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Machine learning-based forecast modelling of dropped call rate in mobile networks: A random forest and support vector regression approach

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Abstract

This study evaluates the historical performance and forecasts the DCR of Nigeria's four major mobile networks: Airtel, 9mobile, Globacom, and MTN, using long-term monthly data from January 2015 to December 2024 obtained from the NCC. Two machine learning regression models, Random Forest Regression (RFR) and Support Vector Regression (SVR), were applied to predict DCR trends for 2024, with performance assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Historical analysis revealed that Airtel, Globacom, and MTN consistently met the NCC benchmark, while 9mobile recorded only one month of non-compliance during the 132-month study period. Forecasting results showed that Random Forest outperformed SVR for Airtel, 9mobile, and Globacom, while SVR achieved superior accuracy for MTN. These findings demonstrate the potential of machine learning techniques as effective tools for network performance forecasting, supporting proactive fault management, capacity planning, and regulatory compliance in the Nigerian telecommunications sector.

Keywords: Dropped Call Rate; Machine learning; Random Forest; Support Vector Regression; Forecast modelling

1. Introduction

Dropped calls remain one of the most significant indicators of service quality in mobile networks, directly affecting user satisfaction, loyalty, and trust [1-3]. The Dropped Call Rate (DCR) measures the percentage of calls that terminate unexpectedly due to network issues [4-5] such as congestion, handover failures, interference, inadequate signal quality or infrastructure limitations [2]. High DCR values disrupt personal, business, and emergency communications, often prompting subscribers to consider switching to alternative Mobile Network Operators (MNOs) [3].

In Nigeria, the Nigerian Communications Commission (NCC) has set a regulatory benchmark stipulating that DCR should not exceed 1% [1-2]. Despite this standard, subscribers continue to report frequent call terminations, raising concerns over network reliability and compliance [6-10]. Evaluating the degree to which MNOs comply with this benchmark is therefore critical for improving service quality and strengthening regulatory enforcement [11-37].

Previous studies on DCR performance in Nigeria have often relied on drive test data, which although useful are geographically limited and provide only short term performance snapshots [38-39]. Such approaches do not adequately capture nationwide continuous performance trends [38-39]. To address this gap, the present study uses comprehensive long term datasets obtained from the Network Operations Centres (NOCs) of Nigeria's four major MNOs: MTN, Airtel, Globacom and 9mobile, collected through specialised network counters. This approach enables an extensive and reliable assessment of both compliance and performance patterns.

Beyond compliance assessment, there is a growing need to anticipate future DCR performance to guide proactive network optimisation and strategic planning [40-50]. This study applies machine learning forecasting models,

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specifically Random Forest Regression (RFR) and Support Vector Regression (SVR), to predict DCR trends for the period January to December 2024. These models were selected for their proven ability to capture complex nonlinear relationships in datasets and to deliver high forecasting accuracy [51-53].

Focusing on these two objectives, evaluating compliance with the NCC benchmark and predicting future DCR patterns, this research provides both a regulatory performance check and a decision support tool for MNOs and policymakers. The findings aim to support proactive interventions that will improve network retainability, reduce dropped calls, and enhance the overall quality of mobile communication services in Nigeria.

2. Methodology

This study employed a two-phase approach: data acquisition and analysis of compliance with the NCC benchmark, followed by machine learning-based predictive modelling of the Dropped Call Rate (DCR).

2.1. Data Collection

Monthly DCR data for the four major GSM networks in Nigeria, namely MTN, Airtel, Globacom and 9mobile, were obtained from the NCC. The dataset spans January 2015 to December 2024 and was collected using specialised counters at the NOCs of the respective MNOs. Each data point represents the percentage of calls that were terminated unexpectedly due to network-related issues.

2.2. Compliance Assessment

To determine adherence to the NCC benchmark of not more than 1% DCR, the proportion of months in which each MNO's DCR met or exceeded the benchmark was calculated. This analysis provided insight into each network's reliability and its ability to maintain acceptable service quality over time.

2.3. Predictive Modelling Using Machine Learning

To forecast DCR trends from January 2024 to December 2024, two machine learning regression algorithms were implemented: Random Forest Regression (RFR) and Support Vector Regression (SVR). Both models were selected based on their ability to model complex, non-linear patterns in network performance data.

