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Development of QoS Predictive Model for Major Network Operators in Nigeria using C4.5 and ID3 Algorithms.

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ABSTRACT
The use of mobile telecommunication in Nigeria, especially in the era of COVID-19, is vital; it is also an agent of the country's socio-political and economic advancement. The number of subscriptions grew from one million to one hundred and eighty million between 2002 and 2019. However, increase in the number of users without the corresponding increase in the expansion of network resource is a challenge, which raises Quality of Service (QoS) issue in the country, especially in the COVID-19 era hence the justification for this research. This work aims to develop a predictive model for audio QoS for the major network operators in Nigeria. The major service providers in Nigeria are labeled X_1, X_2, X_3, and X_4**,** the other minor operators are labeled X_0. The crowdsourcing technique employed to collect primary data for this research. Machine learning approach, specifically ID3 and C4.5 algorithms, were used to develop models for each of four major mobile network operators in Nigeria. The telecom sector generates large and complex data that need to be analyzed and draw the inference to help the stakeholder. Hence the justification for the use of machine learning paradigm. Congestion rate, received signal strength, call success setup rate, and call drop rate are the four QoS parameters applied for this work. Furthermore, the performance evaluation metrics used are precision, accuracy, false alarm rate, and true positive rate. The result shows that the ID3 had better accuracy than C4.5 in only one of the datasets. The C4.5 and ID3 decision trees algorithm had an equal performance on the X_3, X_4, and other network datasets. The C4.5 Area under ROC is 0.998 for X_1, X_2, X_3 and X_4. Similarly, ID3 Area under ROC for X_1, X_2, X_3, and X_4 are 0.995, 0.998, 0.993 0.990 respectively. Since the results show that, the ID3 and C4.5 accuracy, precision and ROC are high; hence; they are good classifiers for determining the QoS of major mobile network operators.
Key words: Crowdsourcing, Quality of Service, C4.5, ID3, Algorithms, Mobile Network Operator.

1. BACKGROUND OF THE STUDY

Previous studies show that an information management system will not be effective without the input of the telecommunication sector (Adediran et al., 2014 Popola et al. 2019). The telecommunication sector provides a good platform for an information management system. From the beginning of human existence, starting from the Stone Age to the present digital age, there has been communication between two or more parties. In the COVID -19 era, where people were restricted to their homes, efficient communication needed to allow people to carry out their activities. The digital age experienced by introducing the Global System for Mobile communication (GSM) and later cellular network (CN) enhanced efficient communication among users. There are now audio and data communication under the platform of a communication network (Mebawondu et al., 2012; Adediran, 2014).

Furthermore, the cellular network (CN) telecommunication renders services to all sectors such as government, education, agriculture, health, banking, and defense, which bring numerous advantages that the citizen enjoyed with the deployment of CN into the national economy. However, mobile telecommunication is bedeviled with some challenges. The quantum of services and the number of subscribers of GSM increase drastically without a corresponding increase in infrastructure, hence the low quality of services experienced by users (NCC, 2018). National Communication Commission (NCC) sanctions the major mobile operators in Nigeria, namely AIRTEL, and 9Mobile, Global communication Plc, Mobile telecommunication of Nigeria plc (MTN), due to low quality of service. To achieve a good quality of service, service providers need to plan and monitor both services rendered with available infrastructure to achieve the desired goal.

Nigeria's experience is quite enjoyable because the stakeholders embraced the technology due to the fact that the subscription number rose from one million in 2002 to one hundred and eighty million in 2019 (NCC, 2019). With this high subscription rate without matching increase in the facilities, resulted to low service quality in the sector. The CN’s QoS gives an understanding of the requirements and capabilities of the network. Hence, the information retrieved from the analysis and useful evaluation of the network is a sound basis for network planning and implementation.

For the service providers to render effective and efficient QoS, there is a need to carry out a predictive classification model of their services. Some researchers have attempted to estimate one or two service providers' QoS over limited geographical areas (Osahenvemwen and Emagbetere (2014) are not sufficient. Some researchers applied data mining (DM) techniques because of the complexity and massive amount of data generated daily from the sector (Ojoko et al., 2020). DM applied for this work because of its suitability to analyze, classify, and model the large volume of call logs data generated by the service providers. The classification of each network service provider QoS is a fundamental requirement for accurate capacity planning.

