PERFORMANCE EVALUATION OF PREDICTIVE MODELS FOR KEY PERFORMANCE INDICATORS IN TELECOMMUNICATION NETWORKS

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Abstract: *Quality of service (QoS) has been a main issue in the Nigerian Telecommunications industry, and how to improve it has been a challenge. The robustness of the KPIs is affected by meteorological variables like temperature, humidity, and rainfall. Intelligent monitoring systems that can anticipate the state of the KPIs and enable the policymakers in the telecommunication to take appropriate action before disruptions occur. These are necessary for mobile operators to lessen the effect of the meteorological parameters on KPIs and to also improve mobile services and user experience. Predictive models such as bagging, boosting (LSBoost), and Neural Networks (NN) were used to develop models for the key parameter indicators (KPIs) using meteorological parameters and evaluated using the mean absolute error (MAE) as the performance metric to be evaluated. The evaluation for Ado-Ekiti, Nigeria was evaluated using the MAE. After evaluation, it was concluded that the bagging model had the best performance for Ado-Ekiti mobile network designs out of the three models.*

1. INTRODUCTION

The telecommunication industry has suffered from poor Quality of Service (QoS), so three models were proposed to be developed to improve the QoS. Four network service providers namely: 9mobile, Airtel, Glo, and MTN were considered and six locations in South West Nigeria were used as the case study. 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) and Quality of end-user Experience (QoE) of their networks and to continue to improve them most efficiently and effectively as possible to maintain competitive edge [2]. One of the six locations will be considered in this paper.

Poor QoS is a result of network operators' reliance on sending signals down the troposphere without first evaluating and characterizing the troposphere [3]. 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 [4]. At the poles and equator, the troposphere is located at an altitude of about 10 km and 17 km, respectively [5].
Researchers have leveraged the use of artificial intelligence in understanding networks [6]. The prediction of the channel state on a given link was done by [7] through measurements on other links, thereby decreasing 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 channel state on a given link through measurements on other links, achieving an RMSE of 10 dB and 73% accuracy using a dataset of RSSI measurements of real-world Wi-Fi operating networks. The paper should have discussed the computational complexity of the proposed methods, which could be a potential limitation in practical implementations.

In the study of [8], an automatic artificial neural network (ANN) predictive quality of service model was used to evaluate the efficiency of services rendered by the Global System for Mobile Communication (GSM) network in Nigeria, and the results of the evaluation 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 improve the accuracy and robustness of the model.

[9] used a walk-test methodology to measure KPIs for internet access on the 4G network by the users who subscribe to various mobile network operators (MNOs) within the University of Ilorin. Data was gathered using TEMS Investigation 16.3.4 and analyzed 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.

[10] proposes a traffic congestion prediction model using machine learning techniques used for the prediction of the existence of traffic congestion in LTE networks as perceived 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 based on the output of the Jupyter Notebook for each classifier. Out of all the techniques used in predicting the existence of traffic congestion, k-Nearest Neighbour outperforms them all. It was concluded that online machine learning techniques will be considered for future studies, and they can continuously read data from network operators so as to obtain the relevant features and traffic congestion prediction performance in real-time to assist the traffic providers in engaging mechanisms to reduce traffic congestion to the barest minimum.

[11] measured and analyzed the Key Performance Indicators (KPIs) of a 24-cell cluster of 4G/LTE Telecom of Kosovo (TK) network. The results of the analysis of the KPIs in a 24-cell cluster of 4G/LTE Telecom of Kosovo (TK) network show that the availability KPI has lower values than the threshold (>99%). Future studies will focus on analyzing the QoS and QoE in the overall 4G/LTE network implemented in TK. The main challenges the Operators will face during the transition process from 4G to 5G technologies will also be addressed.

[12] used network statistics to evaluate the Quality of Service of a cellular network service provider covering an area during a church event. The Call Setup Success Rate, Percentage Drop Call Rate, Handover Success Rate, Percentage TCH Congestion Rate, and Percentage of unsuccessful Control Channel Setup were the KPIs investigated and compared with the benchmark defined by Nigerian Communications Commission (NCC). The study results showed that the cellular network service provider's 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.

