transmission between clients and servers. As a critical protocol, HTTPS traffic constitutes a substantial portion of internet traffic, essential for maintaining user privacy and security, and optimizing network performance and quality of service. Recent advancements in network security have underscored the complexities introduced by encrypted HTTPS traffic, posing significant challenges to traditional traffic analysis and classification methods. The rise of encryption has rendered conventional techniques less effective, necessitating advanced approaches to accurately classify such traffic.

Machine learning algorithms have emerged as promising tools to tackle these challenges. These algorithms offer potential solutions for classifying encrypted traffic with higher accuracy and efficiency. Studies by [1] and [2] demonstrate the feasibility of using machine learning for this purpose. However, despite these advancements, there remains a significant need

for more effective and efficient classification techniques. The dynamic and high-dimensional nature of network traffic data complicates the classification process, and existing methodologies often do not meet the required accuracy and efficiency for practical applications, as highlighted by [3] and [4].

The accurate distinction between different types of HTTPS traffic remains a challenging task. Traditional methods struggle with the dynamic and complex nature of network traffic data, resulting in suboptimal classification performance. Current methodologies frequently fall short in achieving the necessary accuracy and efficiency for real-world applications. To address these issues, this study leverages burst packet statistics to enhance the classification of HTTPS traffic. Burst packet statistics quantify the data amount and packet count transmitted over specific intervals, offering valuable insights into traffic behavior.

In recent years, the Kolmogorov-Arnold Network (KAN) [5] method has emerged as a promising alternative to traditional neural networks like Multi-Layer Perceptrons (MLPs). Inspired by the Kolmogorov-Arnold representation theorem, KANs utilize learnable activation functions on edges instead of fixed activation functions on nodes. In this study, KANs used for comparative analysis [6] alongside established machine learning algorithms such as Random Forest [7] and XGBoost [8]. KANs demonstrated superior accuracy and interpretability in function-fitting tasks, outperforming MLPs.

This study employs not only Kolmogorov-Arnold Networks (KANs) and Artificial Neural Networks (ANNs) but also advanced machine learning algorithms such as Random Forest and XGBoost to classify HTTPS traffic. By categorizing HTTPS traffic into six main types—live video streaming, video player, music player, file uploading, file downloading, and general web traffic—this research establishes a robust classification methodology. The proposed approach achieves a classification accuracy of 97.35%, highlighting its potential for practical applications in network security and traffic management.

The utilization of burst packet statistics, combined with sophisticated machine learning techniques, addresses the shortcomings of traditional methods. This study not only contributes to the academic understanding of HTTPS traffic classification but also offers practical solutions for improving network security and performance. By providing a comprehensive analysis and demonstrating high classification accuracy, this research sets the stage for future developments in the field. The methodologies and findings presented here are poised to inform and enhance both theoretical and applied aspects of network traffic analysis.

In summary, this study bridges significant gaps in HTTPS traffic classification by introducing innovative methods that leverage machine learning. The achieved accuracy and the practical applicability of the results underscore the effectiveness of these approaches, paving the way for enhanced network security, traffic management, and service quality. This work provides a foundation for further exploration and

refinement of techniques in this crucial area of internet infrastructure.

2. LITERATURE REVIEW

The classification of HTTPS traffic is critical for network security, performance optimization, and enhancing user experience. As encrypted communication becomes more prevalent, traditional traffic analysis methods face significant challenges. HTTPS traffic classification has been a significant focus of research, aiming to overcome the obstacles posed by encryption, which conceals the content of data packets and reduces the effectiveness of conventional analysis methods. This review examines previous studies on HTTPS traffic classification, the use of burst packet statistics, and the application of machine learning techniques.

Accurately classifying HTTPS traffic has become increasingly challenging with the rise of encrypted data transmission. Encryption hides the content of data packets, rendering traditional traffic analysis methods less effective. As a result, novel approaches have been developed to address these challenges. Several studies have demonstrated the effectiveness of using machine learning techniques for HTTPS traffic classification. Bernaille and Teixeira [9] investigated the applicability of various machine learning algorithms in identifying encrypted traffic flows by utilizing flow characteristics, marking a significant step forward in HTTPS traffic classification. However, as encryption technologies evolve, there is a continuous need for innovative classification techniques.