In this work, an attempt was made to develop a predictive model for each country's service providers to enhance the QoS render to their customers. To achieve the classification model, the authors used C4.5 and ID3 DM algorithms. The goal of this work is to develop predictive models for each of the major service providers in the country. The major service providers in Nigeria are labeled X_1, X_2, X_3, and X_4**,** the other minor operators are labeled X_0. So, the work is presented in five sections. The literature review and methodology are presented in sections two and three, respectively. At the same time, section four presents results and discussion, and lastly, the conclusion is in section five.

2. LITERATURE REVIEW

The telecommunication industry's advancement has brought considerable gains to GSM / CN users in the country; nevertheless, there are some challenges. Osahenvemwen and Emagbetere (2014) reported low QoS challenges experienced by clients and other customers' complaints about their inability to access relevant services.

Big data suitable for the enormous data generated in telecommunication, and such data can best be analyzed, classified, and modeled using data mining techniques (Ojoko, 2020). The authors survey the importance of big data and DM tools in solving various research works such as health, security, telemedicine, intelligence systems. Mebawondu et al. (2020) reported a hybrid intelligent model for real-time assessment of voice quality of service using a neuro-fuzzy approach. The authors used a combination of neural networks and fuzzy logic in modeling QoS. However, the work is for all the service providers and not for individual operators.

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The GSM /CN systems generate a colossal amount of data daily, but the service provider's data is not readily accessible to researchers. In the past, researchers use the questionnaire method (Alese et al. 2004); but Haider B. *et al.*, 2009 and Obe et al., 2019 used the drive test (DT) technique to measure voice data. Also, Obe and others employed DT to evaluate the operator’s QoS to their clients. Mebawondu (2018) also employed DT in collecting data from Akure, Ondo State, Nigeria, for their works. However, it was noted that the DT is expensive to conduct, especially for a broader geographical scope. Another technique of data collection is crowdsourcing; this is a participatory user technique as used by Dahunsi and Kolawole (2014); Dahunsi et al. (2017); Mebawondu, (2018). The crowdsourcing method, seen to be successful, because the technique was used to collect data for this work. The CS method could be deployed only by using a mobile app developed for the required data collection. Dahunsi and others employed a crowdsourcing approach for voice using mobile devices and did the QoS analysis. Java programming language used to develop an android application on Android smartphones that measured some KPIs. Android smartphones were selected because it has a broader usage or patronage. Galadanci and Abdullahi (2018) reported that not all three-network providers could meet the NCC minimum standard based on the KPIs. However, there was no effort to develop a predictive model for network providers.

There are more than ten KPIs used in determining QoS; the challenge of researchers is which among the KPIs would be selected for estimating QoS. Ponle et al. (2019) attempted to identify KPIs parameters such as call set up success rate (CSSR), call drop rate (CDR), hand over set up rate (HOSR), and congestion rate (TCHR), among others in the work of Assessment of Interdependence of Key Performance Indicators in Voice Traffic of Glomobile Network in Akure, Nigeria. Nevertheless, this work uses four of the KPIs, CSSR, CDR, received signal strength (RSS), and TCHR, as QoS input parameters.
Boz et al. (2019) Opined evaluation and classification based on the QoE of CN; however, QoE is subjective because it is based on users' sense of judgement. An attempt was made to analyze network traffic data services by some researchers. Oluwadare et al. (2019) reported that network traffic analysis using a regression technique to determine network traffic patterns, but voice service evaluation and modeling are not covered in Oluwadare’s work.

Quite a lot of attempts were made by researchers to evaluate, analyze, classify, and model voice QoS of service providers, which carried out on selected urban centers (Ayanda et al. 2019; Obe et al. 2019). A Study of Relative Performance Evaluation of GSM in Urban Settlements in Nigeria, DT was used, and only two operators were considered. Obe et al. (2019) reported Assessment of Quality of Service of Mobile Network Operators in Akure. The paper reported QoS of the Mobile Network Operators in Akure differed significantly. The study recommended that Mobile Network Operators build more base stations to enhance their coverage area. These attempts successfully cover part of a city, town, or one or two of the operators. The scope of the researchers is limited in terms of geographical area and length of period. This work attempts to cover 21 states of the country for each of the four major operators.

