DOI: 10.36108/ujees/4202.60.0160

UNIOSUN Journal of Engineering and Environmental Sciences. Vol. 6 No. 1. March. 2024

VALIDATION OF KEY PERFORMANCE INDICATORS OF MOBILE TELECOMMUNICATION OPERATORS USING ENSEMBLE MODELS AND ARTIFICIAL NEURAL NETWORKS WITH NIGERIAN COMMUNICATION COMMISSION'S THRESHOLDS

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Abstract This paper presents the comparative studies among the predictive models used for the validation of the key parameter indicators of mobile network operators with the Nigerian Communication Commission's threshold. Four Key Performance Indicators were predicted using artificial neural networks and ensemble models which include bagging and LSBoost models. The Key Performance Indicators and weather parameters for six locations in Southwestern Nigeria were employed. MATLAB R2020a was employed to develop the three models. Microsoft Excel was used in the analysis of the dataset. The bagging model gave the best average compliance of 94% and 100% for CSSR and TCH Congestion Rate respectively while the ANN model yielded the best average compliance of 76.7% and 85.2% for DCR and SDCCH Congestion Rate respectively.

Keywords: Quality of Service, mobile network, key performance indicators

I. Introduction

Global System for Mobile Communications (GSM), which was introduced in Nigeria in 2001, has undoubtedly made a significant contribution to the quality of life for Nigerians[1]. However, as mobile services have expanded, it has become crucial for mobile communication operators to accurately measure the quality of service (QoS) of their networks and to continue to improve them as efficiently and effectively as possible to maintain a competitive edge [2, 3].

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Poor QoS is a result of network operators' reliance on sending signals down the troposphere without first evaluating and characterizing the troposphere [4]. A component of the atmosphere that has a direct impact on human life is the troposphere. It is an area of all-weather on earth and the lowest layer of the atmosphere. At the poles and equator, the troposphere is located at a height of about 10 km and 17 km, respectively [5].

It is necessary to understand how weather parameters affect signal propagation and how changing weather conditions can seriously impair system performance in order to characterize the reliability of networks [6-8]. To forecast, simulate, and design high performance communication systems, exact transmission characteristics of radio waves in various environments must be known. Network planning and optimization are required for mobile network providers. There is the need to strike a balance between network operation, QoS, and radio coverage in various situations [9]

The structure of radio refractive index, N, at the lower part of the atmosphere has helped in identifying the weather parameters likely to affect signal propagation and it is stated in Equation 1 given as [10]:

$$N = 77.6\frac{P}{T} + 72\frac{e}{T} + 3.75 \times 10^5 \frac{e}{T^2} \quad (1)$$

where t is the temperature in Celsius, T is the temperature in kelvin, P is the pressure (hPa), $e = H.e_s/100$, H is the relative humidity (%), e_S: saturation vapour pressure (hPa) at the temperature t ($^{\circ}$C).

Studies shows that when signals are transmitted, they interact with tropospheric variables such as wind speed, relative humidity, and temperature. The prediction of the state of a channel on a given link was done by [11] by taking measurements on other links, thus causing a decline in the signaling overhead. The first representative approach considered was Random Dot Product Graphs while the second approach was Graph Neural Network. The proposed graph-based machine learning methods outperformed traditional methods in predicting the state of the channel on a given link by taking measurements on other links, achieving an RMSE of 10 dB and 73% accuracy by making use of a dataset of RSSI measurements of real-world Wi-Fi operating service providers. The paper should have discussed the computational complexity of the proposed methods, which could be a potential limitation in practical implementations.

In the study by [12] made use of an automatic artificial neural network (ANN) predictive quality of service model to evaluate the efficiency of services rendered by the GSM network in Nigeria, after which the evaluation results of the developed GSM QoS prediction model showed that the results of the developed model could perform favorably well but not at its best, compared to how the Nigerian Communications Commission (NCC) approaches it manually. Hence, there is a need to employ more advanced machine learning algorithms or techniques to develop the QoS prediction model, such as deep learning or ensemble learning, to boost the accuracy of the model.

[13] used a walk-test methodology to measure KPIs for accessibility of internet on the 4G network by the users who subscribe to different mobile network operators (MNOs) within the University of Ilorin. Data was gathered using TEMS Investigation 16.3.4 and processed using TEMS Discovery Device 10. The walk test involved uploading files, downloading data, and streaming videos online at various test areas. MNO4 had the best overall quality and throughput, while MNO1 had the poorest service, although it still provided some service in all test locations. The 4G test did not yield exceptional results, but students reported specific locations with optimum 4G speed. Expanding the study to include other universities or public areas to determine if the results are similar or if there are differences in service quality and throughput will be a great advantage.

