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NETWORK-SLICING RECOGNITION

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Abstract : To manage the next generation apps and services, the telecom sector is undergoing a huge digital transformation thanks to the deployment of ML, AI, feedback-based automation, and advanced analytics. AI ideas are not new; numerous companies and technological verticals are already using the algorithms used in machine learning and deep learning. The capacity to predict data proactively, quickly, and accurately is crucial given the massive volume of information that 5G will likely carry along with it and its expanding data. Future communication networks will need to make decisions based on data because of the surge in traffic and the acceleration of 5G network performance by artificial intelligence (AI). 5G networks provide end-to-end network resource allocation utilizing the notion of Network Slicing (NS), and mobile operators are searching for a programm able solution that will enable them to handle several independent tenants on the same physical infrastructure.

Network slicing will be essential to the implementation of numerous 5G use cases, apps, and services. The functions of network slicing will offer end-to-end isolation across slices and allow each slice to be customized according to the needs of the service (bandwidth, coverage, secur ity, latency, dependability, etc.). The task is to build a Machine Learning model that will be able to proactively detect and eliminate threats based on incoming connections thereby selecting the most appropriate network slice, even in case of a network failure.

IndexTerms- Artificial intelligence, Machine learning, Network slicing, 5G communication, Convolutional neural network, Batch normalization, Data packets, Latency, Quality of service.

I. INTRODUCTION

Due to the importance of mobile communication in today's technologically advanced world, the number of communication devices is increasing rapidly [1]. For these devices to meet the demands of communication in the future generation, they must have high bandwidth, mobility, low latency, and improved quality of service (QoS). Prominent instances of the quick development of communication technology are 2G, 4G, and the soon-to-be 5G and 6G [2]. Reliability, flawless operation, and reconfiguration management in heterogeneous wireless networks are also necessary for future generation communication [3]. The service providers are always having difficulty meeting consumer requests and offering trustworthy communication. In order to accomplish these goals and meet 5G network needs, LTE network expansion will increase bandwidth, throughput, and service quality. In addition to traditional mobile broadband services, 5G is expected to enable a number of new vertical industry use cases. These new situations include a wide range of demanding criteria, including mobility management, cost, security protection, and performance. The current networks' one-size-fits-all design approach is no longer practical. Partitioning a solitary physical network into multiple logical networks tailored to distinct needs has surfaced as a propitious method for meeting these disparate demands in a sustainable manner. We present an extensive overview of 5G network slicing in this post.

First, we outline the motivations for and the idea behind network slicing. The discussion then shifts to associated essential enabling technologies, including as management, orchestration, dynamic service chaining, and virtualization and modularization of network functions. This presentation covers the most recent developments in 3GPP standardization and industry application on 5G network slicing. In order to stimulate additional research toward a workable network slicing-enabled 5G system, the paper concludes by identifying a number of significant open concerns and obstacles.

Machine learning has demonstrated its ability to make significant decisions in high-stress situations across a number of fields [5]. Machine learning will monitor the state of various devices in reconfigurable network environments. It will also evaluate network slices and a vast quantity of data created during communication in order to make critical decisions and make predictions. Network reconfiguration, optimal resource reservation based on utilization, optimized mobile tower operation in accordance with requirements, optimal decision-making skills, and real-time performance analysis are all possible with machine learning. The primary goals of the proposed research project are to use a hybrid deep learning model to produce a reconfigurable wireless network slicing for 5G networks that is based on machine learning. LSTM and CNN make up this model. The CNN performs resource allocation, network reconfiguration, and slice selection while the LSTM is used for statistical information regarding network slices.

Main contributions of the proposed research work are:

The major issue facing network service providers is accurate slice assignment. A significant challenge facing the research community and service providers is scenario and need-based allocation for a particular IoT device. To precisely assign the network slices to an unknown device upon request, a clever technique must be created. The precise assignment of the network slice to each and every incoming new traffic request is the first of the suggested study work's many contributions.

Another crucial problem for the service provider is load balancing, as ineffective load balancing leads to crosstalk, delayed connection establishment, and lengthy wait times in queue situations. These problems cause the companies to lose a lot of money, but they also primarily drive customers to alternative network service providers. Optimizing load balancing leads to effective use of all available resources. It is thought that solving this issue will be crucial for today's wireless network service providers. To avoid cross talk, lengthy connection establishment queues, and other issues, a clever design is needed to automatically route all incoming requests to the master slice. Second contribution of this research work is provide an optimum load balancing mechanism in each network slice.

