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Improving resource allocation in 5G networks using traffic segmentation based on machine learning techniques

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Abstract: Due to a significant increase in cellular network traffic, predicting network traffic using traditional methods may lead to inaccurate allocation of available resources. Current and future cellular networks target ultra-low latency, high reliability standards, improved security, better capacity, as well as efficient user's communications. This work adopts 5g network slicing technology to respond to different users' requirements. The optimization of resource allocation to network slices to meet different network traffic is of great demand. Therefore, this work focuses on the implementation of an algorithm of network slicing based on machine learning in order to group IoT devices in 5G networks into three efficient network categories, namely eMBB, URLC, and mMTC, according to the traffic. We utilized KNN, SVN, and LR machine learning algorithms to classify devices according to use cases within the three aforementioned segments. Results show that these algorithms perform excellently in predicting the best suitable slice for the network traffic quality. The basic metrics of performance, including accuracy, F-score, and sensitivity are examined. Comparative analyses illustrate that KNN, SVN, GNB, and LR have the ability to classify network traffic slices with an accuracy of up to 95%.

Keywords: 5G, Network Slicing, Enhanced Mobile Broadband (eMBB), Massive Machine-Type Communications (mMTC), Ultra-Reliable Low-Latency Communications (URLLC), Machine-Learning (ML).

1. Introduction

The fifth-generation mobile network (5G) is a revolutionary leap in wireless communication technology, following the progression from 1G through to 4G. 5G is the 5th generation mobile network. It is a new global wireless standard after 1G, 2G, 3G, and 4G networks [1]. Unlike previous generations, 5G is designed to not only enhance speed but also to support a wide array of advanced services and applications that rely on ultra-low latency and high reliability. By 2026, it is anticipated that there will be 3.5 billion users of fifth generation (5G) mobile networks worldwide [2]. 400 5G use cases across 70 sectors are expected to result in an average monthly data use of 35 GB per user [3]. Expectedly, this network enables connection seamlessly across a range of industries, from healthcare to transportation. In addition, it is thought to have a central function in developing emerging technologies, such as smart cities and IoT. In fact, 5G is anticipated to significantly influence the digitalization of a number of vertical areas, including the Internet of Things (IoT), smart grid, and the automotive industry. It is intended to handle many use cases with very different needs [4]. These applications fall into three general categories[5] as shown in Figure 1 Massive Machine Type Communications (mMTC), ultra-reliable low-latency communications Ultra-Reliable and Low-Latency Communications (uRLLC), and Extreme Mobile Broadband (eMBB) [6]. Enhanced Mobile Broadband (eMBB) Static resource assignment: A slice functions with a predetermined resource. This function ensures a guaranteed distribution of resources to the slices but does not accommodate fluctuating demands. ICI denotes the potential for intra-slice interference.

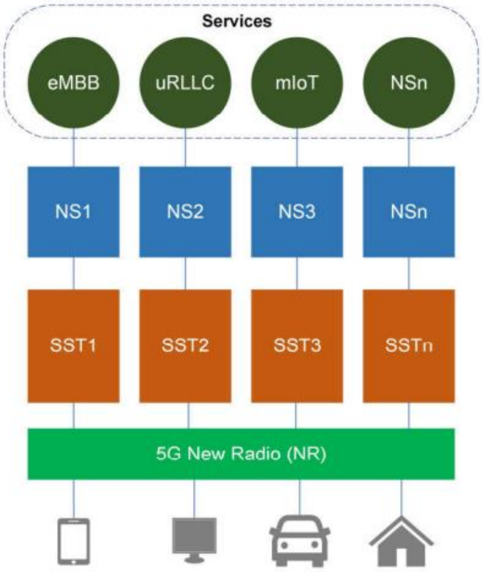

Figure 1. The 5G framework for network slicing based on service-specific technology

The introduction of 5G brings number of groundbreaking capabilities compared to its predecessors, particularly with regard to network capacity, speed, and latency. 5G network enhances the experience of mobility through improved infrastructure, reconfiguration, services, and an extensive variety of activities. It offers diverse potential for the mobilization of several application domains such as healthcare services, traffic monitoring, and seamless mobility [7]. 5G provides speeds up to 100 times greater than 4G, facilitating enhanced multimedia streaming, quicker data transmission, and improved mobile internet experiences. Additionally, 5G is designed to handle a far larger volume of simultaneous connections, providing support for a massive number of devices that require constant and stable communication. A key feature of 5G is network slicing, facilitating the creation of virtual networks tailored to meet specific application demands, ensuring greater flexibility in addition to efficiency. According to the third-generation partnership project (3GPP), network slicing represents one of the essential components of the 5G network, which allows for customized and flexible network operations to meet diverse user needs [7]. Mobile operators have encountered challenges in adapting their network infrastructures to the burgeoning traffic generated by users. This surge can be attributed to the widespread adoption of tablets and smartphones, alongside an escalating demand for video content in recent years [8]. This means that operators can deliver dedicated network resources to different sectors or applications, ranging from high-speed data for consumers to ultra-reliable connections for critical services such as healthcare and autonomous vehicles. 5G is not just about faster internet; it is also about reliability and seamless integration across a variety of services, which is essential for future communication networks. In addition, the future generation communication requires reliability, seamless operations, and reconfiguration management in heterogeneous wireless networks.[9] In this regard, 5G is designed to support an increasingly diverse set of communication requirements, offering a highly reliable network for everything from low-latency applications like remote surgery and augmented reality to high-capacity applications such as streaming high-definition videos and real-time data processing for industrial applications. The impact of 5G is expected to go beyond traditional communication needs, creating a transformative effect on industries worldwide. In healthcare, 5G will enable real-time patient monitoring, remote surgeries, and telemedicine solutions. For smart cities, it will support the integration of IoT devices that control traffic, monitor pollution, and optimize energy consumption. Furthermore, in transportation, 5G will be vital for autonomous vehicles, providing the necessary communication between vehicles and infrastructure to ensure safety and efficiency. According to the data presented in Table 1, the 3GPP delineates 3 standardized SSTs [10].

