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(Research Article)

A Machine Learning Approach to Forecasting TCCH Congestion in Nigerian GSM Networks: Comparing Support Vector Regression and Gradient Boosting Regression

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Abstract

The rapid expansion of mobile telecommunications in Nigeria has intensified the demand on network infrastructure, resulting in persistent Traffic Channel (TCCH) congestion that undermines service quality and user experience. Accurate forecasting of congestion trends is critical for effective resource allocation, regulatory compliance, and network planning. This study applied two machine learning techniques, Support Vector Regression (SVR) and Gradient Boosting Regression (GBR), to forecast monthly TCCH congestion rates across Nigeria's four major GSM networks: MTN, Airtel, Globacom, and 9mobile. A nine year dataset spanning January 2015 to December 2023 was obtained from the Nigerian Communications Commission (NCC) and restructured into a supervised learning format using twelve lagged features and month of year dummy variables to capture temporal dependencies and seasonal patterns. Both models were trained on data from January 2016 to December 2023 and employed a recursive multi step forecasting approach to predict congestion for January to December 2024. Model performance was assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results showed that while both models effectively captured monthly variation trends, SVR consistently produced lower error values and aligned more closely with actual observations, particularly for Airtel, Glo, and 9mobile networks. GBR tended to overestimate congestion, especially at low actual values, leading to higher percentage errors. The findings demonstrate the superior accuracy and stability of SVR for short term TCCH forecasting in Nigerian GSM networks. Incorporating such machine learning models into operational workflows can enhance proactive congestion management, optimise frequency resource planning, and support compliance with regulatory benchmarks.

Keywords: Traffic Channel Congestion; GSM Networks; Machine Learning; Support Vector Regression; Gradient Boosting Regression; Forecasting

1. Introduction

The rapid growth of mobile telecommunications in Nigeria has transformed the nation's communication landscape. With over 200 million inhabitants and one of the largest mobile markets in Africa, Nigeria's reliance on Global System for Mobile Communications (GSM) networks has intensified significantly in recent years [1-3]. This expansion has, however, placed considerable pressure on network infrastructure, resulting in persistent challenges in service quality [4-10]. One of the most critical issues is Traffic Channel (TCCH) congestion, a performance indicator that reflects the availability of network resource allocation and directly influences the quality of service experienced by subscribers [8].

In GSM architecture, once a call setup is completed through the Standalone Dedicated Control Channel (SDCCH), the communication is handed over to a Traffic Channel, which is responsible for carrying the actual voice or data transmission [8,11-12]. When the demand for TCCH resources surpasses available capacity, users experience call blocking, dropped calls, and degraded voice quality [8]. Despite the regulatory threshold, mobile users across the four

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major operators MTN, Airtel, Globacom, and 9mobile continue to face high congestion levels, especially in densely populated urban centres and during peak demand periods. Such service degradation undermines customer satisfaction and loyalty, while also causing financial losses for operators and straining regulatory enforcement [7].

Several factors contribute to the persistent TCH congestion in Nigerian GSM networks. Rapid urbanisation and population growth have fuelled an unprecedented rise in mobile subscriptions, while infrastructure expansion and frequency allocation have not kept pace with demand [13-15]. Inefficient network planning, inadequate capacity upgrades, and interference issues further exacerbate congestion [16]. Additionally, seasonal and event driven spikes in demand intensify the strain on available resources [17-20]. As Nigeria transitions toward advanced technologies such as 5G, addressing these systemic challenges within existing GSM infrastructure remains an urgent priority.

Forecasting congestion trends can provide operators and regulators with insights necessary for proactive planning and capacity optimization [21-32]. Traditional statistical approaches such as the AutoRegressive Integrated Moving Average (ARIMA) model have been widely employed for network performance forecasting [31]. However, these methods often struggle to capture non-linear patterns and complex temporal dependencies in network data [32]. Recent advances in machine learning offer powerful alternatives, with effective methods for handling noisy, non-linear datasets [31-32].