2.3.1. Random Forest Regression (RFR)

Random Forest is a machine learning technique that is extensively used for both classification and regression tasks [51]. It is based on the concept of decision trees, where an ensemble of multiple trees is constructed, and their outputs are combined to generate the final prediction. Each tree in the forest is built from a randomly selected subset of the dataset, with training performed on only a portion of the available data. The outputs from all trees are then averaged or voted upon to produce the overall result [52]. One of the notable advantages of Random Forest is its capacity to handle imbalanced datasets and accommodate variables with missing values. It also mitigates the bias that can arise from arbitrary variable selection, which is a limitation in certain other models. By training numerous trees on randomly chosen subsets of data, Random Forest reduces the risk of overfitting and enhances its ability to generalise to new, unseen data. Regarded as one of the most robust and effective machine learning algorithms, Random Forest is widely applied in domains such as automated classification, predictive modelling, and supervised learning tasks [53].

2.3.2. Support Vector Regression (SVR)

Support Vector Regression applies the principles of Support Vector Machines to regression tasks. It aims to fit a function within a defined error margin (epsilon) while maintaining maximum flatness of the prediction function. By using kernel functions such as the radial basis function (RBF), SVR can capture both linear and non-linear relationships in time series data. In this study, the RBF kernel was chosen due to its strong ability to model non-linear variations in DCR.

2.4. Model Performance Evaluation

The accuracy and reliability of each model were evaluated using three statistical performance metrics: The Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE).

The MAE measures the average size of forecast errors without considering their direction. The RMSE assigns greater weight to larger errors, making it useful for assessing model robustness while the MAPE expresses forecast errors as a percentage, facilitating easy interpretation. In all, the model with the lowest error values across these metrics for each network was considered the best-performing.

2.5. Software and Tools

All analyses were carried out using Python due to its flexibility, strong data processing capabilities and extensive library support for statistical analysis and machine learning. The main libraries used were Pandas for data cleaning, manipulation and structuring. Matplotlib and Seaborn for data visualisation. NumPy for numerical computation. Scikit learn for implementing Random Forest and Support Vector Regression models. SciPy was used for statistical computation and optimisation.

3. Results and Discussion

The historical analysis of DCR performance across Nigeria, the forecasting of DCR for mobile networks from January 2024 to December 2024, and the performance evaluation of the forecasting models have been completed. The results are presented in this section through graphs and tables, with each output discussed in detail.

3.1. Analysis of Historical Trend

In this section, historical graphs are presented for the mobile networks examined in the study. These plots illustrate the DCR data for each network from January 2015 to December 2024.