Research Motivation

The subscribers of user's audio calls have increased rapidly without a corresponding increase in the infrastructure to meet users' demands over the decades. The challenges of the COVID-19 era call for good voice QoS that will enable citizens to carry out their business activities. However, CN users experience erratic services hence their complaints on the quality of service (Galadanci and Abdullahi, 2018; Boz et al., 2019; Azubuike 2014; and; Popoola et al., 2017, 2019; Bakare et al**.,** 2017; Adediran et al., 2016). Most of the researcher works centered on one or two operators and the coverage areas/time are limited. Dahunsi and Kolawole, 2015; Adefehinti and Dahunsi, 2016; Mebawondu et al., 2018 reported that the platform used for data collection limit both the coverage and number of KPIs to be evaluated. Other reasons are the high congestion rate (Ozovehe ***et al*.,** 2017), low received signal strength (Raheem and Okereke, 2014; Emeruwa, 2015). The mentioned problem justifies the need for reliable predictive modeling for each mobile network operator (MNO) for monitoring and evaluating QoS. The main stakeholders will derive great benefit from the work, which aims to develop predictive models for network service providers in Nigeria and compute performance analyses of the developed models based on global best practice (metrics).

3. METHODOLOGY

3.1) Data Collection

This section discusses the work's data collection, the primary method of data used to capture data; the primary method is crowdsourcing. Crowd platform used for the data collection includes a remote cloud server, crowd, and local server. Users access the platform by installing the app on their smartphone devices using the link. The researcher access cloud through the local system to carry out further analysis. As clients call, the app collects call logs and sent remote server periodically.

3.1.1) CN QoS Data Management

The conceptualized star schema of the knowledge warehouse for the QoS is presented in Figure 1. It has type date, type MNO, time, location, and timeframe as dimensions.

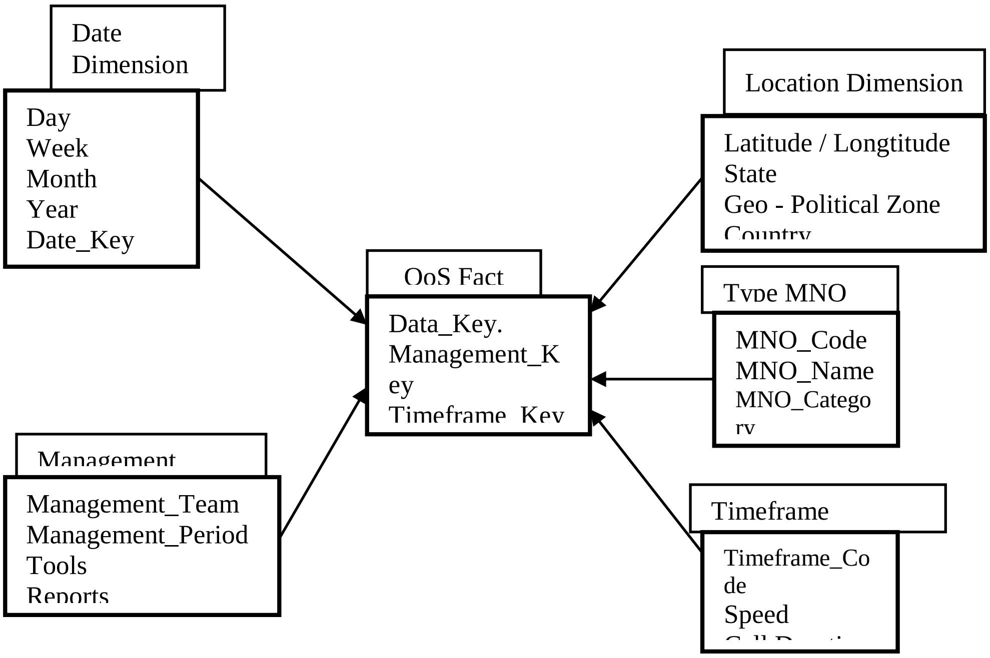

Figure 1. Conceptual Star Schema for QoS Fact Table

Table 1 depicts the attributes description of the audio calls QoS database. There are 23 fields, as indicated in table 1 below. The captured data preprocessed, analyzed, and a predictive model developed.