Although studies on GSM performance in Nigeria have examined congestion trends and applied statistical models for forecasting [30], very limited research has explored the application of advanced machine learning models such as SVR and GBR in this context. Furthermore, to the best of our knowledge, no existing study has systematically compared the predictive capabilities of these two models using long-term Nigerian congestion data. This gap is significant because accurate forecasting is essential for timely infrastructure planning, regulatory enforcement, and ensuring compliance with NCC benchmarks. By filling this gap, the present study provides empirical evidence on which predictive approach is more suitable for modelling TCH congestion trends in Nigeria, thereby contributing to both scholarly literature and practical telecom management.

This study adopts a machine learning approach to forecasting TCH congestion in Nigerian GSM networks. This research applies predictive models to estimate congestion rates. Specifically, the predictive performance of Support Vector Regression and Gradient Boosting Regression is compared using standard error metrics to determine the most suitable technique for congestion forecasting. The results will assist mobile network operators in optimising frequency resources, improving infrastructure planning, and mitigating congestion.

1.1. Support Vector Regressor

The Support Vector Regressor (SVR) is a machine learning algorithm derived from the principles of Support Vector Machines (SVM) and is used for predicting continuous numerical values. Unlike traditional regression models that attempt to minimise the total prediction error, SVR seeks to fit a regression line (or hyperplane in higher dimensions) that predicts within a specified error tolerance known as the epsilon-insensitive margin. Only the data points lying outside this margin, known as support vectors, influence the model [33-34].

SVR is particularly effective for capturing complex non-linear relationships by using kernel functions such as the radial basis function (RBF) to project input data into higher-dimensional feature spaces where linear relationships can be identified. It employs regularisation parameters to prevent overfitting and to enhance the model's ability to generalise to unseen data [35].

Because of its robustness to noise, ability to handle high-dimensional data, and strong generalisation performance, SVR is widely used in various regression tasks, including time series forecasting, financial market prediction, and telecommunications network performance modelling [33,35].

1.2. Gradient Boosting Regressor

The Gradient Boosting Regressor (GBR) is an ensemble machine learning algorithm that builds a strong predictive model by combining multiple weak learners, typically decision trees, in a sequential manner. Each tree is trained to correct the residual errors made by the previous ensemble of trees, and their outputs are combined to produce the final prediction [36].

GBR minimises a specified loss function, commonly the mean squared error in regression tasks, using gradient descent optimisation. By focusing successive trees on the hardest-to-predict data points, the model progressively improves its accuracy. It can model complex non-linear relationships and is highly flexible due to its numerous tunable hyperparameters, such as learning rate, number of estimators, and maximum tree depth [37].

Despite its high accuracy and ability to capture intricate patterns, GBR can be prone to overfitting if not properly regularised. It is widely applied in time series forecasting, financial risk modelling, and telecommunications performance prediction due to its strong predictive performance and adaptability [38].

2. Research Methodology

The dataset used for this study was obtained from the Nigerian Communications Commission (NCC), the regulatory authority responsible for monitoring and evaluating telecommunications performance in Nigeria. Monthly Traffic Control Channel (TCCH) congestion rate data were collected for the four major GSM network operators in the country, namely MTN, Airtel, Globacom, and 9mobile. The dataset spanned a nine year period from January 2015 to December 2023, providing a sufficiently long and consistent time series for developing reliable forecasting models of congestion behaviour.

To implement the Gradient Boosting Regressor (GBR), the historical monthly TCCH values were first transformed into a supervised learning format suitable for regression analysis. For each target month to be forecast, twelve lagged features were created to represent the TCCH values from the preceding twelve months, thereby capturing temporal dependencies within the data. In addition, twelve month of year dummy variables were introduced to account for seasonal patterns in congestion. For example, when forecasting January 2024, the model used as input the TCCH values from January 2023 to December 2023 together with a binary indicator denoting the month of January. The first twelve months of the dataset (January to December 2015) were reserved exclusively for generating lag features and were not included in the training phase.