[13] evaluated the quality parameters of a 4G-LTE communications' base station in the rural area of Peru using 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 quality parameters of the 4G-LTE communications base station in a rural area of Peru comply with the ITU's E-800 recommendation, which ensures optimal mobile phone coverage in rural areas and accessibility to the entire mobile phone network nationwide. Future studies could focus on analyzing the impact of environmental factors, such as weather conditions and terrain, on the parameters of the communications' base station. Additionally, studies could be conducted to evaluate the performance of the base station during peak usage hours and in areas with high population density. This study focuses on comparing the performance of Bagging, LSBoost and Artificial Neural Network in the prediction of some telecommunication KPIs which include Call Setup Success Rate (CSSR), Dropped Call Rate (DCR), Standalone Dedicated Control Channel (SDCCH) congestion rate and Traffic Channel (TCH). The rest of the paper is organized as follows: Section 2 provides the experimental setup. Section 3 provides the results and discussion. Section 4 presents the conclusion.

2. EXPERIMENTAL SETUP

Historical monthly data of air temperature, air pressure, relative humidity and wind speed for Ado-Ekiti of Nigeria was collected from Nigerian Meteorological Agency (NIMET) in comma-separated values (CSV) using Modern Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) [14]. Data on QoS KPIs such as CSSR, DCR, SDCCH, TCH congestion rate of different telecommunication service providers for the selected states was also collected from the website of the Nigerian Communications Commission [15]. The collected data spanning a period of seven years (from January 1, 2015 to December 31, 2021) will be curated to produce a multimodal dataset. Ado-Ekiti is the capital of Ekiti State: Nigeria. It is the administrative centre of Ekiti State, Nigeria. The land in Ado-Ekiti rises Northwards from 335 metres in South East and attains a maximum elevation of about 730 metres in the Southwest [16].

The flowchart in Figure 1 illustrates the experimental setup employed in this research study. The inputs are inserted into the models. The models' errors are then minimized for weight updating. If the iterations were not satisfied, backpropagation was used for retraining the models, and the models were developed when the iteration was satisfied.

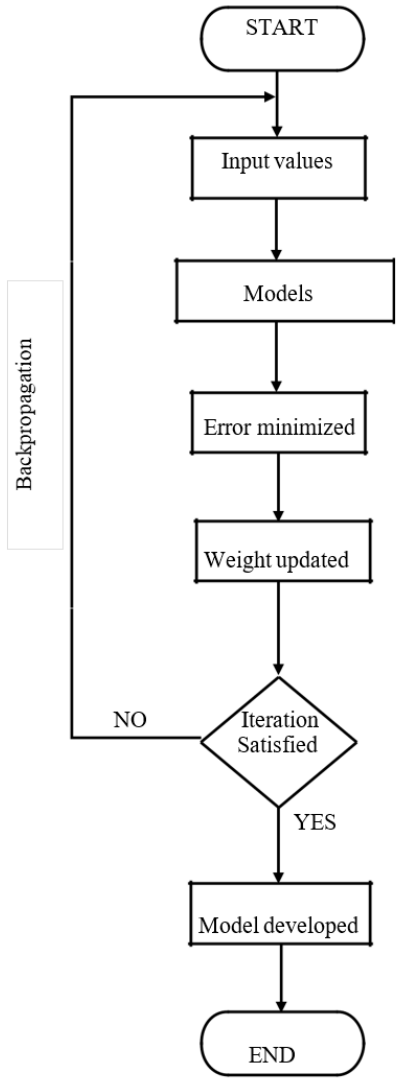

Figure 1: Backpropagation Flowchart

Data preprocessing was performed on the dataset. This ensures that missing data and outliers are catered for. The Normalization employed was the min-max method in MATLAB R2022a. This study employed machine learning to evaluate the four KPIs. Ensemble models which combine several decision trees by bagging and boosting techniques, and a neural network (NN) model were developed using MATLAB R2022a. Ensemble models is the combination of a single decision tree models together in order to enhance predictive ability of the model. Ensemble models ensure the robustness a model. The number of trees in the ensembles models were 100. The neural network has nine inputs and four outputs. The number of neurons in the hidden layer are fifteen as shown in Figure 2. The developed models were trained with the meteorological parameters as inputs and the KPI values as the outputs. The trained models were then used to predict the KPIs given new meteorological information. The best-performing model for the prediction of each KPI was then determined.