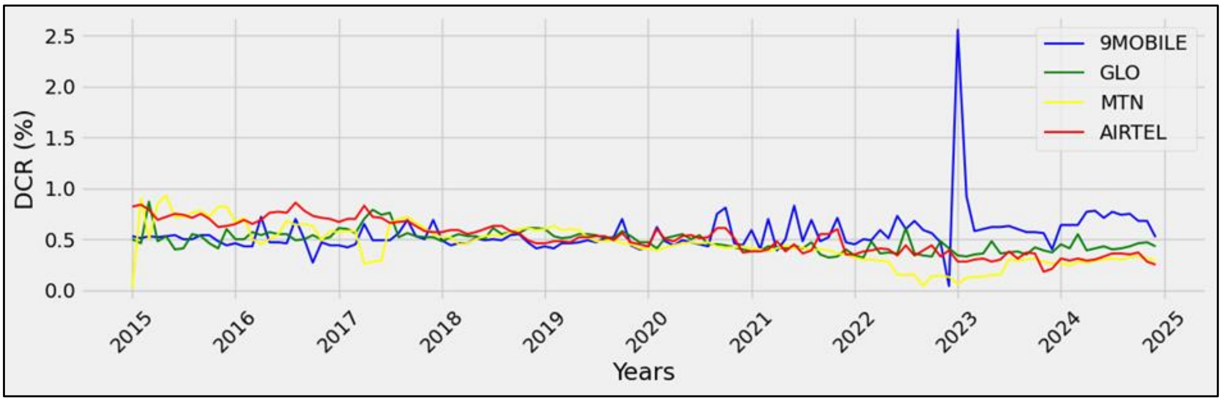

Figure 1 Monthly DCR trends from January 2015 to December 2024

Figure 1 shows the monthly variation in DCR over the study period. Distinct colours were assigned to each network for clarity: red for Airtel, blue for 9mobile, green for Globacom, and yellow for MTN. Based on the NCC benchmark of a maximum of 1% DCR, Airtel, Globacom, and MTN consistently maintained values within the benchmark across all months. Hence, the demonstrated excellent network retainability and reliability for the NCC's dropped call rate benchmark.

For 9mobile, compliance with the benchmark was observed in 131 out of the 132 months analysed. This shows strong performance while the single month of non-compliance suggests an isolated performance issue rather than a recurring problem.

3.2. Analysis of Forecast Models

The historical DCR data spanning January 2015 to December 2023 for the four mobile networks were employed to train the Random Forest and the SVR model.

In deploying the Random Forest model for forecasting, the monthly historical data were first transformed into a supervised learning format. For each target month, twelve lag features were generated to capture the DCR values from the preceding twelve months, allowing the model to learn temporal dependencies and patterns in call retention performance. In addition, month-of-year indicator variables were introduced to account for seasonal effects. For example, the forecast for January 2024 was based on the DCR values from January to December 2023, together with a binary variable indicating the month of January. The training dataset covered the period from January 2016 to December 2023, with the first twelve months reserved for the creation of lag features. Once the dataset was prepared, the Random Forest algorithm constructed a large ensemble of decision trees, each trained on a bootstrap sample of the data. At each node split, a random subset of features was considered rather than all available features, promoting diversity among the trees and reducing correlation between them. This randomised feature selection, combined with bootstrapping, helped to minimise overfitting while allowing the model to capture complex, non-linear patterns in the DCR data. The final prediction for each month was obtained by averaging the outputs from all trees, a process that generally improves model stability and predictive accuracy. This approach was applied consistently to the four networks under study.

The SVR model was trained using a twelve-month lag window to capture both seasonal and short-term variations in DCR. Standardisation of both the predictors and the target variable ensured that the model treated all features equally, preventing distortion from differences in scale. The choice of a radial basis function (RBF) kernel proved effective in modelling the nonlinear patterns inherent in the DCR data. The forecasts for January to December 2024 were generated recursively, with each predicted value fed back into the model as part of the subsequent month's input. This approach allowed the SVR to maintain awareness of recent trends throughout the forecast horizon.

Using the trained models, monthly DCR forecasts were generated for the period January 2024 to December 2024. The forecast outcomes are examined and discussed individually for each network.