The study by [14] proposed a traffic congestion prediction model using machine learning techniques used for the prediction of the traffic congestion existence in LTE networks as appraised by users. The model was divided into several phases: data preparation, splitting, modelling, classification, model evaluation and tuning, and result. The four machine-learning algorithms were compared and conclusions was hinged on the output of the Jupyter Notebook for the classifiers. Out of all the techniques used in predicting the traffic congestion existence, k-Nearest Neighbour had the best performance. Online machine learning techniques will be considered for future studies, and they can constantly obtain data from network operators with the aim to gather the necessary features and prediction performance of the traffic congestion in real-time to aid the traffic providers in engaging mechanisms to reduce traffic congestion to the barest minimum.

[15] measured and analyzed the Key Performance Indicators (KPIs) of a 4G/LTE Telecom of Kosovo (TK) network 24-cell cluster. The results of the analysis show that the availability KPI has less values than the threshold (>99%). [15] stated that future studies would focus on the analysis of the QoS in the overall 4G/LTE network executed in TK and that the major challenges the operators will encounter during the transition process from 4G to 5G technologies would also be addressed.

[16] used network statistics to evaluate the QoS of a cellular network service provider of an enclosed area during a church event. The CSSR and Percentage Drop Call Rate were investigated and compared with the benchmark defined by Nigerian Communications Commission (NCC). The study results showed that the cellular network service provider's Key Performance Indicators (KPIs) fell below the NCC recommendation, especially during high traffic intensity. The quality of service requires improvement to ensure better service delivery to subscribers. Comparing the QoS of different cellular network service providers in the same area and evaluating the QoS of cellular networks in different geographical locations should be thoroughly examined.

[17] evaluated the 4G-LTE communications base station's quality parameters in the rural part of Peru using Key Performance Indicators (KPIs) defined for 4G LTE Technology, including signal level, Signal to Noise Ratio and quality. The study confirmed that the KPIs comply with the recommendations of the ITU in its E-800 recommendation. The study found that the 4G-LTE communications base station's quality parameters in a rural part of Peru comply with the ITU's E-800 recommendation, which ensures maximum mobile phone coverage in the rural parts and accessibility to the complete mobile phone network nationwide. Future studies could focus on analyzing the impact of environmental factors, such as weather conditions and terrain, on the communications' base station's parameters.

Feature selection is the main step in machine learning based model development [18]. To obtain good model, feature selection algorithm choose the most relevant features from the feature vector and discards the irrelevant ones.

Ensemble modelling involves the use of different basic machine learning model, although as a single model, to forecast an outcome. Reduction of the generalization error of the forecast is the inspiration for using ensemble models. The general principle of ensemble methods is to construct a linear combination of some model fitting methods, instead of using a single fit of the method.

Bagging Tree (BT) algorithm creates a bootstrapped sample, on which either a regression algorithm or classification algorithm is applied. For regression, an average is taken and computed over all the outputs forecasted by the individual learners. For classification, the most voted class (hard-voting) is considered as the output, else the highest average of all the class probabilities (soft-voting)[19]. Mathematically, BT prediction can be represented as in Equation 2.

$$\widehat{Y_{bag}} = \widehat{X_1} + \widehat{X_2} + \widehat{X_3} + \cdots + \widehat{X_n} \quad (2)$$

where $\widehat{Y_{bag}}$ is the output of the bagging tree and $\widehat{X_1}, \widehat{X_2} \ldots \widehat{X_n}$ are the input.

Unlike bagging, LSBoost (LSBT) algorithm trains the basic machine learning models consecutively, and gives weights to all the training records. The training set for the subsequent iteration will be overrepresented by the training records that are difficult to categorize thanks to the boosting process.

Every training record has a weight assigned by boosting, and depending on how tough the classification is, boosting must adaptively adjust the weight. This results in the creation of basic learners' group, skilled at classifying both simple and complex records. By using a straightforward voting aggregation, the model's basic learners are all pooled [20].

Three layers make up an ANN: the input layer, the hidden layer (between the input and the output), and the output layer. The way an ANN processes input signals and converts them into output signals is similar to how the human brain functions. ANN functions essentially the same as the human brain ANNs could learn from data without the need for certain function assumptions. ANN is crucial to improving forecasting accuracy [21].

