Management and Evaluation of the Performance of end-to-end 5G Inter/Intra Slicing using Machine Learning in a Sustainable Environment

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***Abstract*—The 3G Partnership Project (3GPP) defined network slicing as a set of resources that could be scaled up and down to cover users' requirements. Machine learning and network slicing will be used together to manage and optimize resources efficiently. Sharing resources across multiple operators, such as towers, spectrum and infrastructure, can reduce the cost of 5G resources. In the proposed prototype, the end-user is connected to more than eight inter and intra-slices according to the demands. A set of slices is implemented over the 5G networks to provide an efficient service to the end-user using softwarization and virtualization technologies. Traffic is generated over multiple scenarios then End-to-End slicing traffic was analyzed after generating real-time traffic over the 5G networks. Also, all the features extracted from the traffic based on the flow behaviours and a set of elements selected from the datasets according to machine learning behaviours. Multiple machine learning algorithms are applied to our datasets using MATLAB classification application. After that, the best model is chosen to train and predict the slices using less CPU and training time to reduce the computational power in future networks and build a sustainable environment. Furthermore, the regression application predicts the slice type on the third dataset with the minimum squared error.**

***Index Terms*—5G, NFV, Network Slicing, Future Network, Inter-Slice, Machine Learning, Network Services, Intra-Slice, Resources Allocation, E2E.**

I. Introduction

End-to-End slicing is a new technology that promises to provide flexibility, more sustainability, better performance and lower costs in mobile networks. Network slicing enables operators to create multiple virtual networks on a single physical network, allowing for more flexibility and customizability using Software-Defined Networks (SDN) and Network Function Virtualization (NFV). In [1], the authors reviewed all the slicing issues and focused on employing a real-time management algorithm to regulate and manage the virtual network's resource distribution. In addition, network slicing benefits are highlighted with their advantages in future networks. The 5G End-to-End slicing (5GE2ES) also supports using unlicensed spectrum, which could help reduce costs and improve efficiency [2]. The 5GE2ES significantly improves the performance of mobile networks by reducing latency, jitter, and packet loss. It also enables sharing resources among different types of traffic, resulting in more efficient use of network resources [3]. The main idea of using the NFV in future telecommunications networks is to optimize the functions and services built for future networks. While using the SDN is used to optimize the fundamental system [4]. In future networks, all functions will be implemented and reconfigured on top of the virtual networks to provide scalability and reduce energy. Regarding scalability, the network resources such as computing and storage will be scaled up and down dynamically according to the Service Level Agreement (SLA) between the customers and the service provider [5]. The network slicing concept and Network Slice Subnet Instance (NSSI) function are explained in the 3GPP TS 28.801. Also, the QoS standard values with the priority level are highlighted in 3GPP TS 28.801. Based on the 3GPP TS, there are different types of services: enhanced Mobile Broadband (eMBB), ultra-Reliable Low Latency Communications (URLLC) and Massive IoT (MIoT). In addition, inter-slice mobility management in 5G networks is identified in [6] by reviewing the 3GPP TS 23.501 and 23.502 which discussed mobility management for different types of traffic that have different service requirements. In [6], the authors highlighted that in the 3GPP TS, the continuity between the services was not explained clearly. In [7], authors worked with different types of services to improve the performance of these services on 5G systems and beyond for numerous industrial applications.

Our state-of-the-art research in [1] identified future research directions in this area. The main advantage of using a slicing technique for resource allocation in 5GE2ES is reducing costs and enhancing performance. The performance was evaluated and enhanced in [3] after sending traffic over different slice scenarios. All traffic flows are collected from the system and saved as a dataset. This paper will continue the work by reducing the cost and energy usage in the 5GE2ES model. Moreover, this paper is an extended version of the work initially published in SoftCOM 2022 [3].

The main contribution of this research is to create green

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networks on top of the 5GE2ES networks. In addition, to allocate the resources for the inter and intra slice in the 5GE2ES will employ multiple machine learning algorithms and choose the best model that fits our datasets with less energy usage and less training time to reduce the energy consumption.

The future telecommunication networks will support various services with different Quality of Service (QoS) demands, such as lower latency, higher data rates, and higher capacity. However, machine learning techniques need to be used to predict traffic patterns. In [8], supervised learning is used to predict 5G non-standalone coverage and the performance of the networks. Their model was trained with a labelled dataset using a Support Vector Regression (SVR) model in different scenarios. Their future prediction depends on past learning experiences. Supervised learning [9] is proposed to predict the traffic resources to ensure the QoS of the 5G services.

The research structure is organized as follows: Section II summarises the literature review on the 5G resources allocation and the related works that used machine learning algorithms to classify and analyse the traffic over the slices. In Section III, we propose our slicing prototype to implement and send traffic over the 5GE2ES systems. In Section IV, we highlight our slicing scenarios. In Section V, we clean our dataset for analysis and training. In Section VI, classification and regression analysis are present in our datasets. After that, In Section VII, we explain and evaluate our results. Finally, Section VIII concludes this paper and highlights future works.

II. Literature Review

All telecommunication systems will be programmed and virtualized with one network that fits all services to enhance the performance of the services, reduce the cost and consume energy in future networks. Network slicing will provide flexibility and scalability to all network layers, from the radio access to the core layer. The slices will be selected from programmable services according to the users' needs. The service providers can share the same physical infrastructure with multiple isolated logical networks. Moreover, each logical network will have different QoS, priority and cost. In this section, we will discuss all the related work on slice management and resource allocation for future work.

Learning-based energy-efficient proposed in [10] for resource allocation in the radio access network and NFV in the 5G networks and beyond. The proposed algorithm can jointly optimize the radio and NFV resources to minimize the network's energy consumption while meeting the users' QoS requirements. Moreover, manage the 5G resource dynamically proposed in [11] based on reinforcement learning. Their scheme is designed to optimize the resource utilization of network slices using a Markov Decision Process (MDP), while Q-learning is used to guarantee the QoS of each slice. Further, End-to-End resource allocation is proposed in [12] for heterogeneous networks. Their study aimed to optimize energy efficiency to reduce operational expenditure. Integer linear programming was used to manage the allocation of 5G resources. Additionally, there were fewer physical lines between the source and the destination, which reduced latency for their End-to-End networks [13]. Additionally, authors in [14] designed particular resource blocks for each slice to meet QoS requirements and increase long-term throughput. Future telecommunication systems offer a centralised and distributed learning using reinforcement algorithm to meet user requests in the ground and satellite networks as explained in [15]. The radio access network's services would function better with time scaling, as proposed in [16].