3.2.1. Forecast Description for Airtel Network

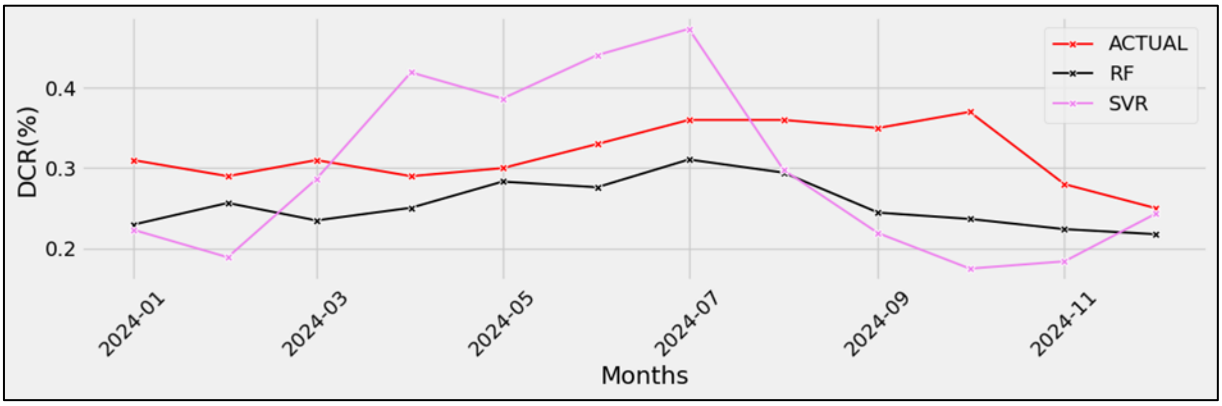

Figure 2 Actual and Forecast DCR Plot for Airtel Network

The actual DCR values and the forecasted values for Airtel network are presented in Figure 2. Again, colour-coded lines were used to represent the plots. Red for the actual value, black for the Random Forest and violet for the SVR plot. As observed in the graph**,** the Random Forest (RF) predictions were consistently closer to the actual DCR values compared to the SVR predictions. The Random Forest model showed smaller deviations from the actual values across all months, while the SVR exhibited larger fluctuations, sometimes underestimating and substantially overestimating the actual values.

This result was affirmed by the performance evaluation metrics presented in Table 1. As displayed in the table, Random Forest clearly outperformed SVR across all metrics, indicating better predictive accuracy for Airtel dataset. SVR's higher MAPE suggests it struggled with percentage errors, possibly due to sensitivity to scaling and the dataset's variation patterns. Hence, for mobile CSSR monitoring, the lower errors from Random Forest mean more reliable forecasts for proactive network optimisation.

Table 1 Performance Evaluation Metrics for Airtel Network

Model	**MAE**	**RMSE**	**MAPE (%)**
Random Forest	0.0617	0.0694	19.01
SVR	0.0952	0.1064	29.44

3.2.2. Forecast Description for 9mobile Network

Figure 3 is a graph of the actual value and forecast models of DCR for the 9mobile network. Here, the DCR is represented by the blue line, the SVR forecasts in violet, and the Random Forest forecasts in black.

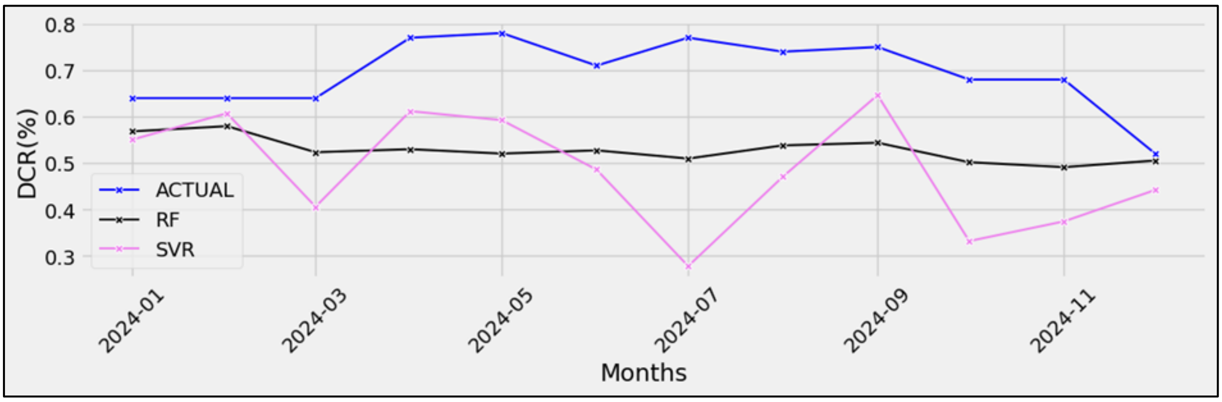

Figure 3 Actual and Forecast DCR Plot for 9mobile Network

The Random Forest predictions closely followed the general shape of the actual DCR curve across the forecast period. However, the RF estimates remained consistently lower than the observed values in most months, indicating a slight underestimation bias. Despite this, the model maintained relatively stable predictions that effectively captured the overall trend.

In contrast, the SVR model also tracked the general DCR trend but exhibited larger fluctuations. This variability was more pronounced around extreme values, where SVR forecasts deviated substantially from the actual data. Such deviations contributed to higher error rates, particularly in months with sharp changes in DCR.