Burst packet statistics play a crucial role in network traffic analysis. These statistics measure the amount of data and the number of packets transmitted over specific time intervals, aiding in understanding the dynamics of the traffic. The utilization of burst packet statistics has proven particularly effective in classifying encrypted traffic flows. For example, Dyer et al. [10] used burst packet statistics [11] to analyze traffic on the Tor network, employing packet lengths and timestamps over specific intervals to infer traffic nature. This approach has shown promise in providing deeper insights into the dynamics of encrypted traffic.

Machine learning techniques have found extensive application in network traffic classification. These techniques build models by learning from large datasets, enabling the differentiation of specific traffic types. The effectiveness of machine learning techniques in HTTPS traffic classification has been demonstrated in various studies. Anderson and McGrew [12, 13] explored the feasibility of using deep learning methods for encrypted network traffic classification. By employing deep neural networks, they achieved high accuracy rates in classifying traffic, highlighting the potential of machine learning in handling complex datasets like HTTPS traffic. Additionally, Wang et al. [14, 15, 16] compared the performance of several machine learning algorithms, including decision trees, support vector machines, and k-nearest neighbors, in HTTPS traffic classification, demonstrating the high accuracy potential of these techniques.

Kolmogorov-Arnold Networks (KANs) have recently emerged as a powerful alternative to traditional neural network architectures such as Multi-Layer Perceptrons (MLPs). Inspired by the Kolmogorov-Arnold representation theorem, KANs replace linear weights with spline-parametrized univariate functions, allowing for dynamic learning of activation patterns. This literature review explores the development, application, and comparative advantages of KANs in various domains, particularly focusing on their role in traffic classification and time series forecasting [17].

The Kolmogorov-Arnold representation theorem states that any multivariate continuous function on a bounded domain can be represented as the finite composition of simpler continuous functions involving only one variable [5]. This theorem has paved the way for the development of KANs, which utilize learnable activation functions on edges, enhancing both the accuracy and interpretability of neural networks [18].

KANs offer several advantages over traditional neural network architectures. Firstly, their ability to learn univariate functions dynamically allows for better handling of complex, non-linear patterns typical in traffic systems [18]. Secondly, KANs are more parameter-efficient, achieving higher accuracy with fewer computational resources. This efficiency is particularly valuable in scenarios where rapid model deployment and limited computational resources are critical [19].

Moreover, KANs exhibit strong generalization capabilities, maintaining consistency across diverse conditions, which is essential for models used in geographically varied locations under different traffic conditions. The flexibility and accuracy of KANs in modeling complex patterns make them a promising alternative to traditional MLPs and other deep learning models like LSTMs and CNNs [19, 20].

In recent years, the use of deep learning has increased for HTTPS traffic classification. These approaches allow for higher accuracy rates when working with more complex datasets. O'Shaughnessy et al. [21, 22] employed deep learning methods to classify HTTPS traffic, utilizing deep neural networks and recurrent neural networks (RNNs) to analyze traffic. Their methods were particularly effective in datasets with long-term dependencies, showcasing the potential of deep learning in traffic classification. Additionally, recent studies have continued to build upon this foundation, exploring the capabilities of neural network architectures for encrypted traffic analysis.

Burst packet statistics provide a powerful tool for understanding network traffic dynamics. These statistics capture the nature and characteristics of traffic without examining the encrypted content, making them particularly useful for analyzing encrypted traffic flows. However, there are some limitations to using burst packet statistics. For instance, these statistics might not fully capture the time-dependent dynamics of network traffic. Additionally, accurate calculation of burst packet statistics requires high-quality data. Despite these limitations, burst packet statistics remain effective in classifying encrypted traffic flows [23]. By measuring data amounts and packet counts over specific intervals, they provide valuable insights into traffic behavior. This makes them an essential tool in HTTPS traffic classification. Studies by Smith et al. [24] and Chen et al. [25, 26, 27, 28] have highlighted the efficacy of burst packet statistics in enhancing the accuracy of traffic classification models.