Table 1. Standardized SST features and values.

SST	SST Value	Expected Features
eMBB	1	Extreme throughput Better spectral efficiency Expanded coverage
uRLLC	2	High reliability Low latency High accessibility
mMTC	3	Higher linking density Fewer complications Prolonged coverage

Network Slicing is one of the most innovative features of 5G technology, designed to enable operators to establish numerous virtual networks in a singular physical 5G infrastructure. In addition, it allows operators to customize and optimize network resources according to specific use cases, thus providing tailored services to different applications or industries. Network Slicing (NS) entails customizing a physical network for certain applications and services based on three fundamental criteria: isolation, end-to-end connectivity, and application-specific requirements [11] Unlike traditional networks, where all users share the same network infrastructure, 5G network slicing creates isolated "slices" of the network, each with its own characteristics, such as bandwidth, latency, and reliability. With the advent of 5G, the demand for highly specialized services is increasing, and network slicing serves an essential purpose for meeting that demand. An effective slice formation mechanism is employed that supports Key Performance Indicators (KPIs) related to 5G and ensures resource allocation by adjusting inter- and intra-slice allocation methods [12]. 5G's ability to deliver varying levels of services in order to a wide range of applications relies heavily on the efficiency and flexibility provided by network slicing. Next-generation networks facilitate end-to-end network resource allocation with network slicing (NS), which gives mobile carriers the adaptable solution they need to handle several tenants on the same infrastructure [13]. NS facilitates the deployment of specific services that require different network characteristics, ensuring that uses, e.g., autonomous vehicles, smart healthcare, and industrial IoT function efficiently without congestion or latency issues. NS offers support to three service types: MIoT, URLLC, and eMBB [14]. Figure 2 provides a summary of varying methods of sharing the slice spectrum between into three slices. Each of these services is offered using a unique NS. For example, eMBB is designed to treat user mobile broadband, such as high-quality video streaming and the transfer of large files fast. On the contrary, URLLC is critical for the uses that require low latency and high reliability, such as Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), as well as Device-to-Device (D2D) communication. MIoT, on the other hand, supports the efficient and cost-effective operation of many IoT devices, which is essential for industries that rely on vast IoT deployments, such as smart cities and industrial automation. Moreover, future generation communication requires reconfiguration management, seamless operations, and reliability, in heterogeneous wireless networks [14].

In this regard, 5G network slicing is essential in managing heterogeneous wireless networks that support not only mobile devices but also a wide range of connected devices requiring constant communication. By creating isolated slices, 5G ensures that these diverse devices can coexist and function optimally without interference, providing a seamless experience for both consumers and businesses.5G slicing enables for diferent degrees of isolation that share network services or functions across numerous slice instances[١٥]. Network slicing enhances network management by enabling the efficient allocation of resources. [16].

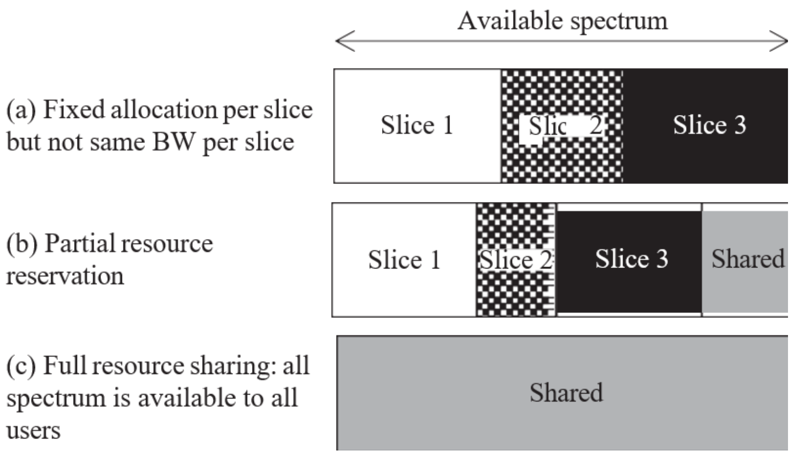

Figure 2. Types of network slicing.