Table 1. Attributes Description of Voice Calls QoS

S/N	Attributes	Description	Attributes Type	S/N	Attributes	Description	Attributes Type
1.	Id No	User' ident.		14	P_Brand	Phone brand	Character
2.	Dates	Call dates	Date	15.	D_No	Dialed No	Character
3.	Time	Time of calling	Numeric	16.	D_Net	Dialed Network	Character
4.	Lat	Latitude	Numeric	17.	TCHR	Congestion rate	Numeric
5.	Long	Longitude	Numeric	18.	CSSR	Call Success Rate	Numeric
6.	RSS	Signal strength	Numeric	19.	CDR	Call Drop Rate	Numeric
7.	M_ID	Master ID	Character	20.	HO	Hand Over	Numeric
8.	M_Area	Master Area	Character	21	RSS	Received signal strength	Numeric
9.	State	Name of State	Character	22	QoS	Quality of Service	Character
10.	Operator	M. N. O.'s Name	Character	23	Address	User Address	Character
11.	Country	Country	Character				
12.	C_Type	Call type	Character				
13	My phone	User phone No	Character	.			

The researchers captured data directly from the volunteers' smart mobile devices. An existing Voice QoS app installed on the volunteers' smartphones. While the smartphone's Internet service is active, the application measures the Internet KPIs metrics and gets the location parameter and network information.

3.1.2) QoS Parameters

Four parameters are considered for the development of the models. The KPIs metrics measured by the Voice QoS Application are CSSR, CDR, TCHR, and Received Signal Strength (RSS) in dBm. Data collected from twenty-one states and FCT were covered over 12 month period. Four hundred eighty-two thousand five hundred twenty audio calls were captured for 21 states and FCT in Nigeria. The captured data preprocessed to lead to 5157 records. The records are divided into sub – dataset for each network provider. The standard benchmark as approved by NCC used for each KPIs. The 2% is the benchmark for TCHR and CDR; 96% used for CSSR. Besides, an approved range or standard is used for RSS. As discussed in section two, the previous work justified the parameter selection (Popola et al., 2019). Furthermore, each parameter is classified into poor, moderate, and excellent.

After data were preprocessed, statistical analyses were first carried out on the data collected, as reported in previous publications. Crowd sourced data collected showing four parameters for each operator per period, i.e., CSSR (%), RSS (dBm), CDR (%), TCHR (%), were collated.

3.1.2) Voice Dataset Description of Service Provider

The data set of service providers voice calls are analyzed per MNOs. Following the analysis of the data set collected from the various sites surveyed for the identified mobile networks, the predictive model for determining the quality of service (QoS) at various sites formulated using the C4.5 and ID3 algorithms identified and simulated using the Waikato Environment for Knowledge Analysis (WEKA) software.
From Table 2, it is observed that the majority of the data collected from **X4** (32.2%) followed by **X2** (21.9%), **X3** (20.9%), and **X1** (19.2%).

Table 2. Distribution of the Dataset collected across Mobile Networks

Network Operator	Total	Percentage (%)
X_1	990	19.20
X_2	1131	21.93
X_3	1078	20.90
X_4	1659	32.17
X_0	299	5.80
TOTAL	5157	100.00

Table 3 shows that the data collected showed an even distribution across the different days, with an average of 13.5% each. The unidentified days for which data collected constituted is about 3.5% of the original dataset. Sunday recorded the lowest, and Wednesday has the highest records.

Table 3. Distribution of the Days across Mobile Networks

Days	Network Providers					Total	Percentage (%)
	X_1	X_2	X_3	X_4	X_0		
Unidentified	24	46	34	62	14	180	3.49
Monday	135	153	133	237	46	704	13.65
Tuesday	137	155	155	236	41	724	14.04
Wednesday	158	172	164	255	52	801	15.53
Thursday	146	152	131	214	43	686	13.30
Friday	134	152	164	219	27	696	13.50
Saturday	133	155	160	230	43	721	13.98
Sunday	123	146	137	206	33	645	12.51
TOTAL	990	1131	1078	1659	299	5157	100.00

3.2 Classification Activity Flow Chart

Figure 2 shows the activity flow diagram of this work. The C4.5 and ID3 (decision tree) are employed to classify and model the voice QoS. Each of the techniques discussed in this section.