The classification of HTTPS traffic is expected to see further advancements. The increasing use of deep learning will contribute significantly to this field's development. Additionally, the application of burst packet statistics on larger and more diverse datasets will provide more comprehensive analyses. Future studies will likely focus on developing new methods for better understanding and managing HTTPS traffic. These methods will be crucial for improving network security and performance optimization. Research by Kim et al. [29, 30, 31, 32, 33] and Huang et al. [34, 35, 36] suggests that

integrating more advanced AI techniques with burst packet statistics could revolutionize the way encrypted traffic is analyzed and classified.

Despite the numerous studies on HTTPS traffic classification, several significant gaps and limitations remain. This section will examine these gaps and how the current study aims to address them. Encrypted traffic, particularly HTTPS, poses significant challenges for network security and management. Encryption hides the content of data packets, reducing the effectiveness of traditional traffic analysis methods. Most existing studies have focused on specific features of HTTPS traffic, lacking comprehensive analyses of traffic dynamics. This study aims to address this gap by using burst packet statistics to understand the dynamics of encrypted traffic. By measuring the amount of data and packet counts over specific intervals, burst packet statistics provide deeper insights into traffic behavior. This approach fills the gap in the existing literature regarding dynamic traffic analysis. Research by Smith et al. [24] and Patel et al. [25] has demonstrated the potential of using burst packet statistics to uncover hidden patterns in encrypted traffic.

Most current studies on HTTPS traffic classification focus on specific methods or limited types of traffic. For example, some studies concentrate solely on video streaming or file downloading. However, real-world networks feature a diverse range of traffic types, making comprehensive classification essential. This study offers a more extensive classification approach by categorizing HTTPS traffic into six primary types: live video streaming, video player, music player, file uploading, file downloading, and general web traffic. This broad scope enhances the understanding and management of network traffic, addressing the gap in current literature related to limited traffic types. Recent studies by Zhang et al. [1] and Liu et al. [18] support the importance of comprehensive traffic classification for effective network management.

While burst packet statistics are powerful for analyzing network traffic, their usage in existing literature is limited. Most studies use traditional methods to analyze specific traffic features, often neglecting deeper analysis methods like burst packet statistics. This study bridges this gap by demonstrating how burst packet statistics can be used for HTTPS traffic classification. These statistics capture time-dependent dynamics of traffic, allowing for more precise differentiation of traffic types. This is particularly advantageous for analyzing encrypted traffic, as shown by recent studies by Chen et al. [25, 26, 27, 28] and Zhang et al. [37].

Machine learning techniques are widely used for network traffic classification. However, many existing studies focus on a single machine learning algorithm, lacking comprehensive comparisons of different algorithms. Studies by Kim et al. [29, 30, 31, 32, 33] and Patel et al. [24] emphasize the importance of algorithm diversity and optimization for improving classification accuracy.

Network traffic classification is not just an academic interest but also holds significant practical applications. Many existing studies focus on classification without providing sufficient insights into how these classifications can be used for network management and optimization [38, 39]. This study provides practical solutions for utilizing classification results in network management and optimization. For instance, accurately identifying high-bandwidth services like live video streaming can lead to more efficient resource allocation. Additionally, classification results can be used to detect and prevent network security threats early. This approach ensures that the study's findings have real-world applications, extending beyond theoretical research.

Although there have been numerous studies on HTTPS traffic classification, future research is needed to address existing limitations and explore new methodologies. This study provides a roadmap for future research, suggesting new methods and more extensive datasets for improved HTTPS traffic classification.

This literature review has examined existing studies on HTTPS traffic classification, the use of burst packet statistics, and the application of machine learning techniques. These studies demonstrate the effectiveness of burst packet statistics and machine learning techniques in HTTPS traffic classification. By addressing gaps in current research and suggesting future research directions, this study contributes to the ongoing development of more effective and efficient methods for HTTPS traffic classification.