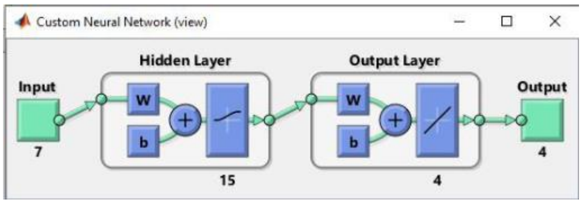

Figure 2: Neural network with 15 neurons

The performance of the proposed models were evaluated using Mean Absolute Error (MAE) [17], the performance metric is expressed in Equation 1 [17].

$$MAE = \frac{\sum_{i=1}^{n} |m_i - p_i|}{n} \qquad (1)$$

where m_i is the actual dataset, p_i is the predicted dataset, n is the total number sample, i is the index of the dataset which starts from 1 and $\sum_{i=1}^{n}$ is the summation of all the datasets. The closer the metric is to zero the better the model performed. [18] employed deep learning for the prediction of rainfall in Taiwan. The authors developed neural network and support vector regression. [19] used neural network trained using MATLAB software for the development of a model for the prediction and optimization of energy consumption in a building.

3. RESULTS AND DISCUSSION

This research paper investigated the key performance indicators from four service providers in six different locations in South-West, Nigeria. The results of the four predicted KPIs for each of the service providers were presented in this chapter. The evaluation of the four predicted KPIs using MAE as a performance metric was also presented. The prediction of Ado-Ekiti 9mobile CSSR, Bagging model had the best MAE value of 0.3228 while LSBoost and ANN had 0.4205 and 0.6736 respectively. Bagging, with MAE of 0.8886, did best in the prediction of Ado-Ekiti 9mobile DCR and the corresponding values of LSBoost and ANN are 1.1163 and 1.1308 respectively. Bagging did best in predicting Ado-Ekiti 9mobile SDCCH congestion rate. It has an MAE value of 0.0809 against LSBoost and ANN with MAE values of 0.1553 and 0.3268 respectively. For the prediction of Ado-Ekiti 9mobile TCH congestion rate, Bagging has the best model, with MAE of 0.0767 while LSBoost and ANN had MAE values of 0.1044 and 0.128 respectively as shown in Figure 3.