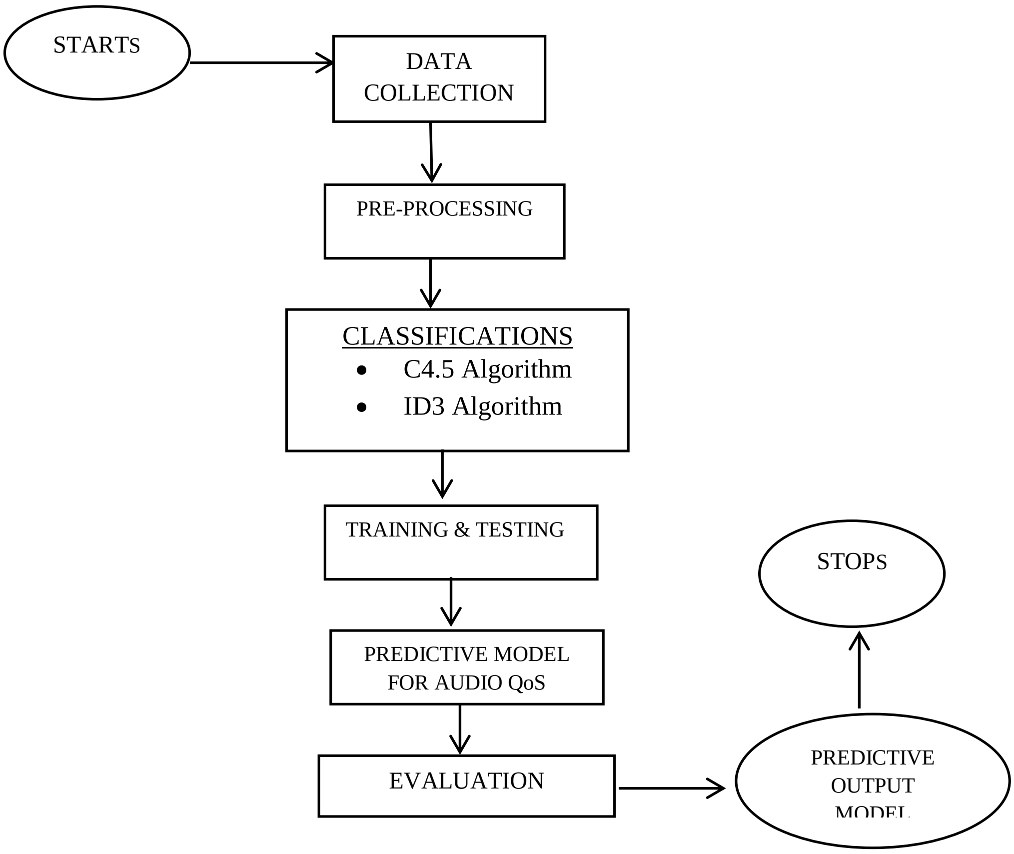

Figure 2. System activity flow diagram

3.3 Decision Tree using C4.5 Algorithm (Classification Tool)

A decision - tree is readable; a path to each leaf transformed into an IF-THEN production rule. The IF part consists of all tests on a path, and the THEN part is a final classification. Decision trees using decision rules are used for this work because it is a robust solution to solve audio QoS classification problems. It is also an efficient method of producing classifiers, which are derived from a decision tree. The C4.5 algorithm is the process of generating an initial decision tree from the set of training samples. The skeleton of the C4.5 algorithm rests on Hunt's Concept Learning System (CLS) method for constructing a decision tree using a set T of training samples (Kantardzic, 2014). C4.5 algorithm choice is because it can handle missing data, continuous data, and good at pruning data.

C4.5 algorithm

The Pseudocode of C4.5 Algorithm used for this work shown below:

```
INPUT: R (Non target attribute), C (target attribute) S (training data)
OUTPUT: return decision tree
START:
   Initialize to an empty tree
            Return a single node
   IF S is empty, THEN
          Return a single node
* ENDIF
   IF S is made only for values of the same target
THEN
          RETURN
   ENDIF
   IF R is empty, then
          Return a single node with values
   ENDIF
Dß-- attribute the target Gains (D, S) of all attribute values of R
   RETURN a tree if the root is D and arc are labeled by di, d2 ....dm
```

The model for the classification of the QoS is used to rank attributes to build the decision tree. Each node of the tree is used to locate the attribute with the highest information gain among the attributes. The algorithm presented as follows:

$$\text{Entropy P} = \sum_{i=1}^{n} p_i \text{ x } \log(p_i) \quad (1)$$

$$\text{Gain (p, T)} = \text{Entropy P} - \sum_{p=1}^{n} (p_i \text{ x Entropy } (p_i)) \quad (2)$$

where entropy P is the information distribution, values is the set of all possible values for attributes T, Gain (p, T) is the gain information. The decision tree was used to group the data into three categories, namely excellent, moderate, and poor. C4.5 algorithm generates for the model.