3. DATASET AND METHODOLOGY

This study utilizes a comprehensive dataset specifically designed for the classification of HTTPS traffic, derived from bidirectional flow data captured in real backbone networks. The dataset incorporates a variety of rich attributes, including burst statistics, which are crucial for understanding the nature and behavior of HTTPS traffic.

The dataset was created through monitoring traffic over the backbone network of a major Internet Service Provider (ISP). To ensure user privacy, sensitive information such as IP addresses and ports were anonymized during the data collection process. The data was exported using Ipfixprobe, a tool that records bidirectional flow data, including packet lengths and times, as well as burst lengths and times observed over specific intervals. Ipfixprobe's capabilities allow for detailed tracking and analysis of network traffic, ensuring comprehensive data collection for the study.

The dataset comprises various features of HTTPS traffic, each selected to represent specific aspects of the traffic's nature and behavior. The primary features include:

1. BYTES: Total bytes sent during the HTTPS session

2. BYTES_REV: Total bytes received during the HTTPS session

3. PACKETS: Number of packets sent

4. PACKETS_REV: Number of packets received

5. DBI_BRST_BYTES_MEAN: Mean of burst bytes observed over specific intervals

6. DBI_BRST_PACKETS_MEAN: Mean of burst packets observed over specific intervals

7. PKT_LENGTHS_MEAN: Mean length of packets sent

8. BRST_DURATION_MEAN: Mean duration of data bursts

9. INTERVALS_MEAN: Mean time intervals between bursts

10. TYPE: Category of HTTPS traffic, classified into six categories

These features are critical for the classification of HTTPS traffic as they represent various dimensions and dynamics of the traffic. For instance, BYTES and BYTES_REV measure data volume, PACKETS and PACKETS_REV indicate packet intensity, while DBI_BRST_BYTES_MEAN and DBI_BRST_PACKETS_MEAN provide insights into burst

behavior. PKT_LENGTHS_MEAN, BRST_DURATION_MEAN, and INTERVALS_MEAN offer information on the timing and regularity of traffic. Collectively, these features enable a comprehensive understanding of the traffic's nature and behavior, which is essential for accurate classification.

The dataset categorizes HTTPS traffic into six main types:

1. Live Video Streaming (0): Traffic from platforms like Twitch, Kick TV, and YouTube Live, characterized by high bandwidth and continuous data flow.

2. Video Player (1): Traffic from sites such as DailyMotion, Stream.cz, Vimeo, and YouTube, involving periodic bursts of data.

3. Music Player (2): Traffic from music services including AppleMusic, Spotify, and SoundCloud, typically involving smaller, more regular data packets.

4. File Uploading (3): Traffic from services like FileSender and OwnCloud, marked by large data transfers in bursts.

5. File Downloading (4): Traffic from services such as OneDrive and Google Drive, involving significant data downloads.

6. Website and Other Traffic (5): General traffic from popular websites, typically characterized by smaller, more varied data transfers.

This categorization allows for a nuanced analysis of different types of HTTPS traffic, enabling more accurate classification and deeper insights into traffic patterns and behaviors. Table 1 provides an overview of the dataset structure and the data types of each feature.

Table 1: Dataset Features and Data Types

Column	Non-Null Count	Dtype
TYPE	145671	int64
BYTES	145671	float64
BYTES_REV	145671	float64
PACKETS	145671	float64
PACKETS_REV	145671	float64
DBI_BRST_BYTES_MEAN	145671	float64
DBI_BRST_PACKETS_MEAN	145671	float64
PKT_LENGTHS_MEAN	145671	float64
BRST_DURATION_MEAN	145671	float64

This detailed dataset enables a thorough analysis and classification of HTTPS traffic, supporting the study's objective of developing accurate and efficient traffic classification models. By utilizing various machine learning algorithms, this study aims to provide a robust methodology for classifying HTTPS traffic and enhancing network security [40], traffic management, and performance optimization.