The transformed dataset covering January 2016 to December 2023 was used to train the GBR model. This model constructs an ensemble of decision trees sequentially, where each new tree is trained to correct the residual errors of the combined previous trees. The objective function minimised the mean squared error (MSE) between the predicted and actual TCCH values, allowing the model to capture both linear and non linear relationships in the data. Hyperparameters such as learning rate, number of estimators, and maximum depth were carefully tuned to enhance predictive performance and prevent overfitting.

Forecasting was carried out using a recursive multi step strategy. The GBR first predicted the TCCH value for January 2024 based on the most recent twelve months of lagged values (January to December 2023). This predicted value was then appended to the dataset and used as part of the input to forecast February 2024. The same process was repeated iteratively until forecasts were generated for all months from January to December 2024. While this approach enabled multi step forecasting, it also introduced the potential for error accumulation across the forecast horizon.

The same data preparation strategy was applied to the Support Vector Regressor (SVR) model. The historical monthly TCCH data were reformatted into a supervised learning structure, with twelve lagged features representing the previous twelve months values and twelve month of year dummy variables to account for seasonal variations. For example, when forecasting January 2024, the model inputs consisted of the TCCH values from January 2023 to December 2023 along with a binary indicator for January. As with GBR, the first twelve months (January to December 2015) were used only to generate lag features and were excluded from the training set.

The SVR model was trained on the dataset covering January 2016 to December 2023 using a radial basis function (RBF) kernel to capture non linear relationships between the lagged input features and the target outputs. The SVR seeks to fit an optimal regression hyperplane within an epsilon insensitive margin while maximising the distance between support vectors and the hyperplane, which enhances its ability to generalise even in the presence of noise. Hyperparameters such as the regularisation parameter (C), kernel coefficient (gamma), and epsilon were tuned to achieve an optimal balance between bias and variance, thereby improving prediction accuracy.

Similar to the GBR, the SVR generated the twelve month forecasts for 2024 using a recursive forecasting procedure. The model first predicted the TCCH value for January 2024 based on the most recent twelve months of lagged data (January to December 2023). This predicted value was then incorporated into the historical sequence and used as one of the lagged features for forecasting February 2024. This process continued iteratively until predictions were produced for all months from January to December 2024. While this method allowed multi step forecasting, it also carried the risk of compounding errors across the forecast horizon.

The predictive performance of both models was assessed using three standard evaluation metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). MAE measured the average magnitude of errors without considering their direction, RMSE penalised large deviations more heavily and provided a robust measure of accuracy, while MAPE expressed the prediction errors as percentages, enabling intuitive model comparisons. The model that achieved the lowest values across these metrics was judged to have superior forecasting capability.

All computations and analyses were conducted using the Python programming environment. Data preparation tasks, including loading, cleaning, and transformation, were carried out using the Pandas library, while numerical computations were performed with NumPy. Visualisations for exploratory analysis and presentation of results were generated with Matplotlib and Seaborn. The machine learning models Support Vector Regression and Gradient Boosting Regression were implemented using the Scikit learn library, with hyperparameter tuning performed through its built in optimisation utilities. Additionally, statistical computations and optimisation routines were supported by the SciPy library. The results of the forecasts and the comparative performance evaluation of the two models are presented in the subsequent section using tables and figures, accompanied by detailed interpretation and discussion.

3. Results and Discussion

Forecasts of TCCH congestion for MTN, Airtel, Globacom, and 9mobile were successfully generated for the period January to December 2024 using the GBR and SVR models. The results are presented in tables and graphical plots, allowing both quantitative and visual comparisons between the predicted and observed values. For all four networks, the models effectively captured the month-to-month variations in TCCH congestion. In the plots, the GBR forecast values are represented in black, the SVR forecast values in violet, the MTN actual values in yellow, the Airtel actual values in red, the Globacom actual values in green, and the 9mobile actual values in blue.