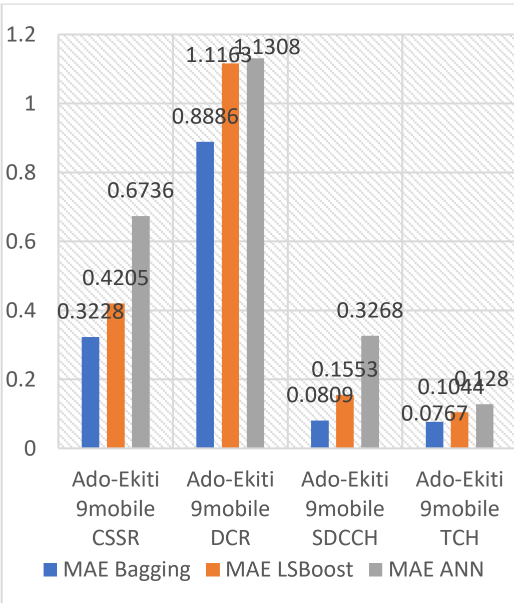

Figure 3: Performance Evaluation of 9mobile Network in Ado-Ekiti

The prediction of Ado-Ekiti Airtel CSSR, ANN model had the best MAE value of 0.5618 while Bagging and LSBoost had 0.7113 and 0.7311 respectively. Bagging, with MAE of 0.4196, did best in the prediction of Ado-Ekiti Airtel DCR and the corresponding values of LSBoost and ANN are 0.4503 and 0.4293 respectively. Bagging did best in predicting Ado-Ekiti Airtel SDCCH congestion rate. It has an MAE value of 0.0314 against LSBoost and ANN with MAE values of 0.0466 and 0.0429 respectively. For the prediction of Ado-Ekiti Airtel TCH congestion rate, Bagging has the best model, with MAE of 0.1011 while LSBoost and ANN had MAE values of 0.113 and 0.1026 respectively as shown in Figure 4.

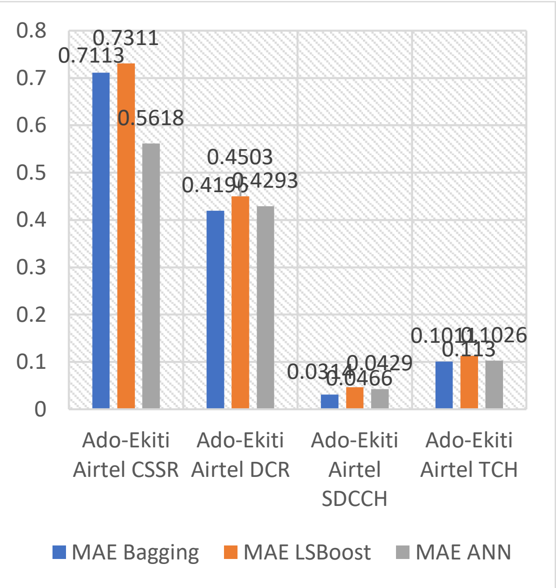

Figure 4: Performance Evaluation of Airtel Network in Ado-Ekiti

The prediction of Ado-Ekiti Glo CSSR, ANN model had the best MAE value of 0.4348 while Bagging and LSBoost had 0.9734 and 0.9657 respectively.

Bagging, with MAE of 0.4752, did best in the prediction of Ado-Ekiti Glo DCR and the corresponding values of LSBoost and ANN are 0.5203 and 0.6793 respectively.

ANN did best in predicting Ado-Ekiti Glo SDCCH congestion rate. It has an MAE value of 0.0415 against Bagging and LSBoost with MAE values of 0.3406 and 0.4463 respectively. The prediction of Ado-Ekiti Glo TCH congestion rate, Bagging has the best model, with MAE of 0.0471 while LSBoost and ANN had MAE values of 0.0831 and 0.1023 respectively as shown in Figure 5.

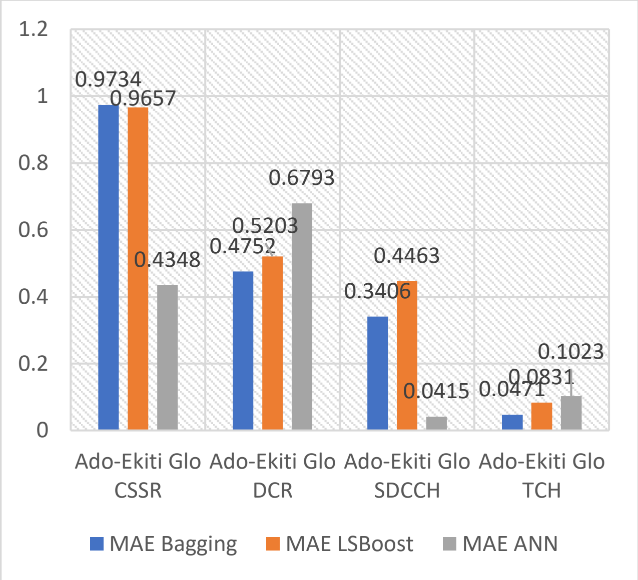

Figure 5: Performance Evaluation of Glo Network in Ado-Ekiti

The prediction of Ado-Ekiti MTN CSSR, Bagging model had the best MAE value of 0.1019 while LSBoost and ANN had 0.1456 and 0.1787 respectively. LSBoost, with MAE of 0.0654, did best in the prediction of Ado-Ekiti MTN DCR and the corresponding values of Bagging and ANN are 0.0816 and 0.0728 respectively.