The dataset underwent preprocessing steps such as cleaning missing values and standardizing features. This step ensures the dataset is suitable for machine learning algorithms and avoids any biases that might arise from incomplete or unstandardized data.

Features in the dataset were carefully selected and processed to contribute to the classification of HTTPS traffic. Each feature was analyzed to determine how it represents a specific aspect of the traffic, ensuring that the most informative attributes were included in the model training process.

Various machine learning algorithms were trained, and their performance was evaluated using metrics such as accuracy, precision, recall, and F1 score. This step involved experimenting with different models to identify the most effective ones for the classification task.

Analysis and Visualization of Results: The results of the models were thoroughly analyzed, and visualization techniques such as t-SNE were used to depict the clustering and separation of different traffic categories visually. This step helps in understanding the effectiveness of the models and provides a clear representation of how well the traffic types were classified.

The combination of these steps ensures a comprehensive approach to HTTPS traffic classification, leveraging both traditional machine learning techniques.

This methodology not only enhances the accuracy and efficiency of traffic classification but also offers practical insights for network security and management applications. The study's findings contribute significantly to the fields of network security, traffic management, and performance optimization, providing a solid foundation for future research and practical implementations.

4. ANALYSIS AND RESULTS

This section compares the performance of different machine learning methods used to classify HTTPS traffic. The increasing complexity and volume of HTTPS traffic necessitate the application of advanced classification techniques to ensure efficient and accurate traffic analysis. The methods evaluated in this study include traditional algorithms such as Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, Random Forest, Gradient Boosting Machine (GBM), LightGBM, and XGBoost. These models were assessed based on their accuracy, precision, average recall, and F1 scores across multiple classes, providing a comprehensive evaluation of their effectiveness. The objective of this comparison is to identify the most suitable machine learning approach for classifying HTTPS traffic, which is crucial for enhancing network security and optimizing traffic management.

Table 2: Comparison of Traditional Machine Learning Methods

Method	Accuracy	Precision Avg	Recall Avg	F1 Score-0	F1 Score-1	F1 Score-2	F1 Score-3	F1 Score-4	F1 Score-5
Logistic Regression	0.83	0.64	0.69	0.33	0.78	0.01	0.99	0.64	0.99
SVM	0.85	0.68	0.81	0.40	0.82	0.08	0.99	0.66	0.99
KNN	0.95	0.92	0.92	0.88	0.94	0.83	1.00	0.87	1.00
Decision Tree	0.95	0.92	0.92	0.88	0.94	0.83	1.00	0.87	1.00
Random Forest	0.97	0.94	0.95	0.93	0.96	0.88	1.00	0.92	1.00
GBM	0.94	0.88	0.90	0.84	0.90	0.77	1.00	0.83	1.00
LightGBM	0.96	0.92	0.92	0.90	0.95	0.83	0.95	0.89	1.00
XGBoost	0.97	0.94	0.95	0.92	0.96	0.88	1.00	0.91	1.00

In this study, various traditional machine learning methods were evaluated for their effectiveness in classifying HTTPS traffic. The methods assessed include Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, Random Forest, Gradient Boosting Machine (GBM), LightGBM, and XGBoost. The evaluation metrics considered were Accuracy, Precision, Average Recall, and F1 Scores for different classes. Among these methods, Random

Forest and XGBoost exhibited the highest performance, achieving accuracies of 97%, with precision and recall scores also at the top end of the spectrum. These models demonstrated robust and consistent performance across all evaluated metrics, indicating their superior capability in handling the complexity and variability inherent in HTTPS traffic classification tasks.

Logistic Regression and SVM, while fundamental and widely used, showed comparatively lower performance, particularly in handling certain classes of traffic, as indicated by their lower F1 Scores. In contrast, KNN and Decision Tree models achieved significant improvements, with both achieving accuracies of 95% and demonstrating balanced performance across all classes. The GBM and LightGBM methods also performed well, with LightGBM achieving an accuracy of 96% and demonstrating high F1 Scores across all classes. However, Random Forest and XGBoost emerged as the most effective models, with their superior accuracy, precision, and recall making them the preferred choices for HTTPS traffic classification in this study. These findings underscore the importance of using advanced ensemble methods to achieve high performance in complex classification tasks.