A abrupt loss of all established connections is referred to as slice failure. In the event of an emergency (sudden fire or disaster, earthquake, and other serious health issues), this situation is more dire. Sometimes, this situation results in the loss of human life. Overcoming this is crucial for 5G and 6G networks. To avoid losing a connection or having user requests in a specific network slice fail, an intelligent mechanism must automatically route all active calls or request the master slice. The creation of an ideal deep learning-based model that guarantees there is no slice failure condition represents the third and most significant achievement of this research effort. To assign a master file as a backup slice in the event that a slice fails or becomes overloaded. The additional network traffic requests will be assigned directly to the master file in the event of overloading situations, which in our case is more than 92% utilization of the network slice. In the event of a slice failure, however, the network traffic is immediately redistributed to other slices to guarantee that these requests are fulfilled normally. To put it briefly, in the event of overloading or slice failure, the master file will function as a backup slice.

II. DATASET DESCRIPTION

1. LTE/5g - User Equipment categories or classes to define the performance specifications
2. Packet Loss Rate - number of packets not received divided by the total number of packets sent.
3. Packet Delay - The time for a packet to be received.
4. Slice type - network configuration that allows multiple networks (virtualized and independent)
5. GBR - Guaranteed Bit Rate
6. Healthcare - Usage in Healthcare (1 or 0)
7. Industry 4.0 - Usage in Digital Enterprises (1 or 0)
8. IoT Devices - Usage
9. Public Safety - Usage for public welfare and safety purposes (1 or 0)
10. Smart City & Home - usage in daily household chores
11. Smart Transportation - usage in public transportation
12. Smartphone - whether used for smartphone cellular data

III. EXPLANATION

3.1 Reading training and testing datasets into DataFrames

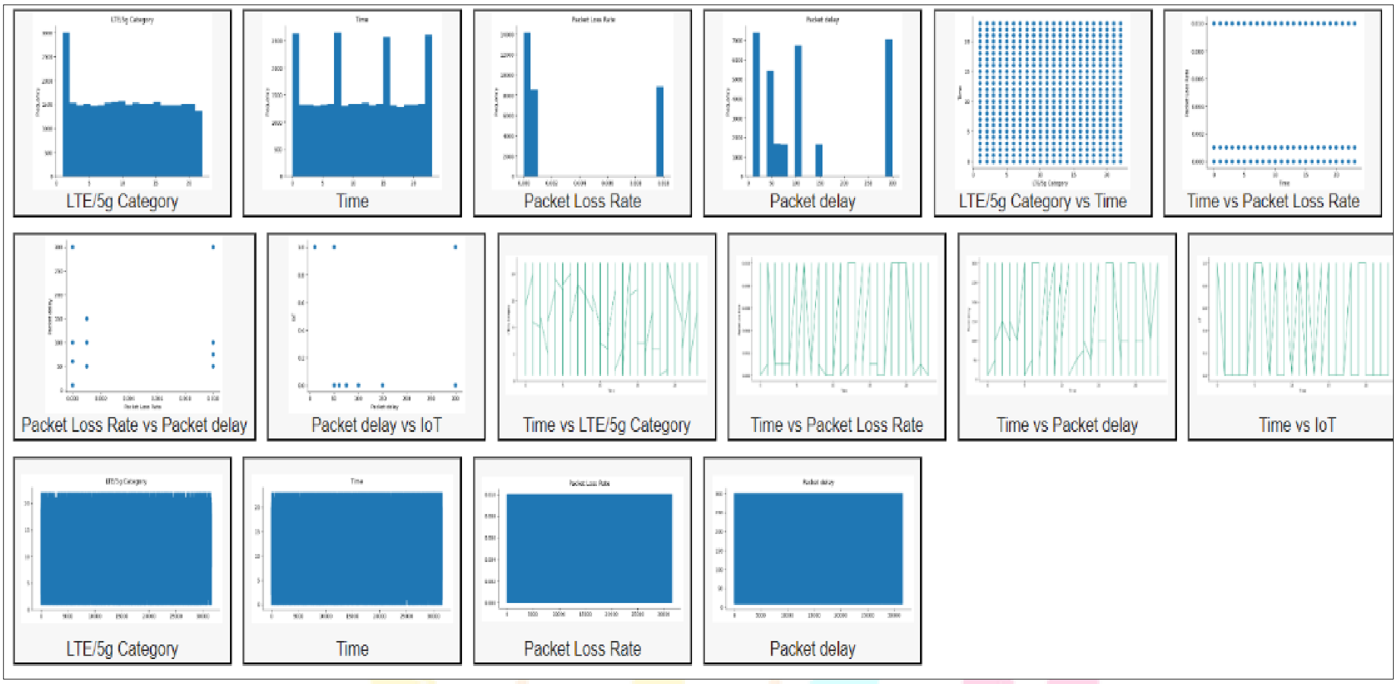
Fig: Reading training and testing datasets into DataFrames