The simulation of the predictive models using the WEKA simulation environment and the performance evaluation metrics applied during model validation to evaluate the performance of the predictive models presented.

a) **Performance Evaluation**

The Performance Evaluation was carried out to validate models developed. The performance evaluation used accuracy, precision, false alarm rate, true positive rate variables and area under curve (AUC). The variables are standard metrics used globally.

b) **Trees Algorithm**

The decision tree is used to make feature selections; from the above table, RSS, CSSR, TCHR are critical for determining audio QoS for X_1 X_2, X_3,, and $\mathbf{X_0}$. In the case of $\mathbf{X_4}$, RSS, CSSR, TCHR, and CDR are critical for determining audio QoS. Generally, for the country's MNOs, RSS, CSSR, TCHR, and CDR are essential for determining audio QoS as demonstrated in Table 4.

Table 4. Attributes Selected by Decision Tree

X_1	X_2	X_3	X_4	X_0
RSS	TCHR	RSS	TCHR	RSS
CSSR	RSS	CSSR	RSS	CSSR
TCHR	CSSR	TCHR	CSSR	TCHR
			CDR	

4. RESULTS AND DISCUSSION

Decision Tree using C4.5 and 1D3 algorithms for each MNO

Each mobile network operators coded as X_1 X_2, X_3, X_4,, and other networks coded as X_0.