The idea of generating distinct, isolated networks inside a single 5G network is called the isolation concept in 5G network slicing. This can help to increase performance and security and gives users more flexibility and control over how different areas of the network are used. In network slicing for future networks, many problems and difficulties were discussed in [17] to enhance the continuity and scalability of the user experience. A new solution for managing mobility should be created to provide seamless changeover for 5G new radio in network slicing. The management of mobility is divided into two levels of mode: idle mode for user reachability and connected mode for handover, making mobility one of the major concerns in a service level for future networks [18]. According to the explanation of the mobility management architecture in [19] based on network slicing, each slice maintains its users across various radio access technologies. The slice configuration and service characteristics for each slice in this architecture regulate several requirements, including latency and speed. The full potential of 5G End-to-End slicing will only be realized when used with other complementary technologies such as edge computing, which can provide low-latency access to data and applications closer to users [20]. While 5G End-to-End slicing presents many potential benefits, some challenges need to be addressed, such as the need for new standards and protocols, ensuring interoperability between different network elements, and ensuring the security and privacy of user data [21].

With a real-time application, the relationship between these connections could be one-to-one or one-to-many. A model optimization approach is applied in [22] using mixed-linear integer programming (MILP). In the end, the authors were able to replicate the 5G core network and slice request, and their simulation result was adequate but still needed improvement. The complexity of the 5G network is addressed in [23], which comprises two Service Function Chains (SFCs) for each user within a slice. Traffic is sent over the slices in the 5G networks and classified and predicted using supervised learning algorithms. Real-time dynamic service allocation occurs for 5G services to programme and predicts the slice decisions; authors used an open-source code in their work [24]. After capturing real-time traffic, the Markov decision procedure was built to anticipate the slice resources and the time for each service in the heterogeneous networks [25]. In End-to-End slicing networks to maximise the heterogeneous needs, the same technique is presented in [26] to govern multi-agent slices. Additionally, Markov chain algorithms proposed in [27] on Vehicle-to-Road slice to deal with video application scenarios to improve multimedia services during video transmission to improve QoS, Quality of Experience (QoE), the efficiency and safety for the 5G slices while the vehicle is moving from one location to another. In addition, feedback from 5G users was gathered via an online survey platform to identify potential tactics for 5G-VINNI stakeholders' experimentation-as-a-service [28]. To forecast DDoS attacks on 5G systems, machine learning algorithms were developed in [29]. Their model's accuracy was 98% during training and 96% during testing. On the other hand, authors in [30] applied Support Vector Machine (SVM) and Random Forest to accurately forecast antenna selection in MIMO channels and detect various attacks, and their accuracy was almost 100%. The K-nearest neighbour (KNN) technique was proposed in [31] with multi-slice scenarios to estimate the slice boundary from their graph datasets based on two parameters: cost and error to deliver the slice resources on time.

Utilizing Long Short-Term Memory proposed in [32] where deep learning was used to regulate autonomous slices dynamically in terms of slice isolation and sharing (LSTM). In a radio portion, CNN-LSTM predicts the channel state for two types of 5G services. Additionally, a mathematical model based on deep Q-Networks was established for performance optimization in energy efficiency [33]. To give an effective result for IoT vertical slice, it was suggested in [34] to utilise machine learning techniques to lower the cost of slice selection and prediction. Based on past data, LSTM is utilised to estimate the utilisation of the VMs over the short and long term. Scaling slice resources and lowering SLA costs are accomplished in [35] through forecasting algorithms. Furthermore, utilising machine learning methods, it was proposed in [36] to save computational power while forecasting user behaviour and providing adequate resources for the users. To assess the model's performance, mean absolute error and mean absolute percentage error was utilised in their research.

In recent years, both business and academia have paid close attention to the development of 5GE2ES. With the help of this technology, operators could offer various 5G services with dedicated network resources, improving performance, cost-effectiveness, and sustainability. By allocating specific resources for various services, 5GE2ES could enhance the service performance and the user experience. For high-definition video streaming, a different slice could be set to assure buffer-free playback [37]. By sharing resources among various services, 5GE2ES could help service providers to reduce the cost of their network infrastructure [38]. For instance, mobile broadband and ultra-low latency services could be offered by a single 5G base station. Using energy-saving technologies such as network function virtualization and 5GE2ES could assist service providers in lowering their carbon footprint to create sustainable environments [39]. In terms of complexity and security, a single SDN controller will not be able to manage the resources in the future network and meets the demands for real-time traffic, especially with complex scenarios such as virtual reality and augmented reality [40].

Different service providers' planned primary slice in [41] that combines sub-slices to deliver 5G services to users. The 5G data was also saved in a SQL database, and numerous SDN controllers were bound together to provide flexible and dynamic resources. The SDN networks produced dynamic resource allocation for the inter and intra slices on the 5G networks, and these resources were assigned to the slices using the SDN controller [42]. To anticipate the optimum choices for allocating the 5G resource for the sub-slice, the neural network is used to analyse the network, including traffic loads and resource availability [43]. The online lazy-migration adaptive interference-aware algorithm was used to deploy the 5G virtual functionalities. Resource migration also uses the same algorithm. In [44], the reward was maximised for the requested service when the user requested it. Multi-layer slicing proposed in [45] on the edge cloud was managed by 5G resources to deal with autonomous vehicles connected to End-to-End slicing networks over the transport layer. Network as a Service (NaaS) is also involved in slice management in [46] for End-to-End 5G networks to separate the 5G slices belonging to various service providers when those service providers disseminate their services over the End-to-End networks. On the other hand, in [47], multiple 5GE2ES scenarios are used to deal with diverse services connected with smart grids to offer flexibility and individualised 5G services.

This study will discuss machine learning algorithms based on supervised learning to categorise 5G traffic and forecast the slices. The mathematical formula will be explained in full when adding. The link between the number of accurate forecasts and the overall number of predictions is viewed using accuracy. The accuracy calculation below assesses how well the predictive model works. Where the True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives components of the accuracy formula (FN) [48].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Mean Square Error (MSE) [35] is the average square of the difference between the value predicted and the value obtained:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad (7)$$

Root Mean Square Error (RMSE) [35] is the square root of two of the differences between the forecast and the actual value:

$$RMSE = \sqrt{MSE} \quad (8)$$

R2 [35] is between the actual value and the predicted value; it is the coefficient of determination, which is the square of the multiple correlation coefficients.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - Y_i^-)^2} \quad (9)$$

where Y_i^- is the mean value of Y at observation time, $\hat{Y}_i$ is the predicted value, and Y_i is the actual value.