Several fields have seen the promise of machine learning to make critical decisions in critical environments [17]. In a reconfigurable network environment, it monitors the status of varying devices and makes analyses of the slices of networks. In addition, the process used to generate massive amounts of data takes place in the communications to make predictions and make critical decisions. Machine learning has an essential function in the reconfiguration of networks, augment resource allocation according to uses, optimize cell tower operation based on needs, and provide optimal decision-making and real-time performance analysis capabilities [18]. Machine learning techniques have shown their potential in many applications. 5G communications will see a huge influx of data due to the large number of devices [19].

In this study, we propose research aims in order to develop a reconfigurable wireless network slicing solution for 5G networks based on machine learning, addressing two primary challenges: Accurate slice classification for IoT devices, efficient network load management.

The research paper is significant because it:

1. Utilizes a framework for classifying incoming traffic to appropriate network slice.
2. Discusses load analysis on slices each hour during the simulation
3. Compares results of applying three ML algorithms; KNN, SVN, and LR.

The following sections take this organization. Section 2 offers a review of the literature. In Section 3, materials, procedures and methods are presented. Discussion of traffic classification through classifiers is explored in section 4. Section5 concludes the work.

2. Related Work

Recently, researchers have investigated varying methods for optimizing network slicing in 5G networks, particularly to ensure the Quality of Service (QoS) across diver types of services, including URLLC, mMTC, and eMBB. These studies employ a variety of methodologies, including but not limited to machine learning (ML), deep learning, and graph theory, to address challenges related to network resource allocation and dynamic adaptation.

In [20], the authors proposed a solution to address different network scenarios, such as throughput, latency, and scalability, to meet the QoS demands for varying service types. Their approach offered a comprehensive evaluation of network performance under diverse conditions, providing valuable insights into how network slicing can be optimized to handle varying traffic requirements. Graph theory was applied in [21] to manage inter-slice communication and store slices in queues based on probabilistic events. This approach not only provided predictive solutions for evaluating network performance but also enhanced QoS by optimizing slice management, particularly in the context of dynamic traffic patterns and fluctuating resource demands.

The study referenced in [22] employed the Support Vector Machine (SVM) algorithm for slice feature selection, specifically designed to meet the unique demands of IoT services. Additionally, an unsupervised algorithm was applied for sub-slice clustering. However, the authors highlighted certain shortcomings of the K-means clustering approach, particularly its limitations in latency, which is a critical aspect for real-time IoT applications.

In [23], regression trees were employed for both classification and prediction tasks, delivering over 90% accuracy when paired with K-Nearest Neighbor (KNN) and cosine KNN models. While these models demonstrated notable success in slice prediction, they encountered difficulties in accurately predicting throughput within non-standard 5G environments.
A machine learning model for throughput prediction in non-standard 5G networks was proposed in [24], where accuracies of 84% and 93% were achieved in throughput forecasting. While the model performed well under certain network conditions, the authors highlighted its difficulties with latency-sensitive applications during network congestion or failures.
Deep learning models were further extended in [25] to predict if a network provider has the ability to meet new slice requests, considering network channel conditions. This approach resulted in a significant reduction in false positives (75%), thereby improving the reliability of slice predictions and resource management. A similar approach was explored in [1], where a machine learning-based network slicing algorithm was proposed for classifying 5G IoT devices into eMBB, mMTC, and URLLC slices using Gaussian Naive Bayes (GNB) and Bagged GNB (B-GNB) algorithms. The algorithm achieved 86% accuracy in predicting the optimal network slice, even during network interruptions, demonstrating the adaptability of machine learning models to fluctuating network conditions.
The study in [14] utilized Naive Bayes and Random Forest algorithms for network slice prediction, optimizing the allocation of resources according to real-time network conditions. This framework achieved an accuracy of 94% with KNN and 92.16% with SVM for slice prediction. Although the Random Forest algorithm showed promising results in real-time accuracy, the authors noted some limitations, particularly when scaling to larger, more complex networks with advanced resource allocation needs.
The authors in [26-27] utilized machine learning for predictions. Furthermore, a variety of ML and metaheuristic algorithms have been employed in studies [28-30] in order to resolve a range of wireless-inspired challenges in recent years. Particularly, NFV and SDN-based slicing models have been explored. Kurtz et al. [31] focused on 5G new radio air interfaces, demonstrating how the combination of NFV and SDN in slicing can provide service guarantees and dynamically allocate data rates in radio air interfaces. Machine learning and artificial intelligence methodologies are regarded as crucial tools for making decisions of forecasting and enhancing judgments inside a sliced-based network framework, as discussed in [32-33]. These methods are increasingly viewed as central to enhancing the flexibility and efficiency of network slicing, particularly in the face of evolving network conditions and increasing demands for real-time data processing.