Performance metrics displayed in Table 2 further highlighted these differences. The Random Forest model achieved lower MAE, RMSE, and MAPE compared to SVR, demonstrating its superior accuracy in forecasting DCR. SVR's comparatively higher error values indicate that it struggled to handle outliers and sudden spikes in the data effectively. In the end, we conclude that while both models captured the general pattern of DCR variations, Random Forest proved to be the more reliable forecasting method for this dataset, offering better accuracy and stability in predictions.

Table 2 Performance Evaluation Metrics for 9mobile Network

Model	**MAE**	**RMSE**	**MAPE (%)**
Random Forest	0.1650	0.1823	22.85
SVR	0.2100	0.2448	29.73

3.2.3. Forecast Description for Glo Network

The actual values and the forecast models are shown in Figure 4. From the graph, actual DCR (green line), SVR(violet line), and Random Forest (black line)

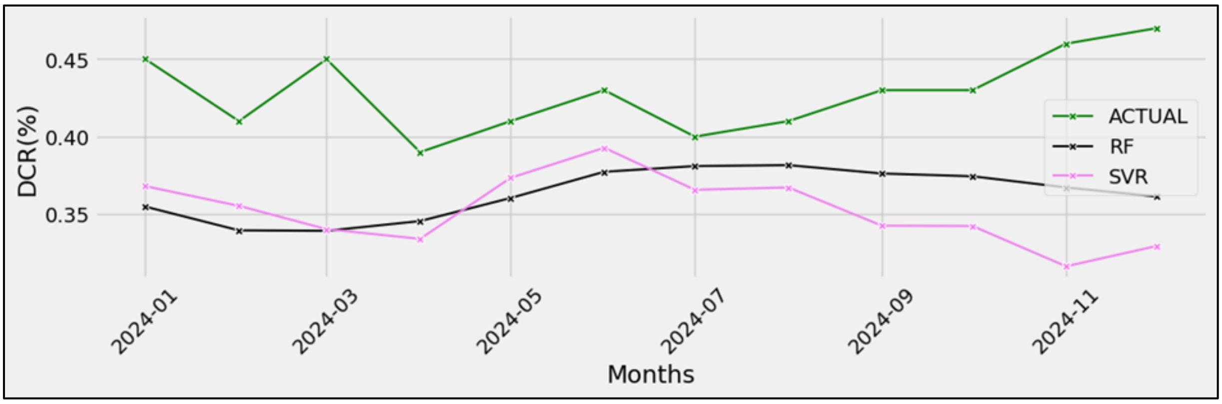

Figure 4 Actual and Forecast DCR Plot for Glo Network

The actual DCR values and forecasts from both models are presented in Figure 4, with the actual DCR represented by the green line, the SVR forecasts in violet, and the Random Forest forecasts in black. From the graph, the actual DCR curve consistently appeared above both the Random Forest and SVR forecast curves throughout the study period, indicating that both models tended to underestimate the true DCR values. Random Forest predictions were generally close to the actual values, maintaining relatively small and consistent gaps across most months. This pattern suggests a stable underestimation bias that could be corrected through model recalibration. Similarly, the SVR predictions tracked the general trend of the actual DCR values but displayed slightly larger fluctuations than the Random Forest forecasts. This variability was more evident during months with sharp changes in DCR, contributing to higher forecast errors.

As shown in Table 3, Random Forest outperformed SVR across all evaluation metrics, recording lower values for MAE, RMSE, and MAPE. Specifically, the MAPE results indicate that Random Forest predictions were, on average, 14.93% different from the actual values, compared to 17.40% for SVR. From a mobile network operations perspective, these findings suggest that Random Forest offers a more reliable approach for predicting Glo's dropped call rates. Improved prediction accuracy can support better capacity planning, quicker fault diagnosis, and enhanced quality assurance, ultimately contributing to more stable and efficient network performance.

Table 3 Performance Evaluation Metrics for Glo Network

Model	MAE	RMSE	MAPE (%)
ARIMA	0.0651	0.0714	14.93
Random Forest	0.0761	0.0848	17.40

3.2.4. Forecast Description for MTN Network

The actual DCR values and the forecasts from both models for the MTN network are illustrated in Figure 5, where the actual DCR is represented by the yellow line, the SVR forecasts by the violet line, and the Random Forest forecasts by the black line.