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Network slicing faced numerous difficulties in 5GE2ES systems, particularly in resource management and virtualization. The requirement to handle numerous distinct services with various requirements in a single, shared infrastructure is one of the significant issues. Resource management and

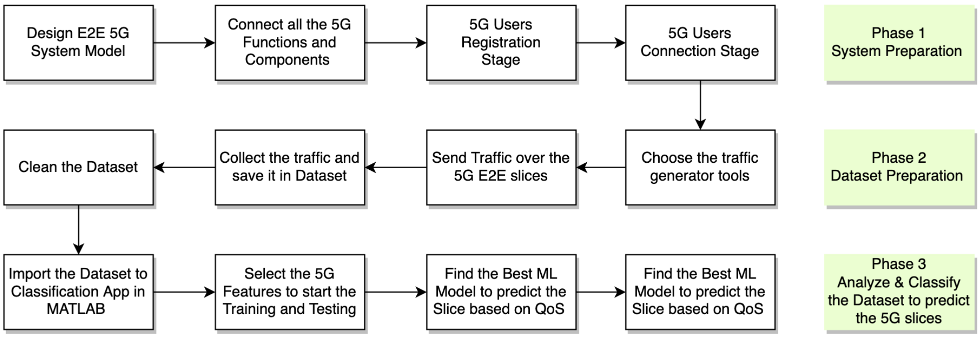


Fig. 1. System Framework

coordination are necessary to avoid conflict and guarantee service quality. Adding, reducing operating expenses (OPEX) as much as possible and increasing the income. Furthermore, troubleshooting and diagnosing issues may be challenging with 5G systems due to their high level of virtualization and abstraction. According to the authors' knowledge, none of the aforementioned research papers addresses how 5G could address unresolved research problems, including resource allocation, mobility, and slice management. We will send and gather the traffic to solve one of these issues, then anticipate the 5G slices using the best machine learning model that fits our dataset. We will propose a collection of slices on top of the 5G core using open-source code. The user's QoS and QoE must be improved when more services are added to future networks. It will also enable simultaneous connections to numerous slices. After that, we will choose the best model to train and predicate the resources with less CUP usage to reduce computational power and create sustainable networks for sustainable environments.

Softwarization methods are built based on SDN and NFV and will be used to create this system. According to the 5G functionalities, all NFs will be realised. As we discussed in the literature, the term "5G" refereed to a wireless network standard developed by several telecommunications entities to improve the capacity, coverage, and speed of data transfer in logical networks as opposed to traditional networks. Real-time dynamic programming services were added to the future networks based on use case demand according to the compensation between softwarization, virtualization, and 5G features.

Figure 1 summarized the methodology framework for the End-to-End 5G slicing system to analyse and predict the 5G recourse's using the best-fit model for our datasets. Our system framework contains three stages. In stage one, we must prepare an End-to-End 5G Slicing model to collect slicing traffic. All the available projects in our paper [1] and two open-source code projects selected one for the 5G functions [49] and the second for the 5G users and RAN [50]. Then, all the 5G functions should be connected and placed in the 5G core and UPF in the user plan and connected to the RAN. All the 5G users will be registered and connected to the 5G networks. In stage two, traffic will be sent over the slices from the user's device to the DNN. Later, slicing traffic will be collected and saved in different files after sending traffic by the traffic generator tools and Iperf. Data files must be cleaned from unwanted data and labelled before moving to stage three. In stage three, The collected traffic will be analyzed after choosing specific features for training to predict the slices based on user demands. More details about each step will be explained in depth in our system model part and machine learning part.

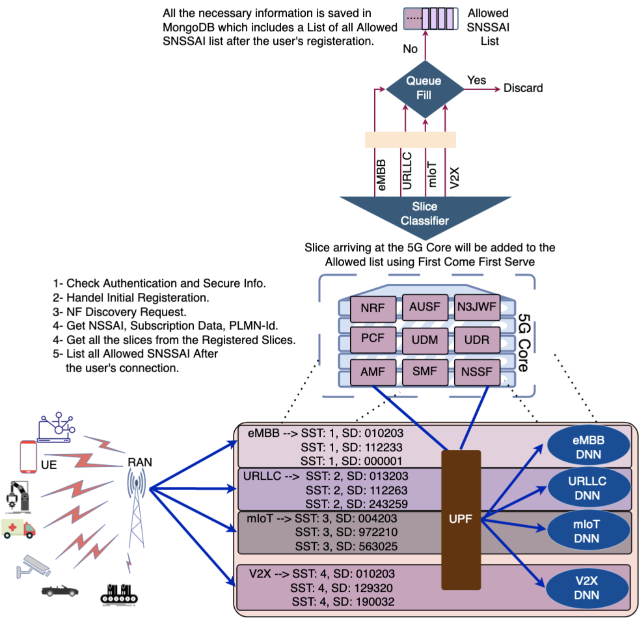


Fig. 2. System Design

From Figure 2, the user plane functions connected to all slice types (inter and intra slice) in the physical layer as virtual Tenants linked with the radio access network and the data network. This layer will be connected with the 5G core layer, which contains all the functions and entities needed to control the 5GE2ES networks. Further, when the user registers to the 5G networks, all the slice details will be saved in MongoDB. Then in the connection stage, the user will connect to the slices available in the SNSSAI-allowed list only. The Proposed 5GE2ES model will be built on top of 5G emulator open-source code for the 5G core [49], and UERANSIM open-source code is used for the users, and radio access network [50]. The 5G core uses the N4 interface to configure and change the slice resources and services. The user plane's slices, including slice policy, data flow, and slice management, must be managed by the 5G core. All upcoming networks must implement all 5G core network slices to control users on the user plane. Additionally, according to the needs of the slice management in the future network, all 5G functions will be programmed in the core network and subsequently executed in the user plane.

III. Traffic Generation Scenarios

Inter and intra slice were configured over the 5G core, UPF and RAN. Each user can connect to more than eight slices and generate traffic over them based on the user's requirements. Multiple scenarios are considered to be running over the End-to-End 5G networks to evaluate the QoS of the networks after sending multiple streams using traffic-generated tools, as is shown in Table I. Traffic is generated over the slices and the 5G core. The number of packets in scenario 2 was 10000 packets sent over seven slices, then the number of the slices increased to eleven by adding a new user. After the new user was added to the system and connected to the new four slices, the average transmission rate increased by 1.425 Mbps.