3. Materials and Methods

3.1 Data Collection

The set of data employed in the present paper includes 31,584 rows, covering 16 special cases. Among these cases, 4 are related to network issues, while the 12 cases represent various network uses. Network parameters are based on the prediction of the network's effectiveness and stability. These parameters include packet success rate, variable latency, and many others. In contrast, network uses represent varying scenarios in which the network is applied, such as health protection, cities, homes, etc. For this reason, the 16 cases study the target variable, which is the sector type, which is divided into three different values: side 1, slice 2, and slice 3. The work is shown in Figure 1. First, the dataset was analyzed and then analyzed for diversity data (70%) and experimental data (30%). The study of intelligent learning algorithms was used, which enables the identification of relationships between all the numbers in the dataset. This section can be subdivided based on subheadings. The description must be succinct and accurate, encompassing the results, discussion, and inferences which may be derived from the experiment.

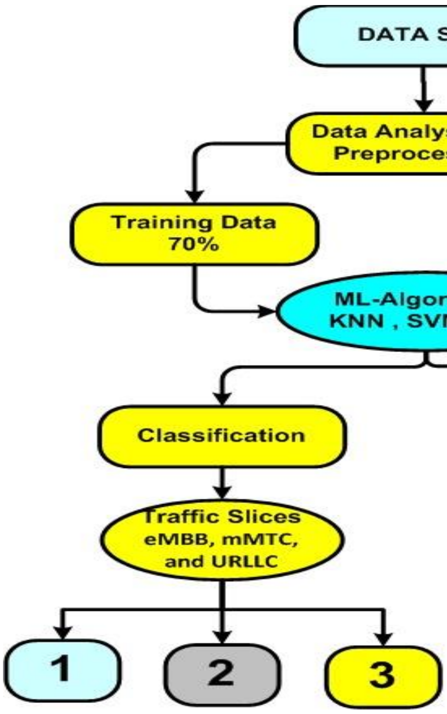

Figure 3. Methodology process

3.2 Data Analysis

This is done to reveal the relationship between each network performance measure and each network slice. This helps us understand how network conditions and usage affect choosing the most appropriate slice and measuring the load on each slice. Table 2. displayed set of features found in the data set.

Table 2. Features with the description of network slicing in 5G Dataset.

Feature Name	Description of feature
Time	Packet passage time
Packet Loss Rate	number of packets not received divided by the total number of packets sent.
Packet delay	The time for a packet to be received.
LTE/5G	The classes or categories of user equipment to define the specifications of performance
GBR	Guaranteed Bit Rate
Non-GBR	Non- Guaranteed Bit Rate
Public Safety	Usage for public welfare and safety purposes (1 or 0)
Healthcare	Usage in Healthcare (1 or 0)
Industry 4.0	Usage in Digital Enterprises (1 or 0)
IoT Devices	Usage in IoT Devices (1 or 0)
Smart City & Home	usage in daily household chores
Smart Transportation	usage in public transportation Smartphone - whether used for smartphone cellular data

3.3 Methodology

The following ML algorithms are used for the multi-class Classification of network slices (Slice 1, 2, or 3):

3.3.1 Support Vector Machine (SVM)

This algorithm searches for the hyperparameter to divide varying classes of the data. SVM also supports multi-class prediction [34]. In this study, a "one-versus-all" approach was used for the multi-class prediction task. In this approach, three binary classifiers (Classifiers 1, 2, and 3) were created. Each classifier discriminates one slice from the set of remaining slices. Classifier 1 learns to discriminate between slice 1 and slice 2 and 3, and so on. The predicted slice is the one that achieves the highest decision score among these classifiers. The most commonly used equation in Support Vector Machines (SVM) is the decision function, which is used to classify data points. The basic form of the equation is:

$$f(x) = w \cdot x + b \qquad (1)$$

in which:

- f(x) represents the decision function that outputs the value for classification.
- w denotes the weight vector that identifies the orientation of the hyperplane.
- x represents the input feature vector (the data point).
- b denotes the bias term which shifts the decision boundary.

In order to classify, we predict the class label by using the sign of the decision function:

$$\text{Class label} = \begin{cases} -1 & \text{if } f(x)<0 \\ +1 & \text{if } f(x)>=0 \end{cases} \qquad (2)$$

When addressing linear SVMs, the hyperplane separates the space into two classes, and the objective is to define the optimal hyperplane that increases the margin between these classes.

3.3.2 K-Nearest Neighbors (KNN)

The 'K' parameter in KNN specifies the number of neighbor points used in the classification task. This method is based on selecting an unlabeled data item by examining its K nearest neighbors and then classifying it into the most common class among those neighbors.

Key Concepts:

- Instance-based Learning: KNN represents the learning algorithm based on instances. In other words, it doesn't learn an explicit model in training. In contrast, it stores the data of the training and predicts at the time of testing based on that data.
- Distance Metric: KNN relies on a distance metric to measure how close or similar two points are. Commonly used distance metrics are:
    - Euclidean distance: Most commonly used, especially when dealing with continuous features. The distance between two points p=(x1,x2,…,xn) and q=(y1,y2,…,yn) is calculated using the following equation:

$$d(p,q) = \sqrt{\sum_{i=1}^{n}(xi - yi)2} \qquad (3)$$

3.3.3 K-Nearest Neighbors (KNN)

A linear regression model (LM) represents one of the statistical techniques employed in order to have a modeling of the relationship between the dependent variable and one or more independent variables. Supposedly, the response variable and explanatory ones have a linear relation. The LM is fitted using methods such as least squares or maximum likelihood estimation. The goodness of fit for a linear regression model is often assessed using mean squared error (MSE) measures. The MSE is a measure of the average squared difference between the predicted values and the actual values of the response variable. When MSE is low, it denotes that the model fits the data better.