3.1. Forecast and Performance Evaluation for MTN Network

Figure 1 shows the monthly variations of actual and predicted TCCH congestion values for the year 2024, for MTN network. The plot contains three lines representing the actual values, the GBR model predictions, and the SVR model predictions. The actual TCCH congestion values fluctuate markedly between 0.14 and 0.45, displaying several peaks and troughs across the twelve months. The GBR prediction line remains consistently lower than the actual values, ranging from approximately 0.18 to 0.29, and appears smoother with dampened peaks. The SVR prediction line, ranging from about 0.23 to 0.31, follows the pattern of the actual values more closely, particularly during months of high congestion. Although both GBR and SVR captured the general trend and direction of monthly variations, their lines exhibit reduced amplitude, indicating underestimation of peak congestion levels. In all, the graph demonstrates that while both models tracked the overall trend of TCCH congestion, the SVR predictions were visually closer to the actual values than the GBR predictions.

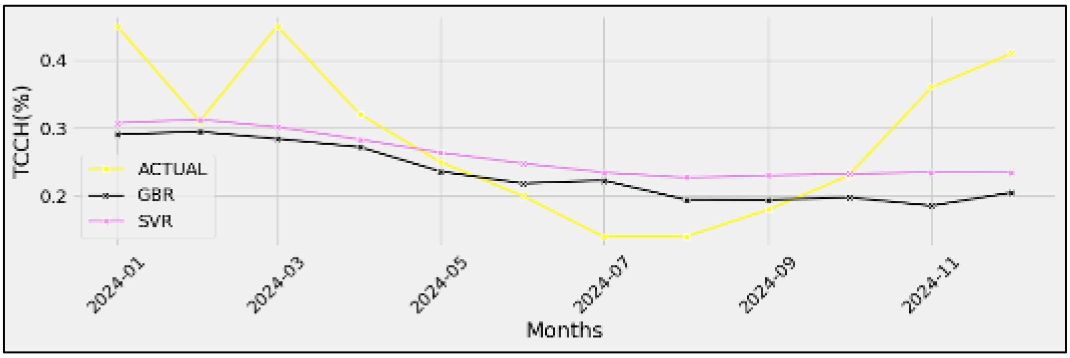

Figure 1 Actual and Forecast TCCH Plot for MTN Network

Table 1 Performance Evaluation Metrics for MTN Network

Model	MAE	RMSE	MAPE (%)
GBR	0.0820	0.1078	27.11
SVR	0.0773	0.0965	28.56

In terms of performance, as presented in Table 1, an interesting pattern emerged. The GBR recorded a MAE of 0.0820, a RMSE of 0.1078, and a MAPE of 27.11%. On the other hand, the SVR showed slightly lower error values, with an MAE of 0.0773 and an RMSE of 0.0965, although its MAPE was a bit higher at 28.56%.

This meant that SVR was marginally more accurate when measuring absolute differences between predicted and actual TCCH values, while GBR performed slightly better in terms of percentage-based accuracy. Both models, however, demonstrated strong predictive ability, with their average absolute errors staying below 0.1 units of TCCH. In practical terms, this suggests that either model could serve network operators well for short-term TCCH forecasting. If the goal is to minimise absolute errors, SVR would be the more suitable choice, whereas GBR would be more appropriate if percentage-based accuracy is considered more important.

3.2. Forecast and Performance Evaluation for Airtel Network

Figure 2 illustrates the monthly variations of actual and predicted TCCH congestion values using the GBR and SVR models, for Airtel network. The actual values fluctuate moderately between 0.14 and 0.39, showing a gradual rise and fall across the twelve months. In contrast, the GBR prediction line starts extremely high, with values above 1.0 in the early months, before declining sharply in the later months to values below 0.3. This produces a steep downward trend that deviates strongly from the actual values, showing significant overestimation in the first half of the period.

The SVR prediction line, however, remains much closer to the actual values, ranging from about 0.33 to 0.69. It generally follows the pattern of the actual line, capturing the moderate peaks and troughs, though with slightly higher amplitudes at certain points. In all, the plot shows that while SVR closely tracked the shape and range of the actual TCCH values, GBR predictions were largely inconsistent, particularly at the beginning of the period, where they were far above the actual observations. This visual comparison suggests that SVR provided a more stable and realistic prediction pattern than GBR.