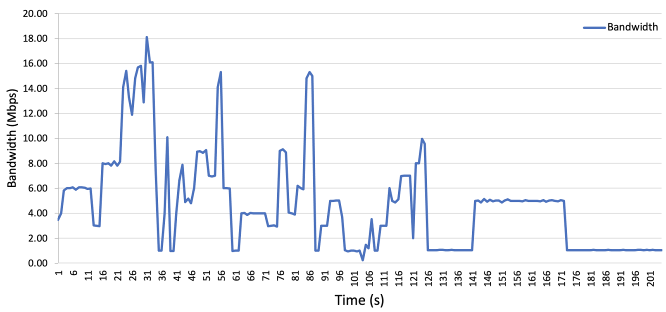


Fig. 3. bandwidth sent over the slices

In Table I, when the slices are given to the users based on their needs, as is provided in scenarios 2, 3, 5 and 7, the average transmission rate is between 57 Mbps and 70 Mbps. On the other hand, when the users connect to all the slices listed in the allowed list, the average transmission rate is higher than 70 Mbps, as given in scenarios 6 and 8. In addition, all these scenarios are sent the same amount of packets over the networks. All the scenarios discussed in depth in our paper [3]. After the user connects to the 5G core, traffic generator tools such as iperf and GTP are used to send traffic over the slices to measure the performance for the End-to-End slicing. The traffic will be sent to the data network via the virtual tunnel for each slice. Traffic generators will send packets containing TCP, UPD, ICMP and ARP to check network diagnostics. The traffic is sent over Inter and intra slices to evaluate, enhance the network performance of slices and reduce the cost. The bandwidth is sent over the End-to-End 5G slicing is shown in Figure 3.

IV. Analysis

A. Cleaning the Data Files

In this section, data files will be analysed to prepare our datasets for the following stages, which are the training and testing stage.

1) After the traffic is generated, the data will be gathered in files.
2) Unwanted data and commands will be removed, such as slice IP address, 5G core IP address, UPF IP address and the commands for the traffic generated tools and Iperf.
3) Unsuccessful traffic will be removed from the file.
4) All the units need to be the same for each row in a related column. For example, ms, KBite and Mbits. Then all units will be removed to deal with numerical data.
5) Remove the duplication, all NaN values and zeros from the datasets.
6) Filter all files by removing all signs such as space, slashes and hyphens.

B. Datasets Preparation

The traffic is sent over the slicing from the 5G users through the user plane function to reach the DNN. All data collected in a file and a new dataset need to be prepared for the analysis stage. The pcaps files will be checked first, and the data in these files are already labelled as follows: Number, Time, Source IP, Destination IP, Time-delta, Protocol name, Packets Length and Packets Information. Irrelevant data, such as The number and Packets Information columns, will be removed from these files. In addition, the Data cleaner application in MATLAB will be used for organising and cleaning the data from null values and replacing it with NaN. The datasets will be called dataset1 and dataset2. After connecting 100

TABLE I
Apply Different Scenarios to check the slices' performance [1]

Scenarios	Users	Number of the Slices	Slices	Packets	Average TR	GTP Streams
Scenarios 1	1	9 slices for UE1	9 Slices	1000	45.98762342 Mbps	24
Scenarios 2	3	UE1: 4, UE2: 2, UE3: 2	7 Slices	10000	63.1267305 Mbps	40
Scenarios 3	4	UE1: 4, UE2: 2, UE3: 2, UE4: 4	11 Slices	10000	64.55263382 Mbps	33
Scenarios 4	3	9 Slices each UE	27 Slices	140000	65.203378 Mbps	78
Scenarios 5	6	UE1,2,3,4: 9 , UE5,6: 4	44 Slices	10000	69.946225 Mbps	132
Scenarios 6	7	9 Slices each UE	63 Slices	10000	71.416840 Mbps	189
Scenarios 7	11	UE1: 6, UE2: 10, UE3,6,7: 9, UE4,5,9,10: 4, UE8,11: 5	69 Slices	10000	57.03236434 Mbps	207
Scenarios 8	100	8 Slices each UE	800 Slices	10000	135.9415505 Mbps	2400

users and sending traffic over 800 slices, all data is saved as log files, cleaned from unwanted values and commands and saved in text files. Python command is used inside the Ubuntu server to extract the columns needed to prepare the dataset. The dataset will be labelled as follows: Time, Transmission Rate, Bandwidth, Jitter, Latency Average, Latency Maximum, Latency Minimum, Standard Deviation and Network Power. Furthermore, a data cleaner application will clean the data from null values and replace it with NaN. The datasets will be called dataset 3.

C. Preparation Before Training

All dataset files will be filtered for the training stage. all the noisy and redundant data will be removed from the files, and unwanted columns will be dropped before further processing the datasets. The framework for Datasets 1 & 2 in Figure 4 and the framework for Dataset 3 in Figure 5.

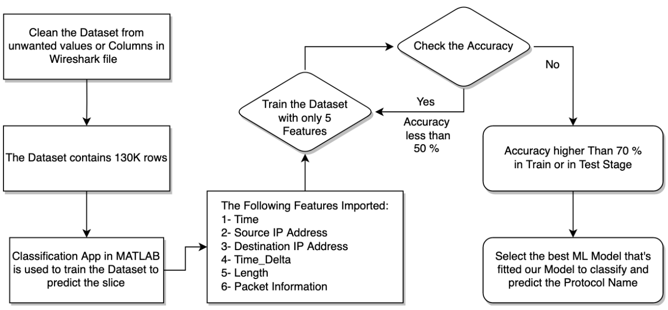


Fig. 4. Preparation Steps for Datasets 1 & 2

1) The dataset1 and dataset2 will be trained after selecting five features and dropping the Packets Information column from the trained features.
2) The dataset3 will be trained after selecting seven features out of nine features and dropping the latency Min and latency Max columns from the trained features.
3) Importing the datasets to Matlab for training and prediction. After extracting several slices and the cleaning process, the datasets will be ready for the training.