The essence of this study is to validate key performance indicators of mobile telecommunication operators using ensemble models and artificial neural networks with Nigerian Communication Commission's thresholds.

II. Materials and Methods

Monthly data of water vapour, air temperature, air pressure and relative-humidity were collected from the Nigerian Meteorological Agency (NIMET) in comma-separated values (CSV) using Modern Era Retrospective Analysis for Research and Applications version 2 (MERRA – 2)[22]. The data collection of seven years spanned from January 1, 2016 to December 31, 2022. Also, the database of Nigerian Communications Commission (NCC), an independent National Regulatory Authority for the telecommunications industry in Nigeria, contains key performance indicators (KPIs) of all telecommunication service providers. KPI dataset was obtained from this database [23].

The scope of this paper is limited to six locations in South western, Nigeria namely Abeokuta, Ado-Ekiti, Akure, Ibadan, Lagos and Osogbo. Key Performance Indicators of four network service providers namely 9mobile, Airtel, Glo and MTN was investigated and predicted in this study. These KPIs include Call Setup Success Rate (CSSR), Dropped Call Rate (DCR), Standalone Dedicated Control Channel (SDCCH) congestion rate, Traffic Channel (TCH) congestion rate. MATLAB R2020a Software programming language tool will be employed for model development in this study. This validation was done after the development of the Ensemble models (Bagging and LSBoost) and the Artificial Neural Network (ANN) model.

The Nigerian Communications Commission NCC has threshold standards for GSM and

CDMA networks in order to conduct cellular network performance for the various operators. Only the caliber of services rendered by these operators determines whether or not customers are satisfied. Operators must constantly analyze and optimize their network to get the greatest performance. The regulatory authority sets KPI thresholds to help mobile providers monitor the services they provide. The NCC's QoS KPI thresholds are given in Table 1

Table 1: KPI Thresholds for quality of service

Key Performance Indicators (KPIs)	Threshold (%)
Call Set-up Success Rate (CSSR)	≥ 98
Dropped Call Rate (DCR)	≤ 1
Standalone Dedicated Control Channel (SDCCH) Congestion Rate	≤ 0.2
Traffic Channel (TCH) Congestion Rate	≤ 2

Validation is a crucial step in modeling because it establishes the reliability of the models to be used in decision-making contexts. There is a need to determine whether the model accurately represents the behavior of the system. This was achieved by acquiring data from NCC and was compared with predicted values from the model. The acquired data points were mapped with the predicted ones to show the distances between the points

III. Results and Discussion

The NCC threshold was adopted and the percentages of both good and bad were recorded. Microsoft Excel was employed for the comparison of the predicted dataset to the KPI threshold values. The NCC threshold was used as standard for CSSR, DCR, SDCCH congestion rate and TCH congestion rate. Microsoft Excel was used to analyze the months that met the threshold requirements an otherwise.