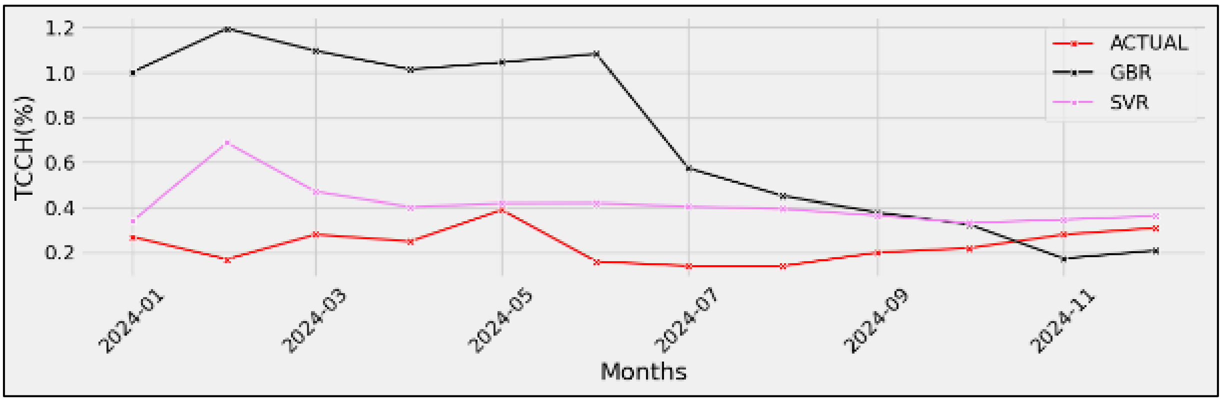

Figure 2 Actual and Forecast TCCH Plot for Airtel Network

Table 2 Performance Evaluation Metrics for Airtel Network

Model	MAE	RMSE	MAPE (%)
GBR	0.5120	0.6093	246.03
SVR	0.1777	0.2201	99.77

As shown in Table 2, the GBR model recorded an MAE of 0.5120, RMSE of 0.6093, and MAPE of 246.03%, while the SVR model achieved lower errors with an MAE of 0.1777, RMSE of 0.2201, and MAPE of 97.77%. These results show that SVR outperformed GBR, producing forecasts that were closer to the actual TCCH congestion values. However, the very high MAPE values for both models are largely due to the small magnitude of the actual congestion values; even slight absolute deviations appear as large percentage errors.

GBR consistently overestimated congestion, which could trigger false alarms and lead to wasted operational efforts. SVR provided more reliable forecasts, aligning better with actual network conditions, and is therefore more suitable for monitoring TCCH congestion trends. It is recommended that SVR be adopted for forecasting, with MAE and RMSE used as the main evaluation metrics, while also applying data transformations to reduce the effect of inflated MAPE values.

3.3 Forecast and Performance Evaluation for Glo Network

Figure 3 presents the monthly variations of actual and predicted TCCH congestion values using the GBR and SVR models. The actual values fluctuate moderately between 0.33 and 0.62 across the twelve months, showing a series of gentle rises and falls.

The GBR prediction line stays within a narrow band from about 0.55 to 0.63 and appears relatively flat, showing less fluctuation than the actual values. It slightly underestimates the higher actual values and overestimates the lower ones. The SVR prediction line ranges from about 0.50 to 0.64 and follows the actual pattern more closely, especially at the higher congestion points where it nearly overlaps the actual values.

In all, the graph shows that while both models captured the general trend, SVR predictions aligned more closely with the actual values, whereas GBR produced a smoother line with smaller variation around the actual trend.