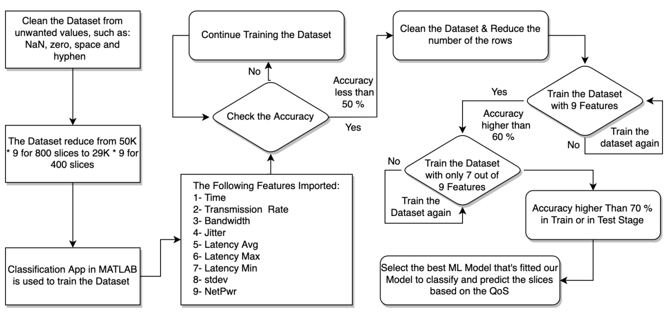


Fig. 5. Preparation Steps for Dataset 3

V. Machine Learning Model

A. Classification Model

In this research, we will classify the 5G traffic for different services using machine learning in Matlab. The idea of using different machine learning algorithms is to choose the best model that's fitted our purpose. We need to apply an algorithm with good accuracy and less training time to decide to choose the services faster to reduce the usage of the computational power in 5G networks. The classification model will help us identify our dataset's best algorithms. Our dataset contains Traffic time, source and destination address, protocol name, packet length, and packet information. Different protocols are generated over the 5G systems, such as: TCP, UDP, ICMP and HTTP. In MATLAB, we will identify all columns as input features except the service name will be the output. Machine Learning Model Classification for the prototype are shown in Tables II, III and IV. Machine Learning models enhanced the prediction accuracy values as shown in Tables II and III. Also, we got higher accuracy compared with the work in [51]. In our system, different types of traffic are classified over the 5GE2ES network. Accuracy is our concern; we must predicate future services in less time. For this reason, the medium tree model has less training prediction time than other models.

TABLE II
Classification Model for Dataset1

Class	Classification Model	Accuracy Validation	Prediction Speed (obs/sec)	Training Time (sec)
Trees	Fine	99.2%	1200000	10.358
	Medium	97.0%	1100000	9.0747
	Coarse	89.3%	950000	11.486
	Optimizable	99.3%	1000000	229.09
SVM	Linear	80.1%	4900	50947
	Quadratic	79.2%	390	67292
Ensemble	Boosted Trees	98.8%	81000	184.95
	Bagged Trees	98.8%	74000	218.69
	RUSBoosted Trees	32.2%	75000	113.76

TABLE III
Classification Model for Dataset2

Class	Model	Accuracy Validation	Prediction Speed (obs/sec)	Train Time (sec)
Trees	Fine	99.9	1900000	13.205
	Medium	99.9	1300000	14.036
	Coarse	99.6	1200000	20.228
	Optimizable	100	1800000	302.5
Ensemble	Boosted Trees	99.9	69000	255.79
	Bagged Trees	99.9	70000	545.29

The classification model for our dataset3 contains nine features which are: the time, transmission rate, bandwidth, jitter, latency Avg, latency Min, latency Max, standard deviation and network power. After extracting several unique slices and the cleaning process, dataset3 will be ready for the training. Finally, dataset3 was imported to Matlab for training and prediction. We only trained and tested seven out of 9 features, and the result is shown in Table IV.

In Tables II, the Optimizable trees model has the highest accuracy. In this model, the estimation of the minimum classification error was 0.8453, and the maximum number of splits was 2. On the other hand, the observed minimum classification error was 0.0065409, and the maximum number of splits was 182. In addition, for the bestpoint hyperparameters, the

TABLE IV
CLASSIFICATION MODEL FOR DATASET3

Class	Model	Accuracy Validation	Prediction Speed (obs/sec)	Training Time (sec)
Tree	Fine	49.8	1100	2.4809
	Medium	44.9	1100	2.0005
	Coarse	29.8	850	2.4566
	Optimizable	50.7	840	43.201
KNN	Fine	73.2	540	2.4577
	Medium	39.5	530	2.4911
	Coarse	22.0	490	2.5228
	Cosine	39.5	520	3.0023
	Cubic	38.5	530	2.5609
	Weighted	70.2	470	3.1235
	Optimizable	71.2	470	61.838
Ensemble	Boosted Trees	62.9	250	11.151
	Bagged Trees	77.1	250	11.709
	Subspace Discriminant	62.4	130	11.791
	Subspace KNN	71.7	130	11.24
	RUSBoosted Trees	29.3	310	14.287
	Optimizable	79.0	21	1593.4
	Hyperparameter	75.1	450	384.9

maximum number of splits was 258 using the Twoing rule as a split criterion as shown in Figure 6.

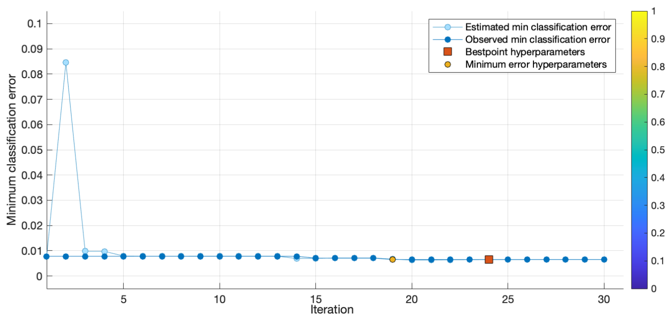


Fig. 6. Minimum Error for Optimizable Trees in Dataset1

In Tables III, the Optimizable trees model has the highest accuracy. In this model, the estimation of the minimum classification error was 0.0001351, and the maximum number of splits was 17612. On the other hand, the observed minimum classification error was 0.00014952, and the maximum number of splits was 282. In addition, for the bestpoint hyperparameters, the maximum number of splits was 469 using the Twoing rule as a split criterion as shown in Figure 7.

In Tables IV, the Optimizable Ensemble model has the highest accuracy. In this model, the estimation of the minimum classification error was 0.31018. AdaBoost is used as an Ensemble method, the number of learners was 39, and the maximum number of splits was 1. Furthermore, the observed minimum classification error was 0.48165. The maximum number of splits was 142 and the learning rate was 0.021339. Adding, for the bestpoint hyperparameters, the maximum number of splits was 108. The bag is used for this model as an Ensemble method and in total, the number of learners was 497 as shown in Figure 8.

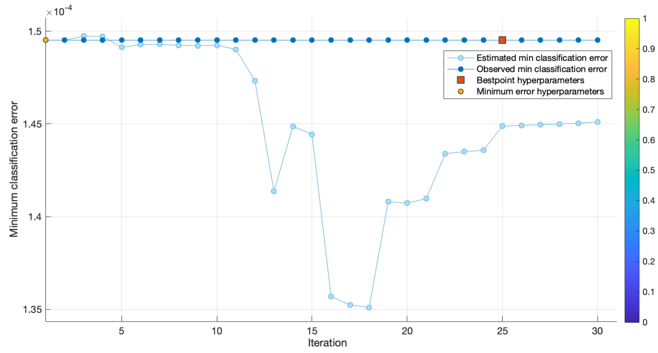


Fig. 7. Minimum Error for Optimizable Trees in Dataset2

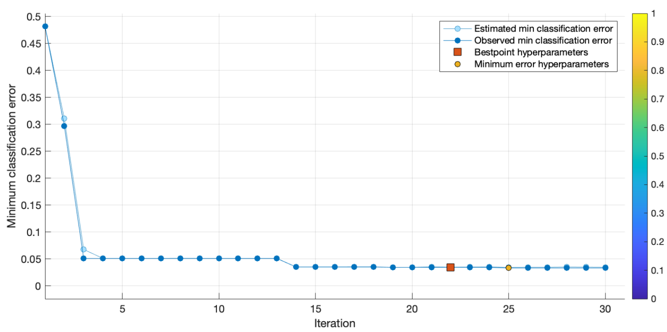


Fig. 8. Minimum Error for Optimizable Ensemble in Dataset3

B. Regression Model

Each machine learning model includes regression analysis to measure the effectiveness of the regression class in terms of the Root Mean Square Error (RMSE), coefficient of determination (R2), Mean Squared Error (MSE), and Mean Absolute Error (MAE). When the regression models are applied to dataset 3, the error in each model is discovered. As illustrated in Table V, we aim to anticipate the slice's resources with a lower prediction error. In terms of slice prediction with the least amount of error, Tree and Ensemble was the best model. The optimizable trees also have decreased RMSE from Table V, which aligns with our objectives.