	LTE/5g Category	Time	Packet Loss Rate	Packet delay	IoT	LTE/5G	GBR	Non-GBR	AR/VR/Gaming	Healthcare	Industry 4.0	IoT Devices	Public Safety	Smart City & Home	Smart Transportation	Smartphone	slice Type
0	14	0	0.000001	10	1	0	0	1	0	0	0	0	1	0	0	0	3
1	18	20	0.001000	100	0	1	1	0	1	0	0	0	0	0	0	0	1
2	17	14	0.000001	300	0	1	0	1	0	0	0	0	0	0	0	1	1
3	3	17	0.010000	100	0	1	0	1	0	0	0	0	0	0	0	1	1
4	9	4	0.010000	50	1	0	0	1	0	0	0	0	0	1	0	0	2

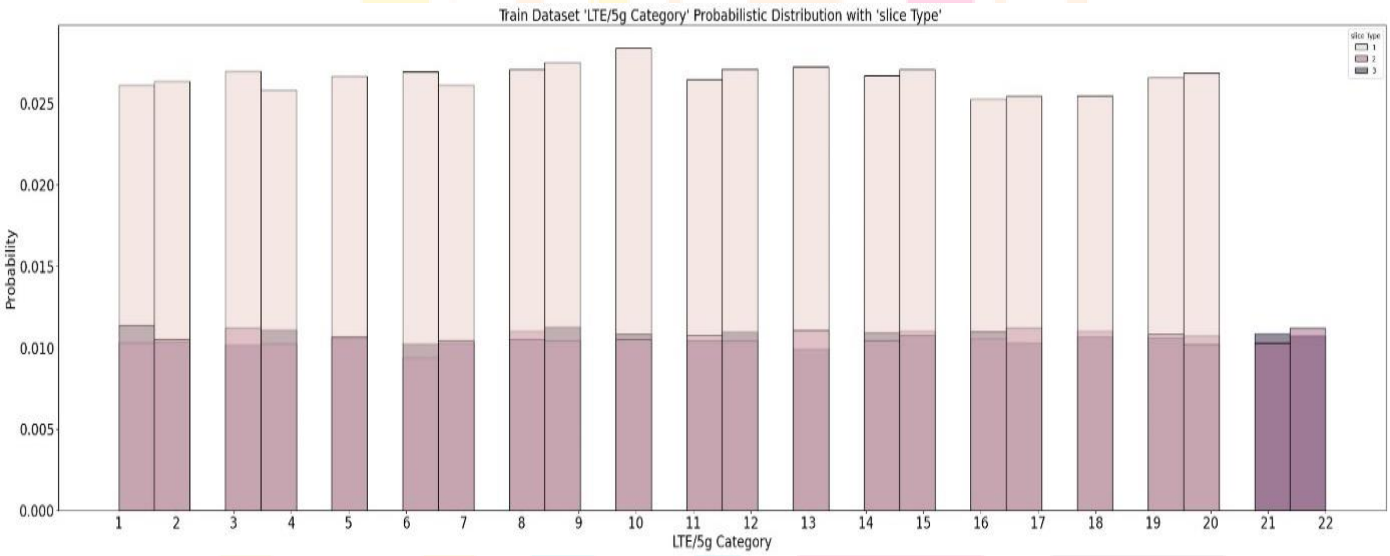
3.2 Description of output plots

Train dataset shape: (31583, 17)