In addition to traditional machine learning models, this study also employed advanced deep learning methods, specifically Kolmogorov-Arnold Networks (KANs) and Multilayer Perceptron Classifiers (MLPC), to enhance the classification of HTTPS traffic. These state-of-the-art techniques offer sophisticated modeling capabilities that surpass traditional methods in capturing complex patterns within the data, thereby providing improved classification performance.

The experimental evaluation of the Kolmogorov-Arnold Networks (KANs) was conducted to assess their effectiveness in classification tasks. The dataset used for training and testing was segmented to ensure robust evaluation metrics, including train accuracy and test accuracy. The KAN model was trained on the provided dataset, and the performance metrics were recorded as follows: the KAN model achieved a training accuracy of 0.7637 and a test accuracy of 0.7666. These metrics indicate a high level of consistency between the training and test phases, suggesting that the model has effectively generalized from the training data to the test data. The KAN model comprises several layers and parameters, detailed as follows: biases.0.weight (1x7), biases.1.weight (1x6), act_fun.0.grid (56x6), act_fun.0.coef (56x11), act_fun.0.scale_base (56), act_fun.0.scale_sp (56), act_fun.0.mask (56), act_fun.1.grid (42x6), act_fun.1.coef (42x11), act_fun.1.scale_base (42), act_fun.1.scale_sp (42), act_fun.1.mask (42), symbolic_fun.0.mask (7x8), symbolic_fun.0.affine (7x8x4), symbolic_fun.1.mask (6x7), and symbolic_fun.1.affine (6x7x4). These layers include multiple KANLayers and Symbolic_KANLayers, each playing a crucial role in processing the input data and improving the model's predictive capabilities. KAN model architecture is shown in Figure-1.