When we compared each model's RMSE, training time and prediction speed, the optimizable trees had less RMSE. On the other hand, if we choose the model based on the training time, the Least Squares Regression Kernel (LSR Kernel) had less training time than other models, as shown in Figure 9.

VI. DISCUSSION & EVALUATION

In this part, we will describe our prototype and the process we used to create the traffic for the 5G networks. The Ubuntu server runs Free5gc, necessary for the 5G core on the core layer. The User Plan Function (UPF), used for the access layer, is executed on the Ubuntu server and links to another server with UERANSIM, which is used for the user device and the Radio Access Layer (RAN).

Both the 5G core and the slices create traffic. Wireshark was used to gather the traffic from the core and user planes. Using the Wireshark file, we evaluated the network's latency, throughput, and window size on several streams. Following

TABLE V
PREDICTION MODEL FOR THE 5G DATASET3

Class	Regression	RMSE	R2	MSE	MAE
Tree	Fine	22.186	0.82	492.2	4.8135
	Coarse	38.37	0.48	1472.3	13.877
	Medium	29.654	0.69	879.38	8.7489
	Optimizable	20.076	0.86	403.04	3.9768
Ensemble	Boosted Trees	27.666	0.73	765.42	6.3685
	Bagged Trees	31.471	0.65	990.42	7.9889
	Optimizable Trees	22.133	0.83	489.87	4.6022
Kernel	SVM Kernel	52.488	0.02	2755	22.428
	Leaset Squares Regression Kernel	45.982	0.25	2114.3	18.672
Gaussian Process Regression	Rational Quadratic GPR	33.896	0.59	1148.9	6.8438
	Squared Exponential GPR	37.226	0.51	1385.8	10.497
	Matern 5/2 GPR	35.086	0.56	1231.1	7.9287
SVM	Fine Gaussian	39.725	0.44	1578.1	8.1309
	Linear	144.7	-6.45	20939	24.892
	Medium Gaussian	37.379	0.50	1397.2	8.6841
	Coarse Gaussian	45.484	0.26	2068.8	15.396
Linear Regression	Robust Linear	48.598	0.16	2361.8	17.386
Stepwise Linear Regression	Stepwise Linear	67.818	-0.64	4599.3	17.739

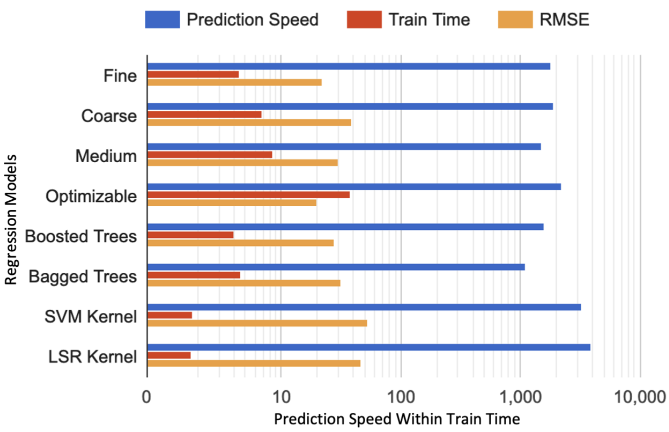


Fig. 9. Performance comparison of Regression Models

a TCP traffic via the slices, Figure 10 shows the number of packets delivered from the users' slices to the 5G core and the user plane function.

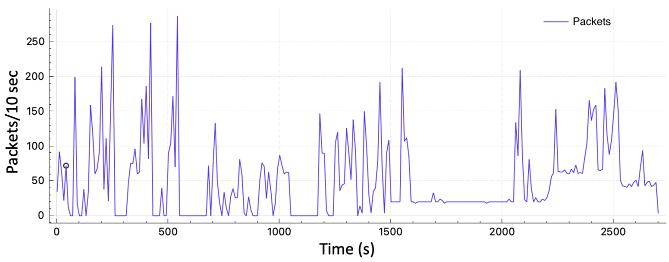


Fig. 10. The number of packets sent to the 5G Core

The number of packets sent from the user slices to the user plane function is seen in Figure 11.

The number of packets sent from the slices over time in

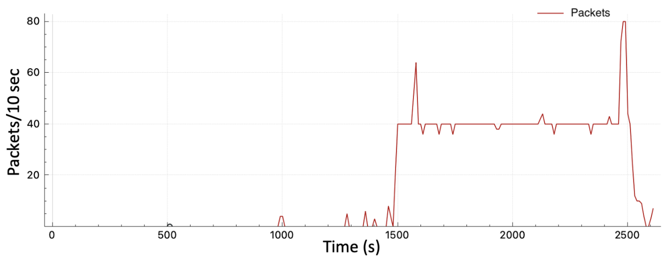


Fig. 11. The number of packets sent to the UPF

Steven's graph is shown in Figure 12 after sending one stream.

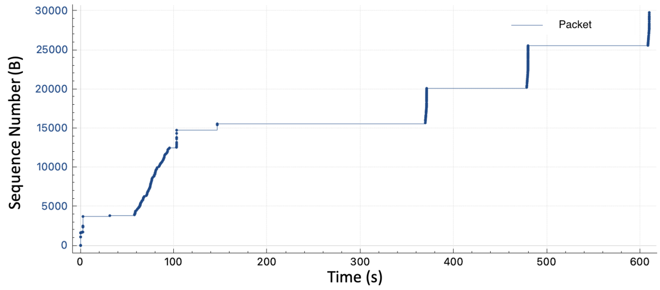


Fig. 12. Steven's graph for TCP traffic one stream

The time a packet takes to send from the user plane to the slices while using the TCP protocol. Round-trip time (RTT) is displayed for one stream in Figure 13.