Bagging did best in predicting Ado-Ekiti MTN SDCCH congestion rate. It has an MAE value of 0.0514 against Bagging and LSBoost with MAE values of 0.0677 and 0.0697 respectively.

For the prediction of Ado-Ekiti MTN TCH congestion rate, Bagging has the best model, with MAE of 0.1062 while LSBoost and ANN had MAE values of 0.1964 and 0.2136 respectively as shown in Figure 6.

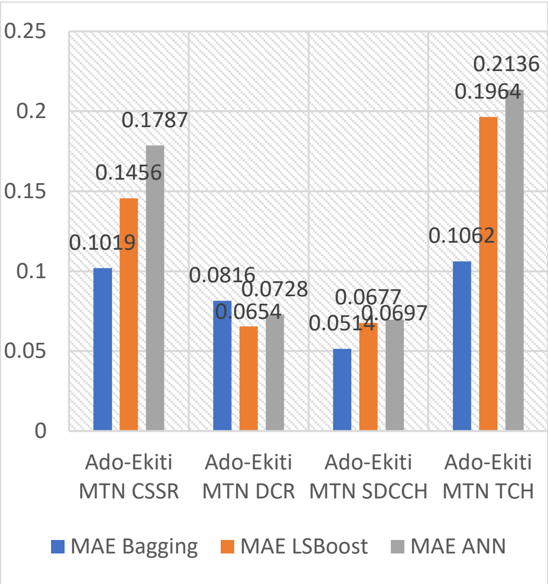

Figure 6: Performance Evaluation of MTN in Ado-Ekiti

Table 1 shows the analysis of the models on KPIs using MAE. The models were evaluated on each of the KPIs for each service providers. Bagging has 100% performance with respect to 9mobile.

With Airtel, Bagging has 75% performance while ANN has 25% performance. Bagging and ANN both has 50 % performance with Glo. Bagging and LSBoost are 75% and 25% respectively for MTN.

Overall, the best performing model for the prediction was the bagging model with the 75% performance, while LSBoost and Neural network has 6.25 % and 18.75 % respectively.

Table 1: Analysis of the models on Ado-Ekiti service providers' KPIs using MAE

ADO-EKITI SERVICE PROVIDER	BAGGING	LSBOOST	ANN
9mobile	4	0	0
Airtel	3	0	1
Glo	2	0	2
MTN	3	1	0
	12	1	3
Models' Performance in %	75 %	6.25 %	18.75 %

4. CONCLUSIONS

The model developed by [20] to access the quality of service (QoS) of GSM in Ilorin metropolis, Nigeria, assessed the QoS Oof Ilorin metropolis. [21] also evaluated the QoS of Kaduna State, Nigeria.

The two models failed to meet the NCC regulations. This indicates that Ado-Ekiti models in this study did better than the Ilorin and Kaduna models.

The performance of the Ado-Ekiti service providers' KPIs met NCC regulations could be due the preprocessing of the dataset used in the study. Furthermore, models employed, ensembles and neural networks may also have significant on the performance of the models.

This study evaluated the performance of the ensemble models (bagging and LSBoost) and ANN on the Ado-Ekiti dataset. The study focused on the four prominent service providers in Nigeria. The bagging model was the best models. The Bagging model has a percentage performance of 75 %. The implication is that, it has the potential to predict the KPIs better and accurately than the other models developed in this study. MAE was employed for the evaluation of the models. The results of this study will assist the service providers to make inform decision that could improve the performance of their network for the benefit of the citizen. This could also translate to healthy competition among the service providers and increment in revenue generation.

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