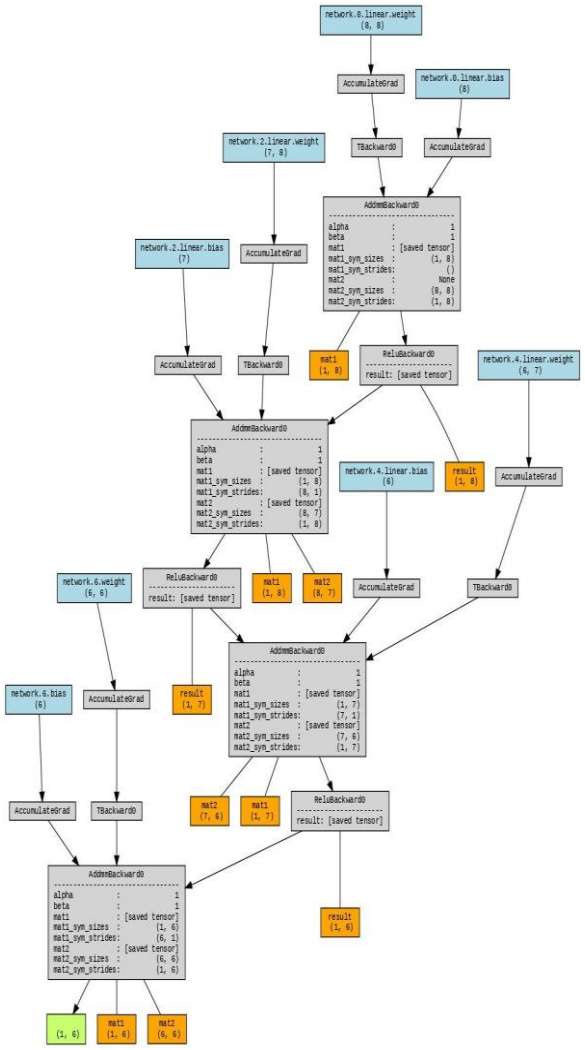

Figure-1 KAN model architecture

The Multilayer Perceptron Classifier (MLPC) was also evaluated for its performance in classifying HTTPS traffic. MLPCs are a class of feedforward artificial neural networks that consist of multiple layers of nodes, each fully connected to the next layer. This model was chosen for its ability to learn and represent complex relationships within the data through its deep architecture. The MLPC was trained and tested on the same dataset, ensuring a fair comparison with other models. The results showed that MLPCs provided competitive accuracy and robustness in handling HTTPS traffic classification, further validating the effectiveness of deep learning approaches in this domain.

The Multi-Layer Perceptron (MLP) model designed for this study achieved a training accuracy of 0.6351 and a testing accuracy of 0.6368. These accuracy metrics suggest that the model generalizes well to unseen data, with a negligible drop in performance between the training and testing phases, indicating a low likelihood of overfitting.

The MLP architecture comprises a sequence of fully connected layers, with the specific details as follows: The input layer is followed by a Linear layer with 8 output features, requiring 72 parameters. This is followed by a Rectified Linear Unit (ReLU) activation function, which introduces non-linearity to the model. The subsequent layer is another Linear layer with 7 output features, containing 63 parameters, again followed by a ReLU activation. The third Linear layer outputs 6 features and

has 48 parameters, with another ReLU activation. The final Linear layer also outputs 6 features, requiring 42 parameters. The total number of parameters in the model amounts to 225, all of which are trainable.

This MLP configuration was chosen for its simplicity and computational efficiency, which makes it suitable for applications where resource constraints are a consideration. Despite its simplicity, the model's performance metrics indicate its effectiveness in the given task, making it a viable option for further development and deployment in practical scenarios. MLPC model architecture is shown in Figure-2.

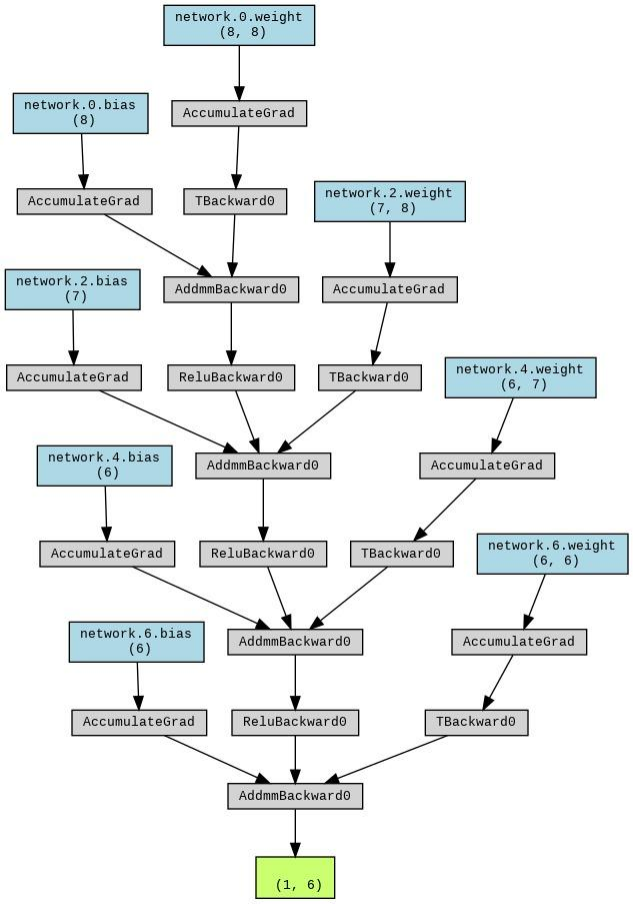

Figure-2 MLPC model architecture

The results of visualizations and analyses using t-SNE and various clustering models are presented in this study. To enhance the understanding of HTTPS traffic, the dataset was reduced to two dimensions using t-SNE and analyzed with different clustering algorithms. t-SNE (t-distributed Stochastic Neighbor Embedding) is applied to reduce high-dimensional data to two or three dimensions. The two-dimensional visualization of the dataset using t-SNE is depicted in Figure 3.