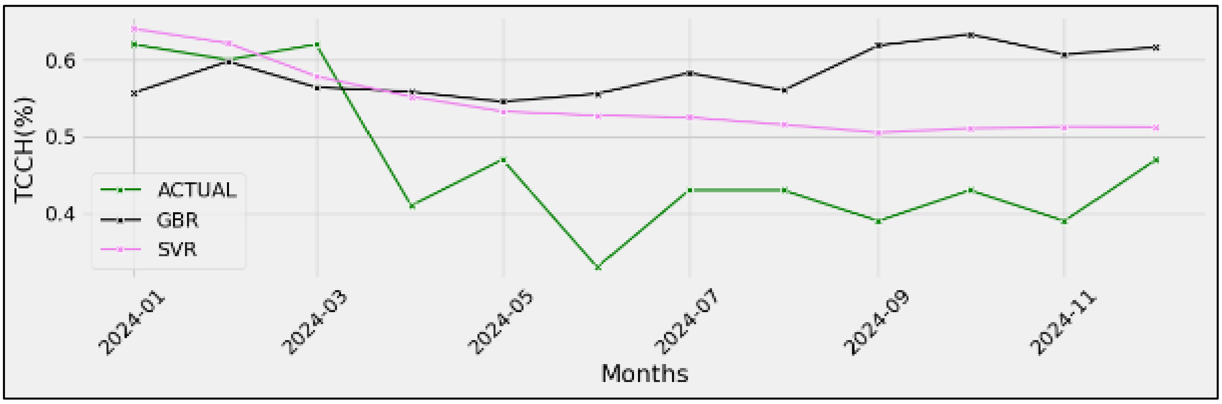

Figure 3 Actual and Forecast TCCH Plot for Glo Network

Table 3 Performance Evaluation Metrics for Glo Network

Model	MAE	RMSE	MAPE (%)
GBR	0.1374	0.1549	33.22
SVR	0.0855	0.0994	21.00

For the Glo network, the Gradient Boosting Regressor (GBR) produced an MAE of 0.1374, RMSE of 0.1549, and MAPE of 33.22%, while the Support Vector Regressor (SVR) achieved lower errors with an MAE of 0.0855, RMSE of 0.0994, and MAPE of 21.00%. This shows that SVR clearly outperformed GBR, giving predictions much closer to the actual TCCH values. The lower percentage error also indicates that SVR captured the actual values more accurately, making it more reliable for forecasting. The improved accuracy compared to earlier datasets likely stems from the larger actual values, which reduced percentage error inflation.

SVR's accuracy makes it suitable for predicting congestion trends and enabling proactive measures before congestion becomes critical. Reliable forecasts support better frequency channel planning, base station load balancing, and handover management, reducing call setup failures and improving user experience. Early identification of rising congestion also allows operators to expand capacity or reconfigure channels, preventing service degradation during peak periods.

In addition, SVR's accuracy reduces false congestion alarms and unnecessary field interventions, cutting costs and ensuring maintenance focuses on real issues. Accurate forecasts also support compliance with KPI targets such as keeping TCCH below 0.2%, helping avoid regulatory penalties. In summary, SVR should be adopted for monthly TCCH forecasting on the Glo network to improve congestion prediction, resource allocation, cost efficiency, and compliance, thereby enhancing Quality of Service (QoS).

3.3. Forecast and Performance Evaluation for 9mobile Network

Figure 4 presents a comparison of the actual TCCH congestion with forecasts from the GBR and SVR models for the 9mobile network, while Table 4 summarises the performance evaluation of the two machine learning models.

As observed in the plot, the actual values range from 0.33 to 0.62, representing the true measured data. The GBR predictions mostly lie between 0.54 and 0.63, showing little variation and tending to stay around the upper range regardless of whether the actual value is high or low. The SVR predictions range from about 0.50 to 0.64, showing more responsiveness to changes in the actual values. In general, GBR tends to overestimate when the actual values are low and underreact to fluctuations, while SVR predictions are closer to the actual values and track their pattern more closely, though they still slightly overestimate higher actual values and underestimate lower ones. In conclusion, the data shows that SVR predictions align better with the actual values compared to GBR, which appears more biased and less variable.