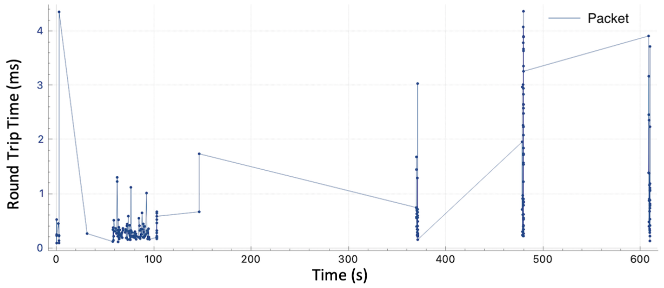


Fig. 13. Round Trip Time for one stream

Figure 14 shows the throughput sent from the online server with IP address 140.110240.80 to the 5G core network. The segment length is shown in blue dots, and the throughput is shown in the brown line.

The throughput sent over the slices is shown in Figure 14 after sending 45 streams.

A computer network protocol called Stream Control Transmission Protocol (SCTP) allows for message transmission in communications at the transport layer. The number of the packets is shown in Figure 15. It resolves various issues with TCP and UDP. The standard header and the data chunks make up each SCTP packet.

After applying many scenarios, we built a high-stress 5GE2ES environment with the help of this deployment as explained in [3]. The traffic was gathered and recorded as a dataset. Before using machine learning to analyse and categorise the traffic, we cleaned the dataset as discussed in

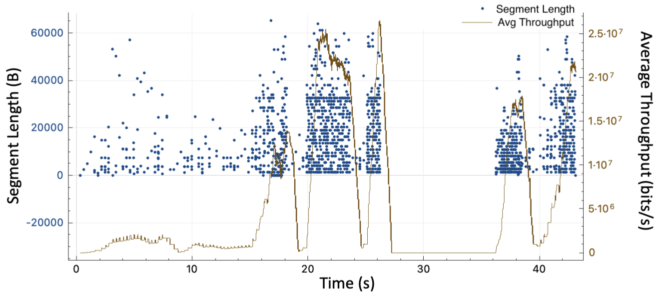


Fig. 14. Throughput over the 5G core after 45 streams

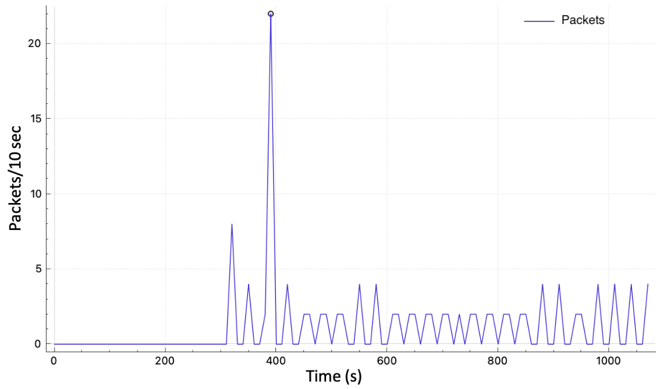


Fig. 15. SCTP over the 5G core

Section VI. Now, we will compare the common algorithms between the datasets and our results with the current research papers.

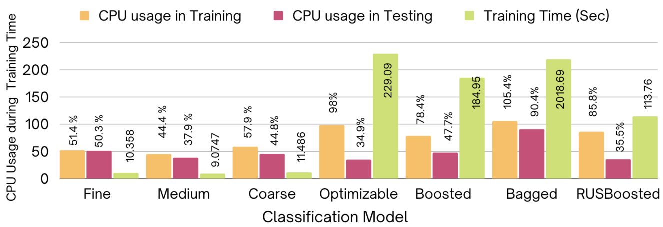


Fig. 16. Computations Power Comparison For Different ML Models for one user eight slices

When traffic is distributed over eight slices for a single user, computational capacity for various machine learning methods is suggested in Figure16. Our dataset is trained using decision trees, as seen in Figure 16. Less than other models, medium trees used 44.4% of the CPU and took 9.0747 seconds to train. Additionally, CPU consumption was lower than the medium tree, with 34.9% and 35.5% for optimizable and RUSBoosted trees, respectively. On the other hand, as shown in Figure 17, the optimizable tree's accuracy was 99% for both validation and testing, while training took longer. Accordingly, the accuracy of medium trees, which is 97% for our model, is the best.

The processing capacity for various machine learning techniques is shown in Figure 18 when the traffic is transmitted through eight slices for three users.

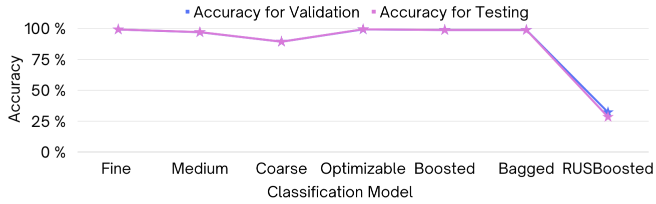


Fig. 17. Comparison between the Accuracies

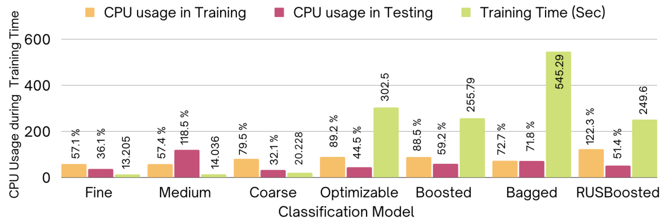
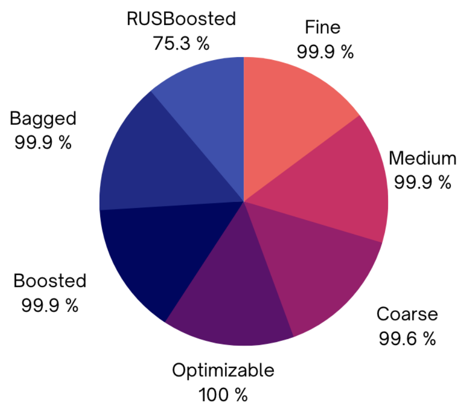
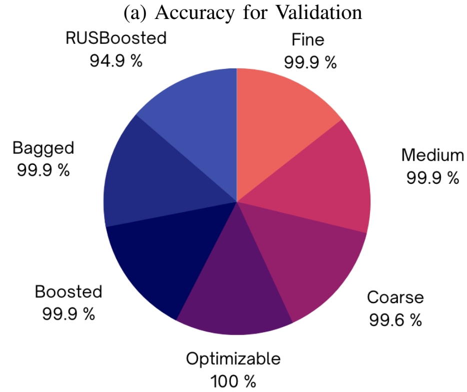


Fig. 18. Computations Power Compression For Different ML Models for three users eight slices each

The fine tree used 57.1% of the CPU and trained in 13.205 seconds, less time than other models. Additionally, Figure 18 shows that the coarse tree's CPU use was 32.1%, which was lower than the fine tree's, but the fine tree's model flexibility is higher than the coarse tree's. Therefore, the fine trees model is the best for computing power. Figure 19 illustrates the correctness of the fine trees, which was 99.9% accurate for both validation and testing.