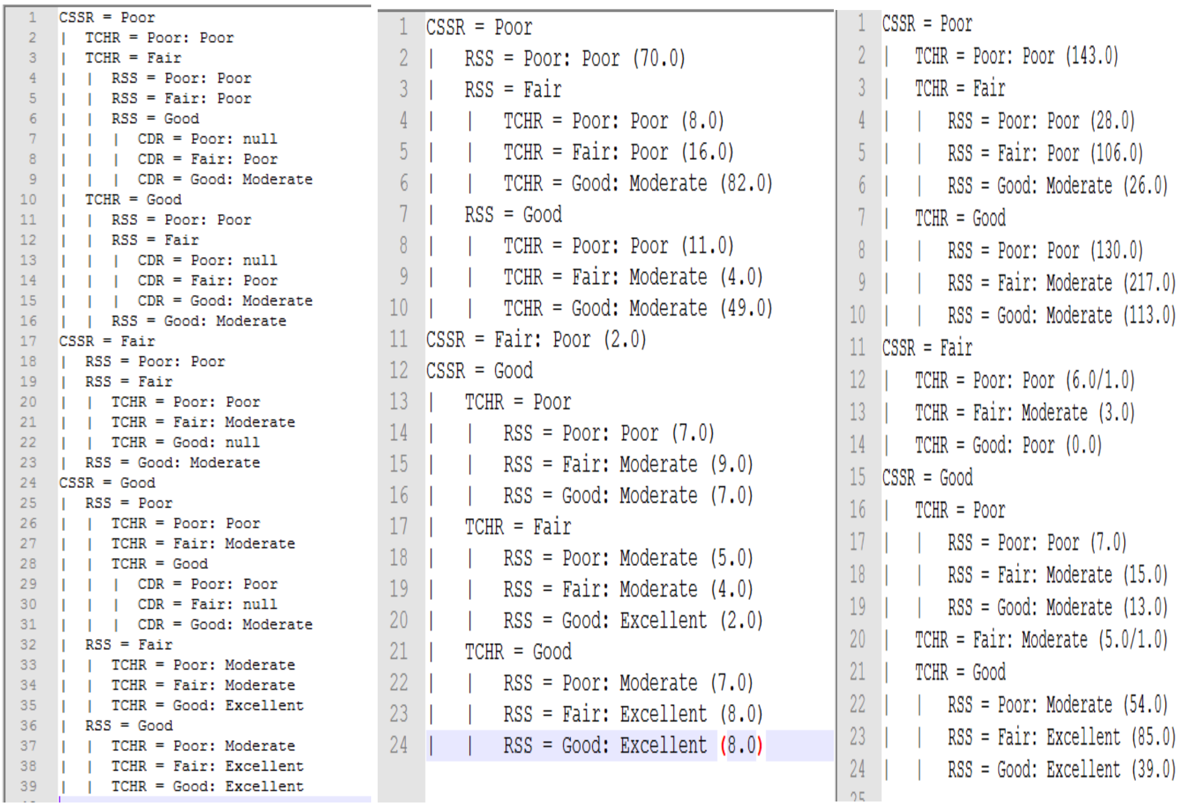

Figure 3. Sample of DT for Service Providers to Predict Voice QoS Model

Distribution of the QoS Parameter

Table 5 shows the Distribution of the QoS Parameters results of classification for each service provider per QoS parameter. Each network provider parameter is further classified into poor, fair, and good grades. For instance, poor, fair, and good grades of RSS are 24.65%, 53.54%, and 21.82%, respectively. Likewise, poor, fair, and good grades of CDR are 0.62%, 2.44%, and 96.94%, respectively.

Table 5. Distribution of the QoS Parameter

%, QoS Parameters		Network Providers					Total	Percentage (%)
		X_1	X_2	X_3	X_4	X_0		
Received Signal Strength (RSS)	Poor	265	304	266	345	91	1271	24.65
	Fair	499	578	565	992	127	2761	53.54
	Good	226	249	247	322	81	1125	21.82
Congestion (TCHR)	Poor	184	191	280	426	60	1141	22.13
	Fair	168	264	197	538	39	1206	23.39
	Good	638	676	601	695	200	2810	54.49
Call Setup Success Rate (CSSR)	Poor	763	787	841	1305	240	3936	76.32
	Fair	9	48	24	91	2	174	3.37
	Good	218	296	213	263	57	1047	20.30
Call Drop Rate (CDR)	Poor	1	6	8	15	2	32	0.62
	Fair	4	24	24	72	2	126	2.44
	Good	985	1101	1046	1572	295	4999	96.94
TOTAL		990	1131	1078	1659	299	5157	

Besides, the results revealed that out of the dataset selected for $\mathbf{X_2}$, the majority had moderate QoS; out of the dataset selected for $\mathbf{X_1}$, the majority had moderate QoS. Likewise, out of the dataset selected for $\mathbf{X_3}$, the majority had poor QoS; out of the dataset selected for $\mathbf{X_4}$, the majority had poor QoS while out of the dataset selected for $\mathbf{X_0}$, the majority had moderate QoS. In general, most of the data collected from all mobile networks showed an equal distribution of moderate and poor, as indicated by X_1 X_2, X_3, and $\mathbf{X_0}$. In contrast, $\mathbf{X_4}$ showed almost twice as many distributions of Moderate QoS for poor QoS.

This work uses two different decision tree algorithms to formulate the QoS measure's predictive model for each operator identified for this study. The C4.5 decision trees algorithm was simulated on the WEKA explorer interface. In contrast, the ID3 was simulated using the ID3 algorithm, both available in the Trees Classifier class of the WEKA Package using the five different datasets containing 5157 records. There is a different database for each service provider.

a) *Performance Evaluation of Models for each Service Operators*

Using the C4.5 and ID3 decision trees (DT) algorithms classifier available in WEKA to train the predictive model developed, using the training dataset for X_2 via the 10-fold cross-validation method.

Results of the decision trees algorithm for the operator X_2

The operator X_2 datasets containing the information used to evaluate the correct and incorrect classifications alongside the models' accuracy developed for the operator X_2 dataset. The results of the performance evaluation of the model simulation process for developing the predictive model for QoS. Using the training dataset for X_2 via the 10-fold cross-validation technique, the result shows that out of the 1131 datasets, there were 1127 (99.65%) correct classifications. Also, it shows 466 for Poor, 506 for Moderate, and 155 for Excellent along with the diagonal and 4 (0.35%) incorrect classifications containing 1 Poor as Moderate and 3 Moderate as Poor as shown in Figure 4 (left). Hence, the predictive model for the QoS showed an accuracy of 99.65%.

The ID3 decision trees algorithm classifier used to train the predictive model developed. Also, using the training dataset for X_2 via the 10-fold cross-validation method, it was discovered that out of the 1131 datasets, there were 1128 (99.73%) correct classifications. The results also show 466 for Poor, 507 for Moderate, and 155 for Excellent – along with the diagonal and 2 (0.18%) incorrect classifications containing 1 Poor as Moderate and 1 Moderate as Poor as shown in Figure 4 (right) with 1 moderate unclassified as null. Hence, the X_2 predictive model for the QoS showed an accuracy of 99.73%.