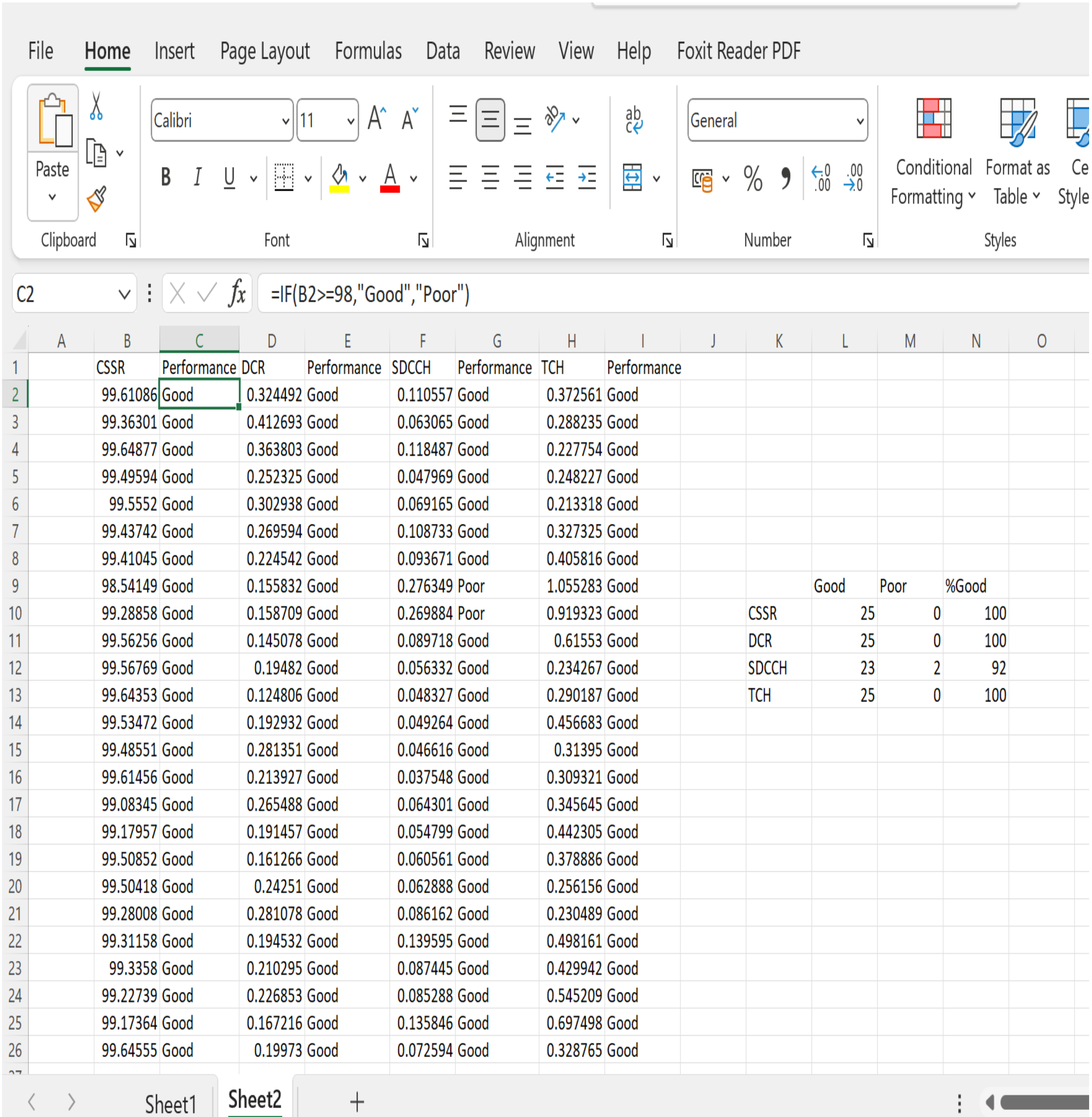
If the following conditions are met: CSSR ≥98, DCR ≤ 1, SDCCH Congestion Rate≤ 0.2 and TCH congestion rate ≤ 2, 'Good' is assigned to the value, otherwise 'Poor'.The same procedure is used for the other three KPIs. Figure 1 shows the sample of the dataset analysis for AkureGloANN.

The same process is done for Abeokuta9mobileBagging, Abeokuta9mobileLSBoost,Abeokuta9mobileANN, AbeokutaAirtelBagging, AbeokutaAirtelLSBoost, AbeokutaAirtelANN,AbeokutaGloBagging,AbeokutaGloLSBoost,AbeokutaGloANN,AbeokutaMTNBagging, AbeokutaMTNLSBoost, AbeokutaMTNANN. This is repeated for the other five locations, after which a table was processed for the results. Tables 2a to 2f show the performance of the percentage good of the three models for Abeokuta, Ado-Ekiti, Akure, Ibadan, Lagos and Osogbo respectively.

From the Tables 2a to 2f, Tables 3a to 3c were derived, with each table giving the summary of the average KPIs %Good performances of the four mobile network operators for Bagging, LSBoost and ANN respectively.

Results of validating the KPIs predicted by the three models with the NCC KPIs threshold across the six locations indicated that the bagging model gave the best average compliance of 94% and 100% for CSSR and TCH Congestion Rate respectively while the ANN model yielded the best average compliance of 76.7% and 85.2% for DCR and SDCCH Congestion Rate respectively.

From the results obtained, it is concluded that the bagging ensemble model has the best performance in predicting the QoS of mobile telecommunication service providers. Hence, it is proposed that to achieve better KPI predictions to enhance the network performance the bagging model should be employed.