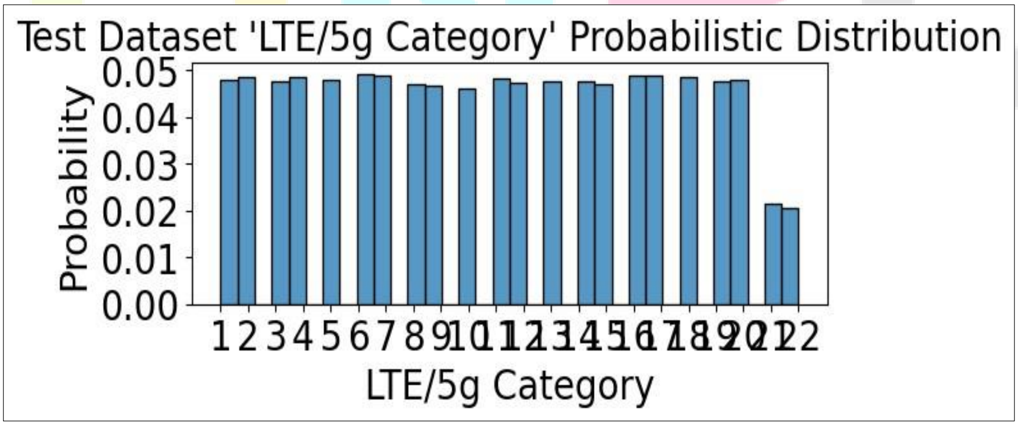
Test dataset shape: (31584, 16)



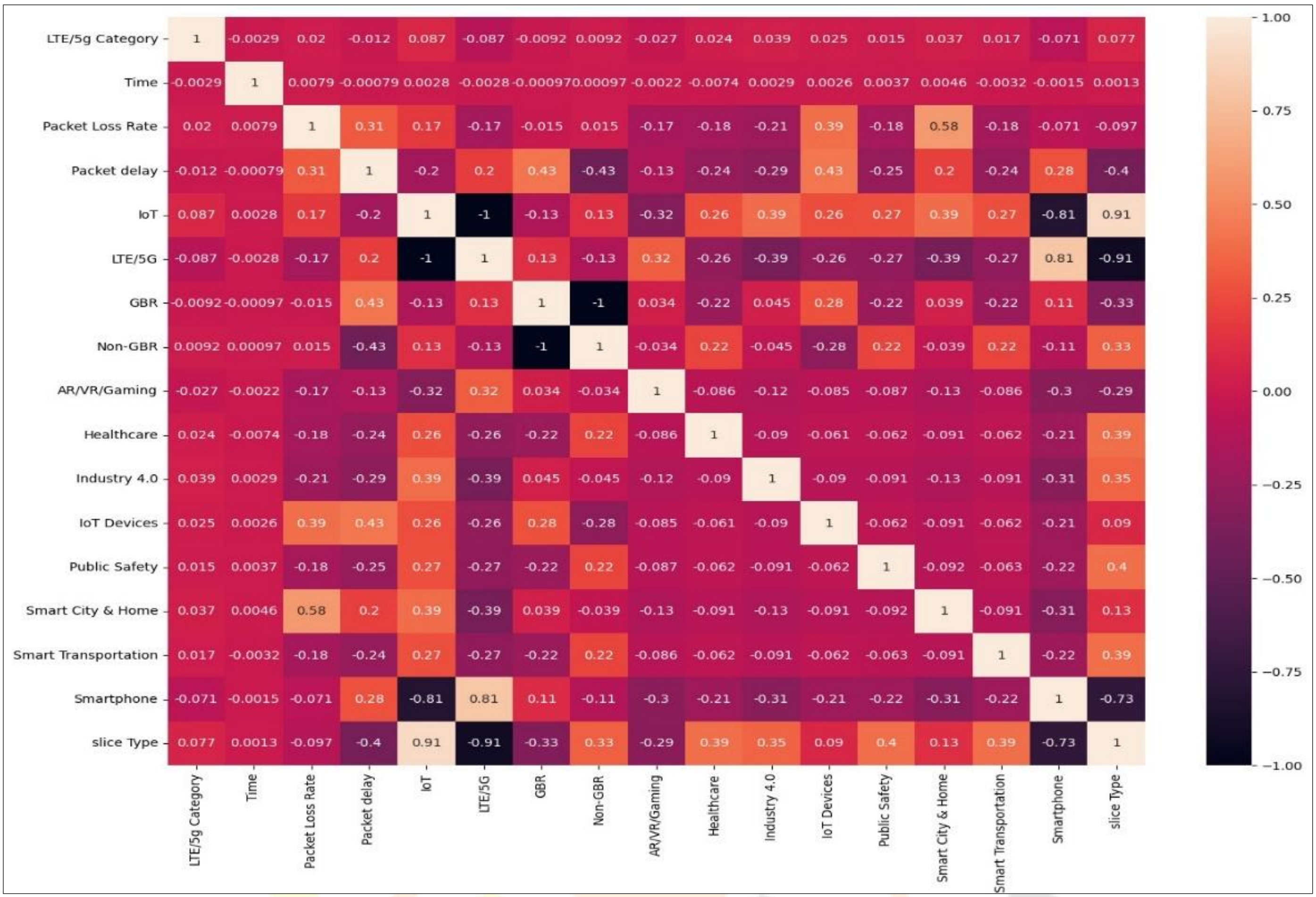
3.3 Train Dataset 'LTE/5g Category' Probabilistic Distribution with 'slice Type'