A	B	C	
466	1	0	A = Poor
1	507	0	B = Moderate
0	0	155	C = Excellent

A	B	C	
466	1	0	A = Poor
3	506	0	B = Moderate
0	0	155	C = Excellent

Figure 4. Confusion Matrix for C4.5 (left) and ID3 (right) on 9Mobile QOS

Discussions of each MNOs Results

Table 6 gives a summary of the simulation results by presenting the average value of each performance metric that was used to evaluate the decision trees algorithms used to develop the classification algorithms for the QoS of each MNO considered for this study. The number of correct classifications, true positive rate, false-positive rate, and precision were (the metrics) used to evaluate the performance of the developed models.

Table 6. Summary of simulation results

Operator' Datasets	Decision Trees Algorithm	Correct Classifications	Accuracy (%)	TP rate	FP rate	Precision	Area under ROC (AUC)
X_2	C4.5	1127	99.65	0.9973	0.0023	0.9973	0.998
	ID3	1128	99.73	0.9987	0.0013	0.9987	0.998
X_1	C4.5	986	99.60	0.9950	0.0023	0.9970	0.998
	ID3	983	99.26	0.9963	0.0027	0.9943	0.995
X_3	C4.5	1069	99.17	0.9937	0.0043	0.9870	0.995
	ID3	1069	99.17	0.9930	0.0037	0.9923	0.993
X_4	C4.5	1659	99.64	0.9953	0.0017	0.9930	0.998
	ID3	1659	99.64	0.9883	0.0057	0.9860	0.990
X_0	C4.5	295	98.66	0.9570	0.0100	0.9923	1.000
	ID3	295	98.66	0.9537	0.0403	0.9353	0.924

From Table 6, it was discovered that the ID3 had better performance in terms of accuracy than C4.5. It is only in the X_2 dataset with a difference of 1 compared to the C4.5 algorithm's performance. The C4.5 decision trees algorithm had the best performance in the X_1 dataset with a difference of 3 compared to the ID3 algorithm. The C4.5 and ID3 decision trees algorithm had an equal performance on the X_3, X_4, and another network dataset. Unlike the C4.5 decision trees algorithm, the ID3 decision trees algorithm had some areas that could not evaluate the QoS value for which showed the incapacity of the ID3 to handle the problem of classification of QoS.

Additionally, the nodes of the decision trees presented for each MNO revealed that the CSSR, TCHR, RSS, and CDR could determine the QoS for the X_2 dataset, CSSR, TCHR, and RSS for the X_1 dataset. CSSR, TCHR, RSS, and month for the X3 dataset, CSSR, TCHR, RSS, and CDR for the X_4 dataset, and CSSR, RSS, and TCHR for other networks. The ID3 decision trees postulated for the X_2 dataset created 27 rules with 4 null values. The C4.5 decision trees algorithm used to postulate for X_1, X_3, X_4, and other networks had 17, 32, 29, and 17 rules, respectively, as shown in Appendix 1.

5. CONCLUSION AND RECOMMENDATION

The state of QoS in telecommunication in Nigeria has justified the development of the QoS predictive model for the four major network operators in the country. This work had shown the standard of each of the services provided by each of the MNO. The use of a decision tree, which is C4.5 and ID3, has created a model to provide a transparent result for each service provider. Since the results show that, the ID3 and C4.5 accuracy, precision and ROC are high; hence; they are good classifiers for determining the QoS of major mobile network operators. Hence, the work provide platform that will help stakeholders to make an informed decision with respect to user based QoS. The authors' further work will have broader scope using a deep learning paradigm. Lastly, there is a need to break the monopoly enjoyed by service providers. Users cannot choose the best service provider; breaking the monopoly will significantly enhance the QoS in the country.

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Appendix 1: Table showing sample of Combine C4.5 and ID3 rules

Rule#	RSS	TCHCR	CSSR	CDR	QoS
1	Poor	Poor	Poor	Poor	Poor
2	Poor	Poor	Poor	Fair	Poor
	Poor	Poor	Poor	Good	Poor
4	Poor	Poor	Fair	Poor	Poor
76	Good	Good	Fair	Poor	Moderate
77	Good	Good	Fair	Fair	Moderate
78	Good	Good	Fair	Good	Excellent
79	Good	Good	Good	Poor	Moderate
80	Good	Good	Good	Fair	Excellent
81	Good	Good	Good	Good	Excellent

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