In terms of performance evaluation, SVR showed slightly better performance than GBR across all metrics, with a lower MAE of 1.0618 compared to 1.1074, a lower RMSE of 1.1904 compared to 1.2330, and a lower MAPE of 74.04% compared to 78.02%. These results indicate that SVR's predictions were generally closer to the actual TCCH values than those of GBR. The MAE values being above 1 show that, on average, both models' predictions deviated from the actual values by a little over 1 unit of TCCH. The RMSE values, which are slightly higher than the MAE for both models, suggest that a few larger errors or outliers increased the overall squared error. The high MAPE values, ranging from 74% to 78%, reflect substantial percentage deviations from the actual values. This high percentage error is largely due to the small size of some actual TCCH values, where even modest absolute errors translate into large percentage differences. Although SVR performed better, the high error levels from both models indicate that they may still misrepresent congestion levels in some months, potentially leading to inefficient network resource allocation, and further model refinement or data transformation is needed to improve prediction accuracy

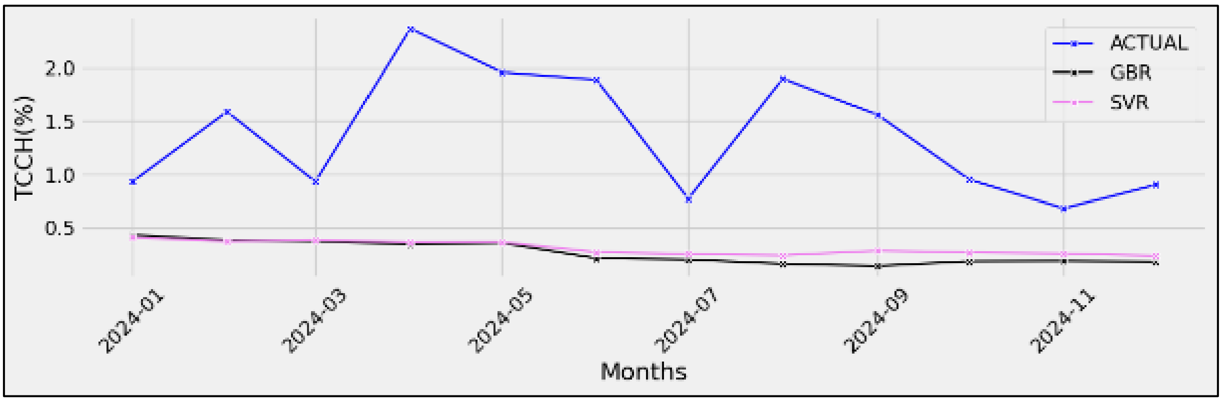

Figure 4 Actual and Forecast TCCH Plot for 9mobile Network

Table 4 Performance Evaluation Metrics for 9mobile Network

Model	MAE	RMSE	MAPE (%)
Random Forest	1.1074	1.2330	78.02
XGBoost	1.0618	1.1904	74.04

4. Conclusion

This study demonstrated the applicability of machine learning techniques for forecasting Traffic Channel (TCCH) congestion in Nigerian GSM networks using long-term performance data from the Nigerian Communications Commission. Two models, Support Vector Regression (SVR) and Gradient Boosting Regression (GBR), were developed and evaluated on monthly congestion data spanning January 2015 to December 2023, with forecasts generated for January to December 2024.

The results showed that both models successfully captured the general patterns and month-to-month variations in TCCH congestion across the four major GSM networks: MTN, Airtel, Globacom, and 9mobile. However, SVR consistently achieved lower error values in terms of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), and produced predictions that aligned more closely with the observed data. GBR often exhibited higher variability and a tendency to overestimate congestion, particularly when actual values were low, which resulted in inflated percentage errors.

In Conclusion, SVR proved to be the more accurate and stable model for short term TCCH forecasting in this context. Its adoption can provide network operators and regulators with reliable early warnings of potential congestion, enabling proactive resource allocation, improved infrastructure planning, enhanced quality of service, and stronger compliance with regulatory benchmarks. Future research could explore hybrid or ensemble approaches combining multiple machine learning algorithms and feature engineering techniques to further improve prediction accuracy and robustness.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed..

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