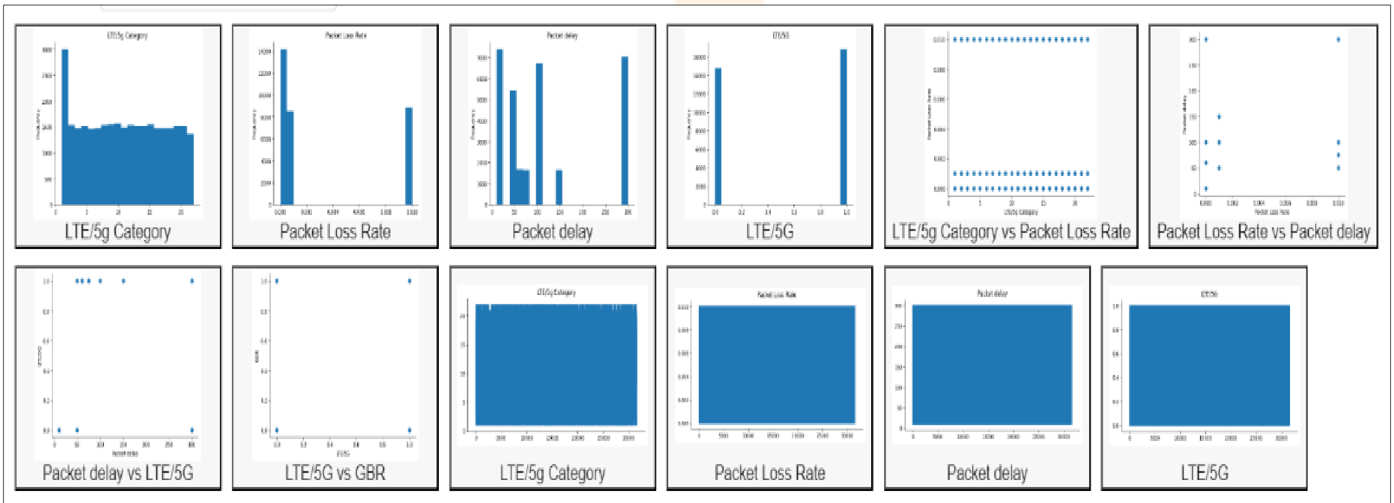
3.4 Test Dataset 'LTE/5g Category' Probabilistic Distribution