The algorithm creates multiple decision trees in this manner and combines their predictions to conclude the final prediction. Each tree in the random forest provides an independent prediction of the outcome, and the final prediction is determined by the aggregation of the predictions from all trees, either through majority voting (for classification) or averaging (for regression). Overall, Random Forest represents one of the flexible and powerful ensemble learning methods that combines the strengths of decision trees with randomization techniques. It can produce accurate predictions, handle high-dimensional datasets, and provide insights into the importance of variables in the model. In Logistic Regression (LR), the most commonly used equation is the logistic function (or sigmoid function) that models the binary outcome's probability (0 or 1). The general form of the logistic regression model is:

$$p(y = 1 \mid x)) = \frac{1}{1+e^{-(\omega.x+b)}} \tag{4}$$

Where:

- p(y=1|x) denotes a probability that the outcome y is 1, if the input features x.
- w is the weight vector (coefficients of the features).
- X denotes the feature vector (the input data).
- b represents the bias term (intercept).
- e is the base of the natural logarithm.

The output of this equation is a probability between 0 and 1, which is then used to classify the input x into one of the two classes (usually 0 or 1). A common classification rule is:

- If p(y=1|x) ≥0.5, predict y=11.
- If p(y=1|x) <0.5, predict y=0.

3.3.4 Gaussian Naive Bayes (GNB)

Variant of the Naive Bayes classifier, which is based on Bayes' theorem. It is particularly useful for classification tasks where the features (attributes) are continuous and assumed to follow a normal (Gaussian) distribution. Here's a breakdown of how it works:

Key Concepts:

Naive Bayes: The "naive" part comes from an assumption that the features are conditionally independent given the class. It makes the calculation of the posterior probability for a given class simple.

Gaussian Assumption: In GNB, we assume that the continuous features of each class are distributed based on a Gaussian (normal) distribution. Each class has its own Gaussian distribution, with a mean and variance specific to that class. Bayes' Theorem: Bayes' theorem is adopted by the Naive Bayes classifier in order to foretell the probability of a class given the features. Bayes' theorem is:

$$P(C \mid X) = \frac{P(X \mid C) \cdot P(C)}{P(X)} \tag{5}$$

where:

P(C|X) is the posterior probability of class C given the feature vector X.

P(X|C) is the likelihood or the probability of observing the feature vector X given class C.

P(C) denotes the prior probability of class C.

P(X) denotes the evidence, or the probability of observing the feature vector X across all classes (this is often ignored when comparing classes since it's constant).

Gaussian Likelihood: For each feature xi in the feature vector X=(x1, x2,…,xn) the likelihood of the feature given the class Cis modeled as a Gaussian (normal) distribution:

$$P(xi \mid C) = \frac{1}{\sqrt{2\pi\sigma C2}} \exp(\frac{xi - \mu C}{2\sigma C2}) \tag{6}$$

where:

μC denotes the mean of feature xi in class C.
σC2 denotes the variance of feature xi in class C.

3.4 Evaluation Matrics

There are many metrics for evaluating metrics to validate the predictions made by each of the employed algorithms for the prediction of network slice. We choose some of them to evaluate our scheme at the end. A binary classifier's confusion matrix illustrates the predicted and actual labels from the problem of the classification by providing these four outcomes:

- True Positive (TP): Observation is positive, with the prediction of being positive.
- False Negative (FN): Observation is positive but with the prediction of being negative.
- True Negative (TN): Observation is negative, with the prediction of being negative.
- False Positive (FP): Observation is negative, with the prediction of being positive.

From the confusion matrix, the following list of rates are computed for the proposed model:

- Sensitivity calculates the extent to which the classifier can have predictions of the ROI as malignant. In fact, it is malignant.
- Specificity calculates the extent to which the classifier can have predictions of the ROI as benign. In fact, it is benign.
- F1−score measures the accuracy of the model, with a value that should be as high as possible for the high performance of the classifier.
- Matthews Correlation Coefficient denotes the balanced measure of the classifier's quality. It is better informative compared to the other measures of the confusion matrix in the evaluation of the binary classifier, even if the classes comprise varying numbers of samples, as it considers the balance ratios of the four confusion matrix classes (FP, TN, EN, and TP).
- Overall accuracy measures how often is the classifier correct.