	CSSR	Performance	DCR	Performance	SDCCH	Performance	TCH	Performance
2	99.61086	Good	0.324492	Good	0.110557	Good	0.372561	Good
3	99.36301	Good	0.412693	Good	0.063065	Good	0.288235	Good
4	99.64877	Good	0.363803	Good	0.118487	Good	0.227754	Good
5	99.49594	Good	0.252325	Good	0.047969	Good	0.248227	Good
6	99.5552	Good	0.302938	Good	0.069165	Good	0.213318	Good
7	99.43742	Good	0.269594	Good	0.108733	Good	0.327325	Good
8	99.41045	Good	0.224542	Good	0.093671	Good	0.405816	Good
9	98.54149	Good	0.155832	Good	0.276349	Poor	1.055283	Good
10	99.28858	Good	0.158709	Good	0.269884	Poor	0.919323	Good
11	99.56256	Good	0.145078	Good	0.089718	Good	0.61553	Good
12	99.56769	Good	0.19482	Good	0.056332	Good	0.234267	Good
13	99.64353	Good	0.124806	Good	0.048327	Good	0.290187	Good
14	99.53472	Good	0.192932	Good	0.049264	Good	0.456683	Good
15	99.48551	Good	0.281351	Good	0.046616	Good	0.31395	Good
16	99.61456	Good	0.213927	Good	0.037548	Good	0.309321	Good
17	99.08345	Good	0.265488	Good	0.064301	Good	0.345645	Good
18	99.17957	Good	0.191457	Good	0.054799	Good	0.442305	Good
19	99.50852	Good	0.161266	Good	0.060561	Good	0.378886	Good
20	99.50418	Good	0.24251	Good	0.062888	Good	0.256156	Good
21	99.28008	Good	0.281078	Good	0.086162	Good	0.230489	Good
22	99.31158	Good	0.194532	Good	0.139595	Good	0.498161	Good
23	99.3358	Good	0.210295	Good	0.087445	Good	0.429942	Good
24	99.22739	Good	0.226853	Good	0.085288	Good	0.545209	Good
25	99.17364	Good	0.167216	Good	0.135846	Good	0.697498	Good
26	99.64555	Good	0.19973	Good	0.072594	Good	0.328765	Good

	Good	Poor	%Good
CSSR	25	0	100
DCR	25	0	100
SDCCH	23	2	92
TCH	25	0	100

Figure 1: Sample of the dataset analysis of AkureGloANN

Table 2a: Abeokuta's %Good performance of the three models

		ANN	Bagging	LSBoost
CSSR	9mobile	100	100	100
	Airtel	100	100	100
	Glo	100	100	100
	MTN	20	0	28
		80	75	82
		ANN	Bagging	LSBoost
DCR	9mobile	100	100	100
	Airtel	100	68	60
	Glo	100	100	100
	MTN	20	92	72
		80	90	83
		ANN	Bagging	LSBoost
SDCCH Congestion Rate	9mobile	100	100	88
	Airtel	100	100	100
	Glo	100	36	44
	MTN	100	96	92
		100	83	81
		ANN	Bagging	LSBoost
TCH Congestion Rate	9mobile	100	100	100
	Airtel	100	100	100
	Glo	100	100	100
	MTN	100	100	100
		100	100	100

Table 2b: Ado-Ekiti's %Good performance of the three models

		ANN	Bagging	LSBoost
CSSR	9mobile	72	100	100
	Airtel	100	100	96
	Glo	96	100	100
	MTN	100	100	100
		92	100	99
		ANN	Bagging	LSBoost
DCR	9mobile	20	0	36
	Airtel	52	40	36
	Glo	76	100	96
	MTN	100	100	100
		62	60	67
		ANN	Bagging	LSBoost
SDCCH Congestion Rate	9mobile	80	92	84
	Airtel	100	100	100
	Glo	100	24	52
	MTN	92	100	96
		93	79	83
		ANN	Bagging	LSBoost
TCH Congestion Rate	9mobile	100	100	100
	Airtel	100	100	100
	Glo	100	100	100
	MTN	100	100	100
		100	100	100

Table 2c: Akure's %Good performance of the three models

		ANN	Bagging	LSBoost
CSSR	9mobile	100	100	100
	Airtel	92	100	88
	Glo	100	100	100
	MTN	100	100	96
		98	100	96
		ANN	**Bagging**	**LSBoost**
DCR	9mobile	20	8	28
	Airtel	92	4	44
	Glo	100	100	100
	MTN	100	100	100
		78	53	68
		ANN	**Bagging**	**LSBoost**
SDCCH Congestion Rate	9mobile	88	100	96
	Airtel	72	100	100
	Glo	12	36	32
	MTN	92	100	100
		66	84	82
		ANN	**Bagging**	**LSBoost**
TCH Congestion Rate	9mobile	100	100	100
	Airtel	100	100	100
	Glo	100	100	100
	MTN	100	100	100
		100	100	100