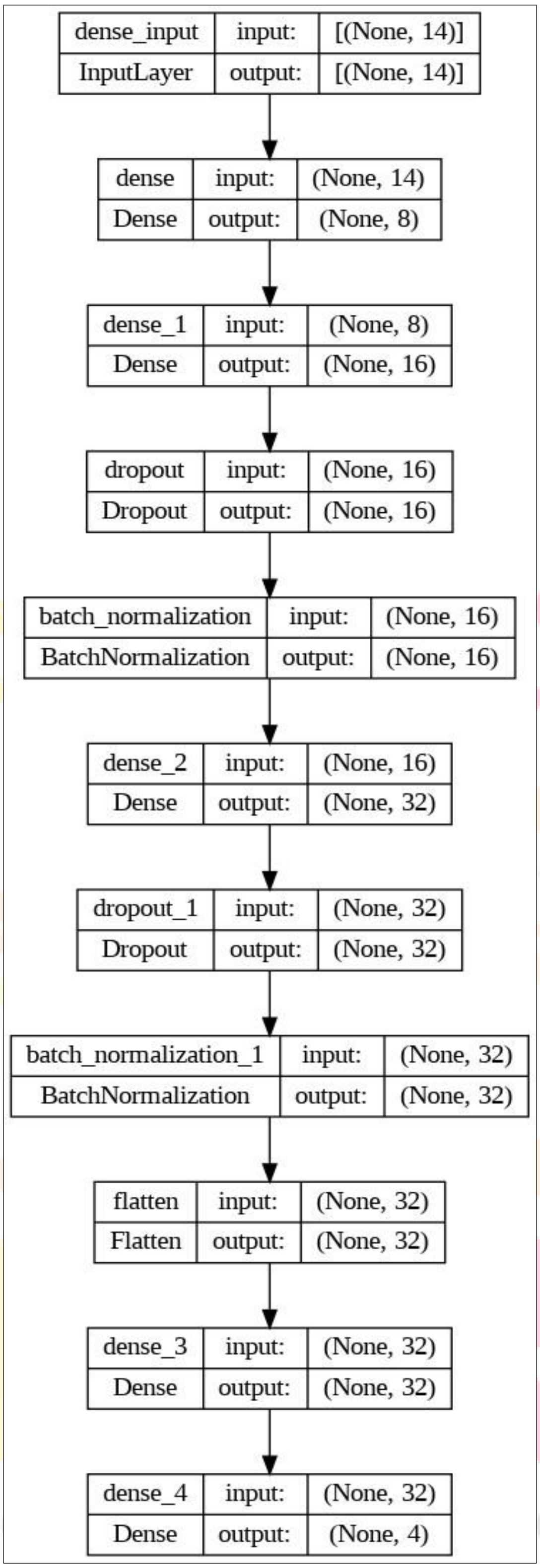
3.5 Calculating the correlation matrix for the training data



3.6 Output plots



3.7 Convolutional Neural Network with Batch Normalization



Model details: "sequential_1"

Layer (type)	Output Shape	Param #
dense_5 (Dense)	(None, 8)	120
dense_6 (Dense)	(None, 16)	144
dropout_2 (Dropout)	(None, 16)	0
batch_normalization_2 (BatchNormalization)	(None, 16)	64
dense_7 (Dense)	(None, 32)	544

dropout_3 (Dropout) (None, 32) 0

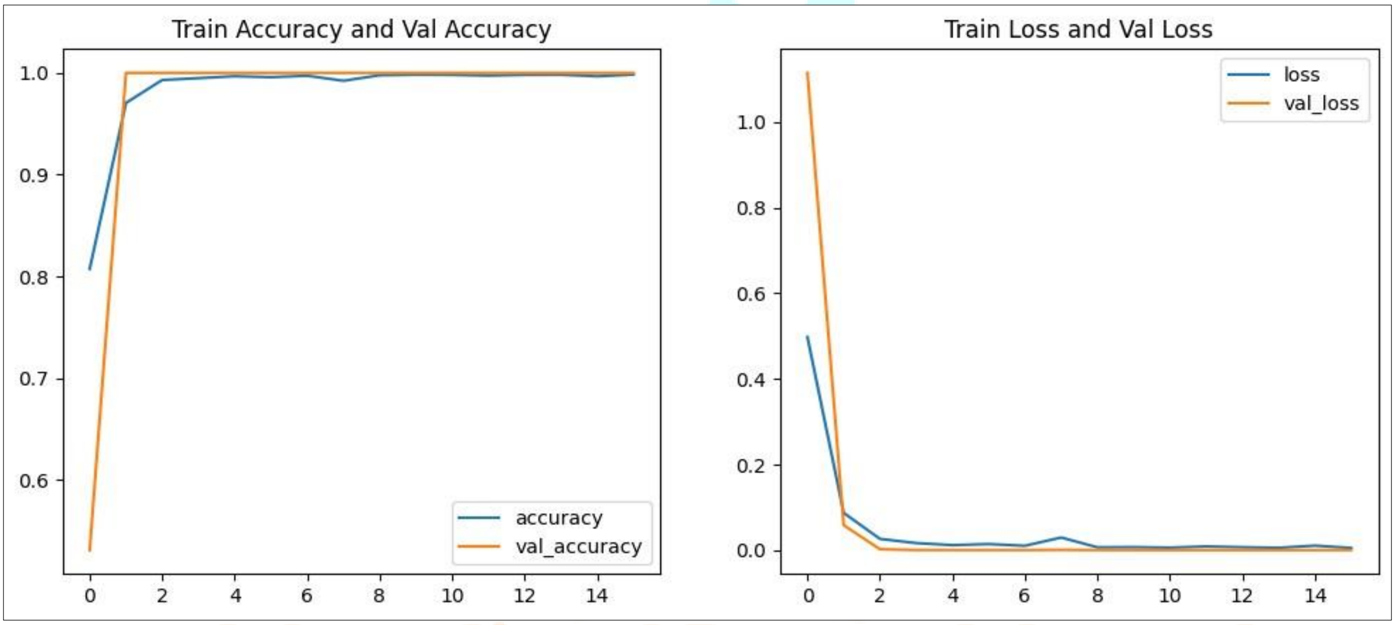
batch_normalization_3 (Bat (None, 32) 128
chNormalization)