Table 3. Evaluation metrics**.**

Evaluation metrics	Formula
Precision Positive Predictive Value	$\frac{TP}{TP+FP}$
Sensitivity (Recall) True Positive Rate (Sens.)	$\frac{TP}{TP+FN}$
Specificity (Spec.) True Negative Rate	$\frac{TN}{FP+TN}$
F1 Score	$\frac{2*Sensitivity*Precision}{Sensitivity+Precision}$
Accuracy (ACC.)	$\frac{TP+TN}{TP+FP+TN+FN}$

3.5 Load Analysis

Load analysis is another critical issue for service providers, as failure to achieve optimal analysis results in interference, connection establishment delays, and long queueing times. These issues not only result in significant revenue losses for businesses but also drive users to switch to other network service providers. Accurate load analysis helps with the efficient use of all available resources. It denotes an essential challenge for wireless service providers today. It requires intelligent architecture that can have automatic routes for all novel requests to the main chip, to avoid interference and connection establishment delays. Figure 9 illustrates the findings of simulating the machine learning model implemented over the first 24 hours. After completion, the model provides the number of users in a given time period. In order to test how much the proposed model is applicable, it has shown superior performance by generating efficient results concerning allocating an alternate slice in case of a single slice failure or overflow circumstances. The maximum utilization rate of 92% for a given network slice is chosen in this research. Thus, to guarantee reliable connectivity, automatic allocation, high security, and high throughput of the most appropriate network slice and optimal bandwidth size required concerning every single request.

4. Results and Discussion

4.1 Data Analysis

4.1.1 Network Usages

This refers to scenarios where the network is applied. Figure.4 provides a visualization of the network use cases for each of the three slices. Slice 1 exhibits the highest number of usages, primarily driven by smartphone usage. slice 2 demonstrates usages related to smart cities and IoT devices. On the other hand, slice 3 highlights significant use cases in public safety, smart transportation, and healthcare, with 2,000 instances each. Based on this analysis, it can be concluded that:

- Slice 1 is specifically designed for small-scale usage.
- Slice 2 caters to medium-scale usages.
- Slice 3 is tailored to accommodate large-scale usage.

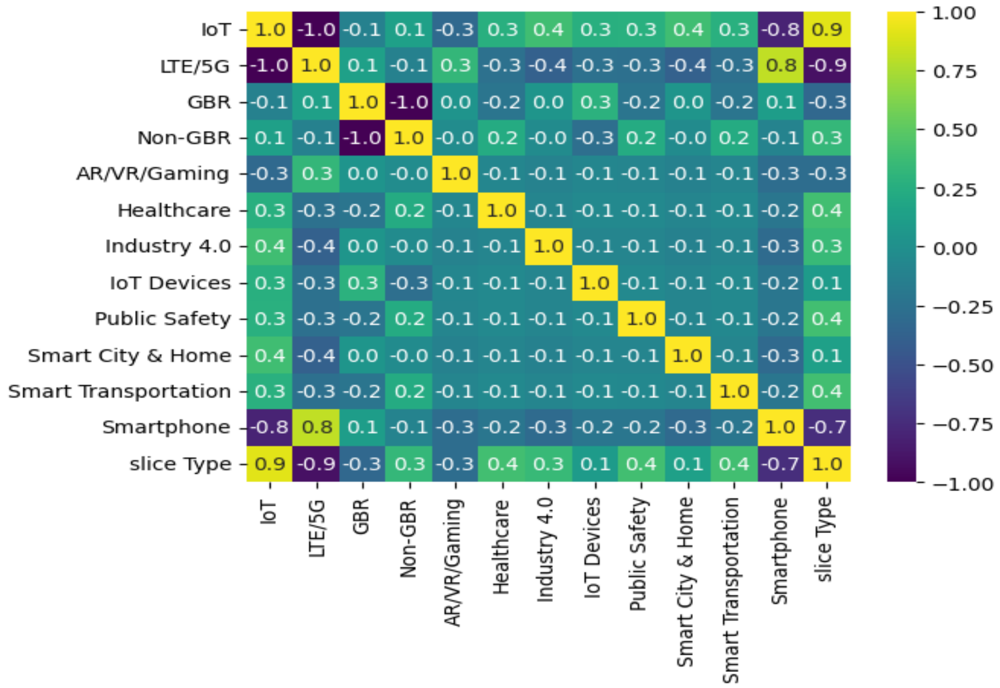

Figure 4. Dataset Heatmap

4.1.2 Network Performance Metrics:

These metrics are employed for the evaluation of the overall effectiveness, performance, and operation of the network.

4.1.2.1 Packet Delay:

Packet delay represents the time a datum packet takes to be delivered from the sender to the receiver. The characteristics of packet delay in different slices are shown below:

- Slice 1 shows a higher density of delays ranging from 50 to 140 ms.
- Slice 2 shows a wider distribution of packet delays, indicating greater variability.
- Slice 3 shows no significant relationship with packet delay, indicating stable and consistent performance.

In short, slice 1 suffers from concentrated delays, slice 2 has greater variability, and slice 3 shows stable performance with minimal delay variations.

4.1.2.2 5G/LTE category:

It is associated with the highest 5G/LTE network performance value, indicating its superiority in some aspects. In contrast, segment 1 has the lowest 5G/LTE network performance value, but it shows a denser distribution, indicating a more concentrated performance range.