(a) Accuracy for Validation



(b) Accuracy for Testing

Fig. 19. Comparison between the Accuracies

The computing capacity for various machine learning techniques was suggested in Figure 20 when the traffic was sent across 200 slices for 25 users. The coarse tree used 101.2% of the CPU during training to predict the slice type and 18% of the CPU during testing, which is lower than those of other machine learning models. Training took 1.9825 seconds for medium trees, compared to 2.5039 seconds for coarse trees. However, compared to coarse trees, training time for fine trees was shorter at 2.4523 seconds.

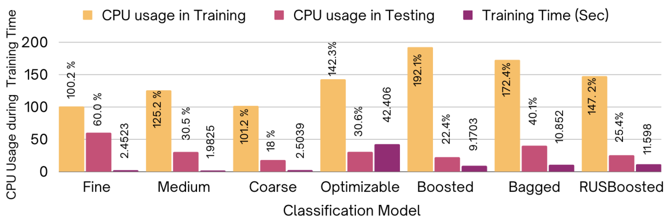


Fig. 20. Computations Power Compression For Different ML Models for 25 users connected to 8 slices each

Further, the maximum number of splits while utilising coarse trees is 4. With medium and fine trees, the number of splits grows to 20 and 100, respectively. The best model for our dataset could be the fine tree. The accuracy for predicting the slice type was 50.7% in the validation stage and 75% in the testing stage. According to Figure 21, the greatest accuracy was 77.1% for bagged trees and 63.3% for boosted trees, and it improved to 100% for both of them during the testing stage.

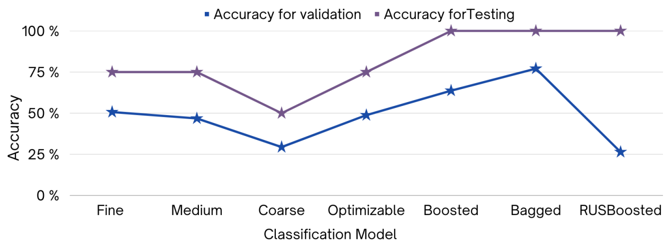


Fig. 21. Comparison between the Accuracies

Along with the aforementioned techniques, KNN is employed to train the model and predict the slice type based on the traffic sent from 25 slices linked to 8 or more slices and their requests. Additionally, there were approximately 200 slices that were concurrently linked to the 5G End-to-End in total.

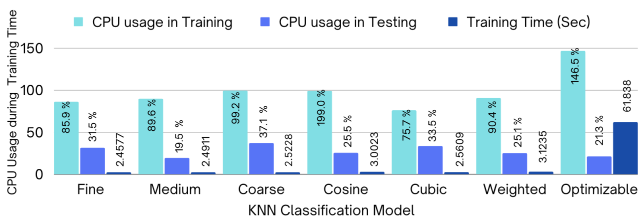


Fig. 22. Computations Power Compression For Different KNN ML Models for 25 users connected to 8 slices each

In Figure 22, the training time for the KNN was 2.4577 seconds, and CPU use during the training stage of the prediction of the slice type was 85.9%, which was lower than other models. On the other hand, compared to other models, medium KNN uses less CPU during testing. As indicated in Figure 23, the accuracy for the fine tree during training was 73.2%. Figure 23 illustrates how the accuracy increased to 100% as new data was provided to test the model. Although the accuracy of all other models increases, fine KNN was the machine learning model that best suited our dataset.

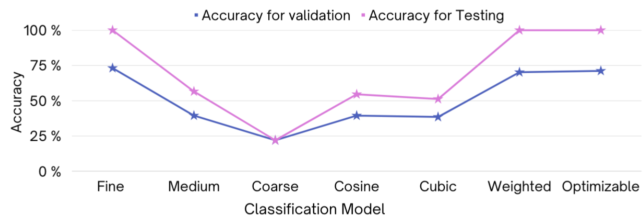


Fig. 23. Comparison between the Accuracies

VII. Conclusion and Future Works

Several techniques were applied to propose an 5GE2ES model in the 5G networks. After proposing multiple scenarios, traffic was generated over inter and intra-slices to check the system performance. Then, several machine learning models were applied to our 5GE2ES models to manage the 5G resource allocation in heterogeneous requirements. Machine learning algorithms were used to classify and predict the slices over the 5G networks to allocate the 5G slice resources efficiently and guarantee the QoS after training our model with various machine-learning techniques. We selected the method best for our model to handle real-time traffic and estimate the services based on the needs. The proposed model performs better than the existing methods when predicting the 5G service in less time and using less computational power. Future directions are listed below in terms of performance, cost, reliability, availability, QoS, QoE, and sustainability with the 5GE2ES:

1) Performance: High performance in terms of data speeds, latency, and capacity is promised by 5GE2ES. However, it is still unclear how well it will perform in practice. Due to the difficulties in successfully applying the technology, there are worries that it may be unable to deliver on its promises.
2) Cost: The 5GE2ES will probably cost more than conventional networking options. This is because additional bandwidth and specialised equipment and software are required.
3) Reliability: There are worries that traditional networking approaches could not be as dependable as the 5GE2ES. This is because it is a novel technology without extensive testing.
4) Availability: When it was first introduced, the 5GE2ES could not generally be accessible. This is because the technology is new, and there might not be adequate infrastructure to support it.
5) QoS: High QoS and QoE are promised by the 5GE2ES.

6) Sustainability: Since 5GE2ES is a novel technology, it is uncertain how long-lasting it will be.

In the future, deep and continuous learning will be used to predict traffic and manage the slice according to the agreement between the user and the service provider. In addition, appropriate coordination needs to be considered in the future if the services spread according to the geographical location. Moreover, security will be considered to deal with multi-chain to improve the efficiency and the QoS in the 5G networks.

Acknowledgment

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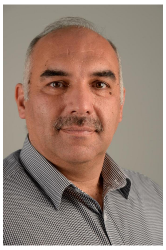

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