flatten_1 (Flatten) (None, 32) 0

dense_8 (Dense) (None, 32) 1056

dense_9 (Dense) (None, 4) 132
===
Total parameters: 2188 (8.55 KB)
Trainable parameters: 2092 (8.17 KB)
Non-trainable parameters: 96 (384.00 Byte)
Validation accuracy: 1.0000

3.8 Train Accuracy and Val Accuracy

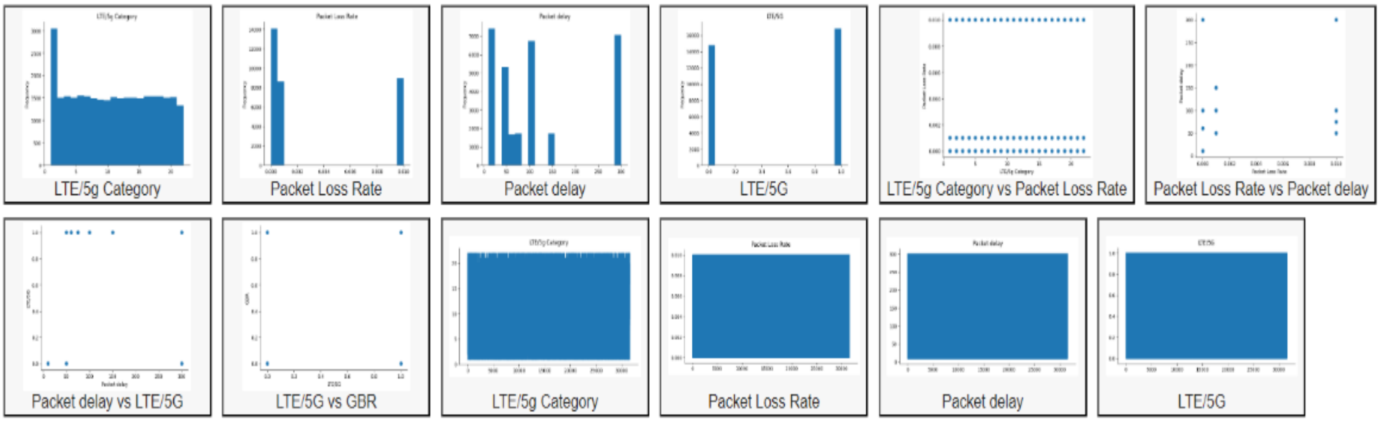


3.9 Evaluation of model on test dataset.

	LTE/5g Category	Packet Loss Rate	Packet delay	LTE/5G	GBR	Non-GBR	AR/VR/Gaming	Healthcare	Industry 4.0	IoT Devices	Public Safety	Smart City & Home	Smart Transportation	Smartphone	predicted_slice_type
0	15	0.001000	100	1	1	0	1	0	0	0	0	0	0	0	1
1	14	0.000001	10	0	0	1	0	0	0	0	0	0	1	0	3
2	11	0.001000	50	0	1	0	0	0	1	0	0	0	0	0	2
3	20	0.001000	50	0	1	0	0	0	1	0	0	0	0	0	2
4	2	0.001000	50	1	0	1	1	0	0	0	0	0	0	0	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
31579	9	0.000001	10	0	0	1	0	0	0	0	0	0	1	0	3
31580	20	0.000001	10	0	0	1	0	0	1	0	0	0	0	0	3
31581	8	0.000001	10	0	0	1	0	0	1	0	0	0	0	0	3
31582	13	0.010000	75	1	0	1	0	0	0	0	0	0	0	1	1
31583	8	0.000001	10	0	0	1	0	0	1	0	0	0	0	0	3

31584 rows × 15 columns

3.10 Recommended plots



IV. KOLMOGOROV SMIRNOV TEST

The Kolmogorov-Smirnov test, often abbreviated as the KS test, is a statistical method used to compare a sample distribution with a reference probability distribution (which could be a theoretical distribution or another empirical distribution). It's particularly useful for testing whether a sample comes from a population with a specific distribution, or whether two samples come from the same distribution.