Table 2d: Ibadan's %Good performance of the three models

		ANN	Bagging	LSBoost
CSSR	9mobile	100	100	100
	Airtel	92	100	96
	Glo	88	100	96
	MTN	100	100	100
		95	100	98
		ANN	**Bagging**	**LSBoost**
DCR	9mobile	4	56	40
	Airtel	60	64	64
	Glo	92	100	92
	MTN	100	100	100
		64	80	74
		ANN	**Bagging**	**LSBoost**
SDCCH Congestion Rate	9mobile	100	100	92
	Airtel	100	100	96
	Glo	36	32	48
	MTN	96	100	84
		83	83	80
		ANN	**Bagging**	**LSBoost**
TCH Congestion Rate	9mobile	100	100	100
	Airtel	100	100	100
	Glo	100	100	100
	MTN	96	100	84
		99	100	96

Table 2e: Lagos' %Good performance of the three models

		ANN	Bagging	LSBoost
CSSR	9mobile	100	100	100
	Airtel	100	100	100
	Glo	100	100	100
	MTN	92	84	76
		98	96	94
		ANN	Bagging	LSBoost
DCR	9mobile	100	100	100
	Airtel	88	72	72
	Glo	100	100	100
	MTN	76	68	48
		91	85	80
		ANN	Bagging	LSBoost
SDCCH Congestion Rate	9mobile	100	100	72
	Airtel	92	100	100
	Glo	100	72	80
	MTN	100	88	76
		98	90	82
		ANN	Bagging	LSBoost
TCH Congestion Rate	9mobile	100	100	100
	Airtel	100	100	100
	Glo	100	100	100
	MTN	100	100	100
		100	100	100

Table 2f: Osogbo's %Good performance of the three models

		ANN	Bagging	LSBoost
CSSR	9mobile	100	100	100
	Airtel	88	100	88
	Glo	100	72	64
	MTN	100	100	100
		97	93	88
		ANN	Bagging	LSBoost
DCR	9mobile	100	16	44
	Airtel	40	24	48
	Glo	100	100	100
	MTN	100	100	100
		85	60	73
		ANN	Bagging	LSBoost
SDCCH Congestion Rate	9mobile	80	84	84
	Airtel	96	100	92
	Glo	12	32	56
	MTN	96	100	76
		71	79	77
		ANN	Bagging	LSBoost
TCH Congestion Rate	9mobile	100	100	100
	Airtel	100	100	100
	Glo	92	100	100
	MTN	100	100	100
		98	100	100

Table 3a: Performance of Bagging model on the KPIs with NCC threshold

	CSSR	DCR	SDCCH Congestion Rate	TCH Congestion Rate
Abeokuta	75	90	83	100
Ado-Ekiti	100	60	79	100
Akure	100	53	84	100
Ibadan	100	80	83	100
Lagos	96	85	90	100
Osogbo	93	60	79	100
	94	71.33	83	100

Table 3b: Performance of LSBoost model on the KPIs with NCC threshold

	CSSR	DCR	SDCCH Congestion Rate	TCH Congestion Rate
Abeokuta	82	83	81	100
Ado-Ekiti	99	67	83	100
Akure	96	68	82	100
Ibadan	98	74	80	96
Lagos	94	80	82	100
Osogbo	88	73	77	100
	92.83	74.17	80.83	99.33

Table 3c: Performance of ANN model on the KPIs with NCC threshold

	CSSR	DCR	SDCCH Congestion Rate	TCH Congestion Rate
Abeokuta	80	80	100	100
Ado-Ekiti	92	62	93	100
Akure	98	78	66	100
Ibadan	95	64	83	99
Lagos	98	91	98	100
Osogbo	97	85	71	98
	93.33	76.66	85.17	99.5

IV. Conclusion

Quality of service is a main feature in the behavioral patterns in telecommunication industry and one of the key performance indicators is the CSSR. Mobile communication engineers have faced the challenges of understanding these parameters which is attributed to achieving optimum quality of end-user experience (QoE) of communication networks.

This study presented a validation analysis of the QoS KPIs with respect to the NCC threshold for the three models employed and it was concluded that bagging model had the best performance.

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