4.2 Machine Learning Models

We assessed how effective our model is. We also examined numerical metrics, including R-squared, and mean-squared error, which comprehensively reviewed the performance of the model.

The results obtained in Table I show that SVM, KNN, and LR showed strong performance, with the accuracy of KNN, SVM, and LR reaching 95% As shown in Table 4. These results confirm the superior performance of SVM, KNN, and LR classifiers in segment prediction, making them the most reliable choices for accurate segment classification in this study.

Although the proposed framework performs well in stable network environments, it assumes relatively constant traffic patterns and network conditions. In dynamic scenarios, such as varying traffic volumes or user behavior, the model's accuracy could be impacted. Future work could focus on integrating real-time learning or adaptive models that adjust to changing network conditions. Additionally, handling network failures or anomalies remains an area for improvement, and exploring this could enhance the resilience of the framework.

Table 4. Performance of ML Algorithms

Algorithms	KNN	SVM	LR	GNB
Accuracy	95%	95%	95%	95%
precision	96%	96%	96%	96%
Recall	95%	95%	95%	95%
F-measure	94%	94%	94%	94%

4.3 Confusion Matrices

The confusion matrix for LR classifiers exhibited equal outcomes. In Figure. 6, the confusion matrix of the LR classifier. The classifier accurately predicted 1694 occurrences of slice 2. However, it made 2 incorrect predictions of slice 2 when the actual value was slice 2. Furthermore, the classifier predicted 517occurrences of slice 3 when the true value was slice 2. On a positive note, the classifier achieved perfect predictions for 5005occurrences of slice 1and 2259occurrences of slice 3.

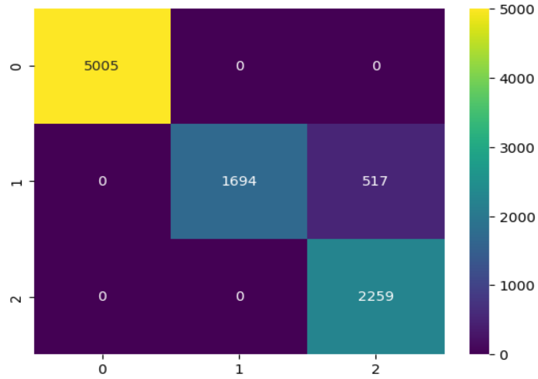

Figure 5. LR confusion matrix

In Figure 6, the confusion matrix of the KNN classifier is shown. The classifier accurately predicted 1694 occurrences of slice 2. However, it made 2 incorrect predictions of slice 2 when the actual value was slice 2. Furthermore, the classifier predicted 517occurrences of slice 3 when the true value was slice 2. On a positive note, the classifier achieved perfect predictions for 5005occurrences of slice 1and 2259occurrences of slice 3.

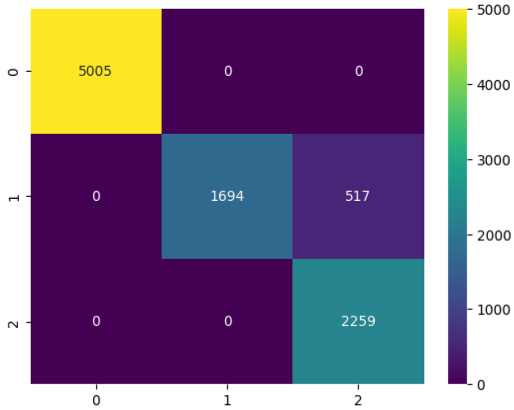

Figure 6. KNN confusion matrix

In Figure 7, the confusion matrix of the SVM classifier is illustrated. The classifier accurately predicted 1694 occurrences of slice 2. However, it made 2 incorrect predictions of slice 2 when the actual value was slice 2. Furthermore, the classifier predicted 517occurrences of slice 3 when the true value was slice 2. On a positive note, the classifier achieved perfect predictions for 5005occurrences of slice 1and 2259occurrences of slice 3.

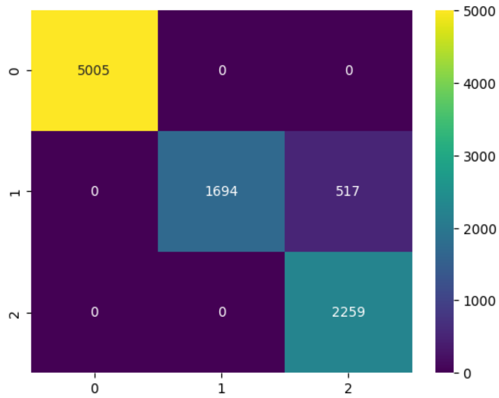

Figure 7. SVM confusion matrix

In Figure 8, the confusion matrix of the GNB classifier is given. The classifier accurately predicted 1694 occurrences of slice 2. However, it made 2 incorrect predictions of slice 2 when the actual value was slice 2. Furthermore, the classifier predicted 517occurrences of slice 3 when the true value was slice 2. On a positive note, the classifier achieved perfect predictions for 5005occurrences of slice 1and 2259occurrences of slice 3.