1. **Purpose**: To determine whether a sample follows a specified distribution (e.g., normal, exponential) or to compare two samples to see if they come from the same distribution.
2. **Null Hypothesis**: The null hypothesis H0H_0H0 typically assumes that the sample comes from the specified distribution or that the two samples come from the same distribution.
3. **Test Statistic**: The KS test statistic DDD is based on the maximum difference between the cumulative distribution functions (CDFs) of the sample(s) and the reference distribution.
4. **Interpretation**: The KS test provides a p-value that indicates the probability of observing the test statistic DDD under the null hypothesis. If the p-value is below a chosen significance level (commonly 0.05), then the null hypothesis is rejected, suggesting the sample(s) do not follow the specified distribution or are not from the same distribution.

Classification Report:

	precision	recall	f1-score	support
1	1.00	1.00	1.00	2061
2	1.00	1.00	1.00	867
3	1.00	1.00	1.00	863
accuracy			1.00	3791
macro avg	1.00	1.00	1.00	3791
wtd avg	1.00	1.00	1.00	3791

Predicted Slice Type: 1

V. RESULTS AND DISCUSSION

The performance analysis of the suggested hybrid model in terms of slice prediction, load balancing, and network availability is described in this section of the paper. In order to assess the suitability of the suggested model, this study develops three distinct scenarios:

5.1 Accurate slice assignment

The primary issue facing network service providers is accurate slice assignment. A significant challenge facing the research community and service providers is scenario and need-based allocation for a particular IoT device. To precisely assign the network slices to an unknown device upon request, a clever technique must be created.

5.2 Load balancing

This is another crucial problem for the service provider because it leads to cross-talk, delayed connection establishment, and lengthy wait times in scenarios involving queues. These problems cause the companies to lose a lot of money, but they also primarily drive customers to alternative network service providers. Optimizing load balancing leads to effective use of all available resources. It is thought that solving this issue will be crucial for today's wireless network service providers. To avoid cross talk, lengthy connection establishment queues, and other issues, a clever design is needed to automatically route all incoming requests to the master slice.

5.3 Slice failure scenario

Slice failure is the condition when a sudden loss of all the established connection occurs. This scenario becomes more severe in case of emergencies (sudden fire/disaster, earthquake, and other critical health problems). This scenario sometimes leads to human life loss. This is a critical issue for 5G/6G networks to overcome. An intelligent mechanism is required to automatically route all the ongoing calls or request the master slice instead, to prevent connection loss or failure of user requests in a certain network slice.

VI. CONCLUSION

One of the important features for commercial enterprises and next-generation wireless networks is 5G network slicing, which is a difficult undertaking. One of the major challenges facing the research community is the creation of an intelligent decision making system for incoming network traffic that can guarantee load balancing, restrict network slice failure, and provide an alternate slice in the event of overloading or slice failure. In order to solve this issue, the suggested research project describes the advantages of utilizing a hybrid slicing mechanism for the best possible prediction of the ideal network slice for each and every incoming packet depending on the essential characteristics of the device. This hybrid architecture can manage several important 5G network problems, including load balancing and network slice failure. These are two serious problems for every network service provider. Every continuing call or freshly made request experiences connection loss as a result of a specific slice failure. However, load balancing is also a crucial problem for the service provider because it causes cross-talk, delays in the formation of connections, and lengthy wait times in scenarios involving queues. These problems cause the companies to lose a lot of money, but they also primarily drive customers to alternative network service providers. By directing both the continuing requests (in the event of a slice failure) and the new arriving requests (in the event of over-flow slice conditions) to the master slice, this model guarantees no connection loss and optimal load balancing conditions. The capabilities of the model are also tested using other performance metrics such as specificity, recall, time consumption, varying training and test sets, true–false rates and f-score. An overall recognition rate of 95.17% is reported for the proposed hybrid model that reflects the applicability of the proposed approach.

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