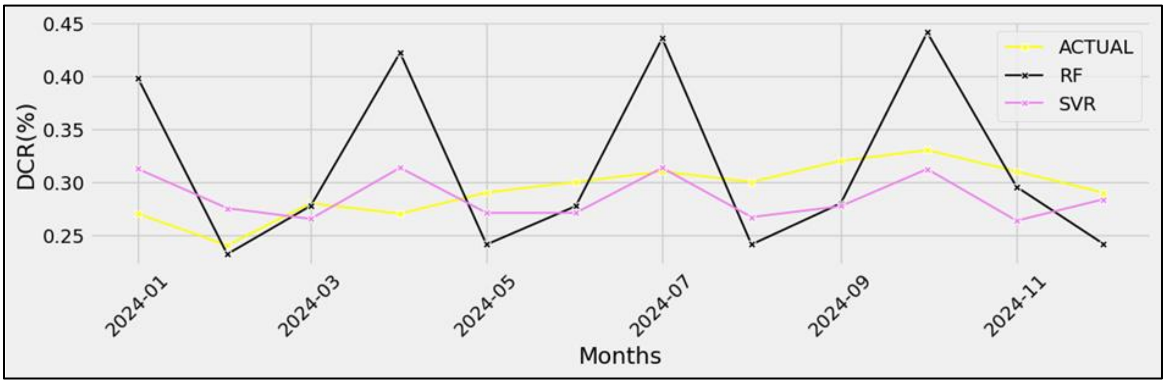

Figure 5 Actual and Forecast DCR Plot for MTN Network

Random Forest predictions display a mixed performance pattern. In some months, the model significantly overestimated the DCR, producing values well above the actual rates. In other periods, RF predictions were closer to the observed values, but this inconsistency indicates that the model's errors were irregular rather than resulting from a consistent bias. Such occasional large deviations reduce its reliability for this dataset. In contrast, SVR predictions were more stable and generally aligned more closely with the actual values across the forecast period. The deviations between SVR forecasts and the actual DCR were smaller, and the model effectively avoided the sharp overestimations exhibited by Random Forest in certain months.

As presented in the performance metrics in Table 4, SVR outperformed Random Forest across all evaluation measures, recording lower Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). This indicates that SVR produced forecasts that were, on average, closer to the actual MTN dropped call rates.

From an operational perspective, the superior performance of SVR suggests it is the more suitable model for forecasting DCR in the MTN network, enabling better resource allocation, proactive fault management, and enhanced network quality monitoring.

Table 4 Performance Evaluation Metrics for MTN Network

Model	**MAE**	**RMSE**	**MAPE (%)**
SVR	0.0279	0.0314	6.62
Random Forest	0.0635	0.0808	15.07

4. Conclusion

This study assessed the historical performance and forecasted Dropped Call Rates (DCR) for Nigeria's four major mobile networks: Airtel, 9mobile, Globacom, and MTN, using long-term operational data from January 2015 to December 2024. The analysis evaluated compliance with the Nigerian Communications Commission (NCC) benchmark of a maximum 1% DCR and applied two machine learning models: Random Forest Regression (RFR) and Support Vector Regression (SVR) to predict DCR trends for 2024.

Historical analysis revealed that Airtel, Globacom, and MTN consistently operated within the NCC limit, while 9mobile had only one month of non-compliance over the 132-month study period. Forecast results demonstrated that Random Forest outperformed SVR in predicting DCR for Airtel, 9mobile, and Globacom, delivering lower MAE, RMSE, and MAPE values and producing stable predictions. Conversely, SVR proved superior for MTN, offering more accurate forecasts and avoiding the large deviations observed in Random Forest predictions.

These findings underscore the importance of selecting forecasting models based on network-specific behaviour rather than a one-size-fits-all approach. The results provide valuable insights for mobile network operators, enabling proactive fault management, improved capacity planning, and enhanced service quality. Furthermore, integrating machine learning into network performance monitoring can help regulatory bodies and operators maintain compliance with NCC standards and improve user satisfaction.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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