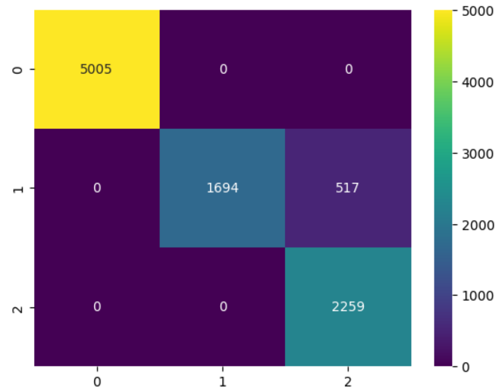

Figure 8. Confusion matrix for GNB

4.4 Load analysis

In a 24-hour simulation, about 31,584 user connections were made, of which 53.2% were mobile broadband services (Slice 1), 23.4% were high-density IoT services (Slice 2), and 23.4% were low-latency connections (Slice 3). As shown in Figure 9, all new incoming traffic is assigned a specific time-to-live (TTL). In Slice 1 in the first hour, for instance, there were 728 active users in a given time period. Slice 1 is assigned more TTL values than Slices 2 and 3 due to its higher bandwidth and large number of active users. It finally helps in analyzing user patterns and making the optimal decision according to the data collected from the devices connected to the network.

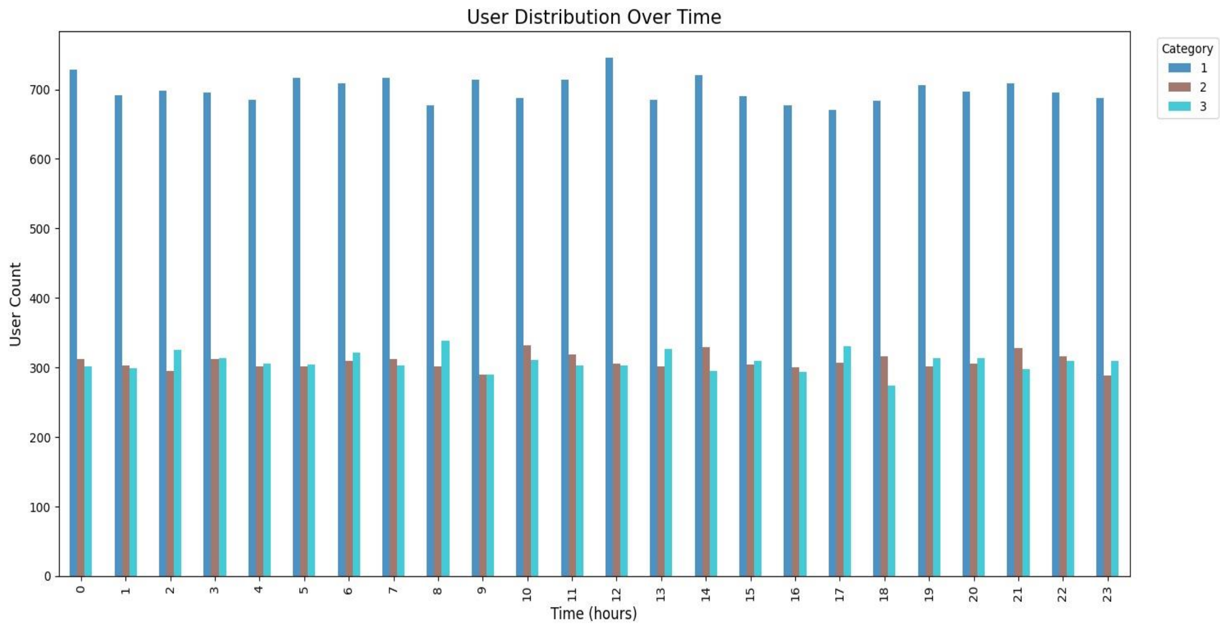

Figure 9. Load analysis for active users observed after every 1 hour

5. Conclusion

This study highlighted that incorporating machine learning algorithms is a valuable approach to accurately predict and classify network slices. This contributes to efficient resource allocation and optimizes network resource utilization. Data analysis revealed that slices 1, 2, and 3 are designed to meet the needs of small, medium, and large users and applications, respectively. By leveraging machine learning techniques, it was demonstrated that network segmentation can be automated, leading to improved network management and assumptions and increased network performance. Our analysis of a variety of performance metrics showed that machine learning algorithms, including but not limited to LR, SVM, GNB, and KNN classifiers, were effective in accurately predicting the optimal slice for incoming connections, with each achieving an accuracy score of up to 95%. For future work, this approach could be extended to support the more dynamic and complex requirements of 6G networks, where ultra-low latency, ubiquitous connectivity, and intelligent orchestration will be essential. Furthermore, integrating this machine learning-based slicing framework with advanced network management techniques, such as Software-Defined Networking (SDN) and Network Function Virtualization (NFV), could enable more adaptive and context-aware slicing strategies.

6. Patents: No patents were generated as a result of this research.

Supplementary Materials: No supplementary materials are provided.

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