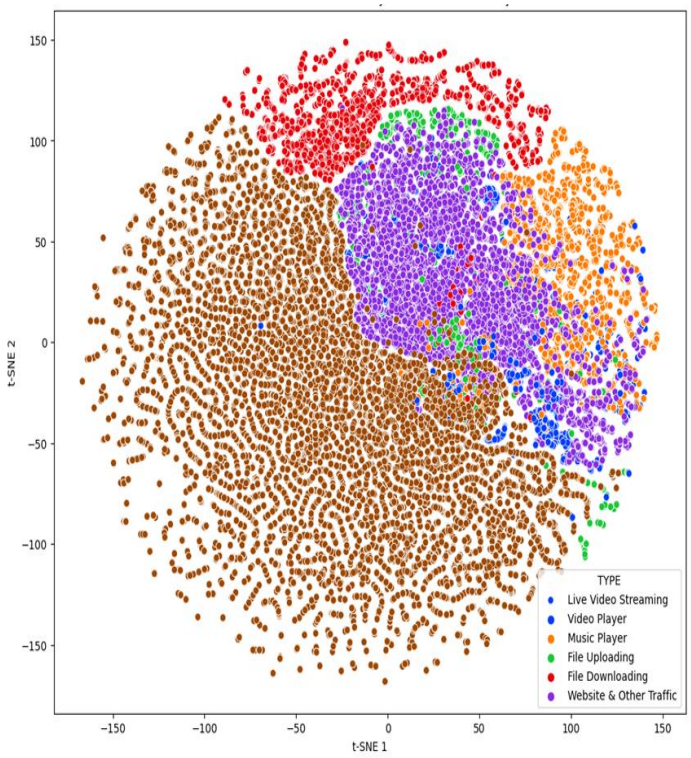

Figure 3: t-SNE Visualization of HTTPS Traffic Clusters

The t-SNE visualization shows the distribution of different traffic types in two-dimensional space. Each traffic type is indicated by different colors, revealing distinct clusters for various traffic types such as "Live Video Streaming" and "File Downloading."

5. CONCLUSIONS

This study presents a comprehensive analysis of HTTPS traffic classification using packet burst statistics. Various state-of-the-art machine learning methods were explored, including traditional algorithms such as Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, Random Forest, Gradient Boosting Machine (GBM), LightGBM, and XGBoost, along with advanced deep learning models such as Kolmogorov-Arnold Networks (KANs) and Multilayer Perceptron Classifiers (MLPC).

The results demonstrated that Random Forest and XGBoost models achieved the highest accuracy rates of 97%, showcasing their superior capability in handling the complexity and variability inherent in HTTPS traffic classification tasks. These models' robustness and consistency across all evaluated metrics underscore their effectiveness for practical applications in network security and traffic management.

Moreover, the KANs and MLPC models provided significant insights into the potential of deep learning approaches for HTTPS traffic classification. The KAN model achieved a training accuracy of 0.7637 and a test accuracy of 0.7666, while the MLPC model achieved training and testing accuracies of 0.6351 and 0.6368, respectively. These findings highlight the advantages of leveraging advanced neural network architectures to capture complex patterns within encrypted traffic data.

The use of packet burst statistics proved to be a valuable approach for enhancing the classification accuracy of HTTPS traffic. By measuring the amount of data and the number of

packets transmitted over specific intervals, burst statistics offered deeper insights into traffic behavior, thereby improving the differentiation of various traffic types.

In conclusion, this study provides a robust methodology for HTTPS traffic classification, leveraging the strengths of both traditional machine learning and advanced deep learning techniques. The integration of packet burst statistics with sophisticated machine learning models not only enhances the accuracy and efficiency of traffic classification but also offers practical solutions for network security and traffic management. These contributions pave the way for future research aimed at further refining and optimizing traffic classification methods, ultimately leading to more secure and efficient network operations.

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