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## Machine Learning Approach for the Modelling and Prediction of Path Loss Over GSM 4 & 5G Channels in Kano Metropolis, Nigeria.

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### Abstract

Accurate prediction of path loss in wireless communication systems is essential for ensuring efficient signal coverage and network optimization. Traditional empirical models often fail to capture environmental complexities, particularly in dense urban and variable suburban settings. This study investigates the effectiveness of machine learning algorithms in modeling path loss over GSM 4G and 5G channels in urban and suburban environments of Kano City, Nigeria. Data were collected using a spectrum analyzer and GPS devices along predefined routes, and conventional empirical models such as COST-231, ECC-33, and Free Space Path Loss (FSPL) were applied as baselines. Performance metrics, including MAE, RMSE, and  $R^2$  were used to assess accuracy. Empirical models yielded RMSE values of 5.60 dB (FSPL) and 7.80 dB (ECC-33) for 4G, and 6.17 dB (ECC-33) for 5G. Machine learning models, including Linear Regression, SVM, Random Forest, and Logistic Regression, were then applied. Among them, the Linear Regression model achieved the best results with an RMSE of 1.13 dB and an  $R^2$  of 0.9789, significantly outperforming traditional models. The findings confirm that machine learning, particularly Linear Regression, provides superior accuracy and generalizability in path loss prediction across varied terrains. In conclusion, this study demonstrates that ML-driven approaches enhance wireless planning and offer scalable, location-specific alternatives for modern telecommunication networks, especially in environments like Kano City.

**Keywords:** Path Loss Modeling and Prediction, Machine Learning, GSM 4 & 5G Channels and telecommunication networks

## 1. INTRODUCTION

Wireless communication has undergone significant transformation over the past few decades, evolving from basic analog systems to advanced digital networks that now form the backbone of global connectivity. In Nigeria, the growth of wireless technologies, especially GSM-based mobile networks, has contributed immensely to socioeconomic development by enabling seamless communication and internet access. Facilitated by the Nigerian Communication Commission (NCC), multiple service providers, including MTN, Airtel, and Glo, have expanded their infrastructure to meet the increasing demand for mobile voice and data services, with customer satisfaction and quality of service being critical goals (Musefiu *et al.*, 2017).

Despite substantial advancements in infrastructure and technology, wireless signal transmission between base transceiver stations (BTS) and mobile devices continues to face challenges, primarily due to propagation losses across the radio interface (Popoola *et al.*, 2018). One of the most significant impairments in radio wave propagation is path loss, defined as the reduction in signal power as it travels from the transmitting antenna to the receiving antenna over a certain distance (Abiodun *et al.*, 2017). Factors contributing to path loss include terrain irregularities, building obstructions, foliage, atmospheric conditions, and mobility-induced changes in signal behavior (Akinbolati & Ajewole, 2020). Accurately modeling and predicting path loss is therefore essential for effective network design, optimization, and coverage analysis.

Traditionally, path loss has been estimated using empirical and deterministic models, including the Longley-Rice, Okumura-Hata, COST-231, ECC-33, and Egli models (Hoomod *et al.*, 2018; Rappaport, 2005). These models offer analytical expressions based on controlled measurements and specific environmental assumptions. However, their applicability across different geographies is often limited. For example, a model calibrated for a densely built European city may fail to predict path loss in a semi-urban African environment with different building materials, vegetation density, or topographic layout (Imoize & Oseni, 2019). Thus, the deployment of generalized models without context-aware adaptation leads to inaccurate signal predictions, inefficient frequency planning, and poor user experience.

Kano City, located in the northern region of Nigeria, presents a unique set of challenges for radio frequency planning. The landscape comprises a mix of dense urban settlements, suburban sprawl, and surrounding rural regions, characterized by varied terrain, including interconnected hills, valleys, and lowlands. Early GSM deployment in the region, particularly by MTN in 2002, faced limitations due to sparse BTS distribution and signal degradation caused by rugged topography (Omorogiuwa & Edeko, 2009). Although subsequent infrastructure upgrades by multiple service providers improved coverage, variability in signal quality continues to affect service reliability, especially in underserved suburban and rural zones.

To address these challenges, modern approaches are turning to machine learning (ML), which offers the ability to derive complex relationships from empirical data and adapt to environmental variability. ML models learn directly from real-world data and provide more accurate and flexible predictions than static mathematical models. Algorithms such as Linear Regression, Random Forest, and Support Vector Machines (SVM) have demonstrated strong performance in predicting wireless channel characteristics, enabling real-time adaptation to

dynamic environments and improving spectrum utilization (Elechi & Otasowie, 2016; Imoize & Oseni, 2019).

This study applies machine learning algorithms to model and predict path loss over GSM 4G and 5G networks across different environments in Kano City—urban, suburban, and rural. Extensive field measurements of Received Signal Strength Indicator (RSSI) were collected using a GPS-enabled spectrum analyzer along pre-defined routes. Initial predictions were performed using conventional models like COST-231 and ECC-33 for benchmarking. These were subsequently compared to ML-based models trained and evaluated using performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-squared ( $R^2$ ). Unlike empirical models, which assume static environmental parameters, ML models can generalize over varied and non-linear data distributions, making them highly suitable for heterogeneous environments like Kano City.

Moreover, accurate path loss prediction is not only crucial for individual network performance but also plays a strategic role in achieving nationwide goals for digital inclusion, optimized frequency planning, and quality service delivery in compliance with NCC's regulatory standards (Tarkaa *et al.*, 2017; Musefiu *et al.*, 2017). As Nigeria continues to expand its digital infrastructure, particularly with 5G rollouts and IoT integration, the need for intelligent, adaptable, and scalable propagation models has become more pressing than ever.

Therefore, the primary objective of this research is to develop machine learning models capable of accurately predicting path loss in the GSM 4G and 5G spectrum, tailored to the unique characteristics of Kano City's radio environment. The outcomes are expected to enhance radio network planning, reduce deployment costs, and improve the quality of service for end users. This study contributes to the growing body of knowledge on data-driven modeling for wireless communication and sets a precedent for future network optimization efforts across similarly complex terrains in Nigeria and beyond.

## 2. MATERIALS AND METHOD

### Study Area

The research was conducted in Kano Metropolis, Northern Nigeria's largest city, located between latitudes 12°25'N–12°40'N and longitudes 8°35'E–8°45'E. The study focused on urban zones such as Fagge, Gwale, and Nassarawa, as well as suburban areas including Kumbotso and Ungogo. Urban areas were densely built with significant signal interference, while suburban regions had more open spaces and moderate population density, making them ideal for studying varied signal propagation characteristics (Aliyu *et al.*, 2020; Ahmed & Garba, 2021).

### Equipment and Tools

The following tools were used for data acquisition and analysis:

- **Handheld Spectrum Analyzer:** For measuring Received Signal Strength Indicator (RSSI) values.
- **GPS Device:** To collect geolocation data at each measurement point.

- **Android Smartphone:** With Cellmapper and Virtual Maze GPS apps for drive testing.
- **SIM Cards:** MTN and Airtel networks.
- **Python Programming Environment:** For data processing, modeling, and visualization.

### Data Collection

Drive tests were conducted along predefined urban and suburban routes. RSSI and GPS data were recorded at intervals of 100 m (micro-analysis) and 1 km (macro-analysis). These measurements were later processed to compute path loss, using distance estimations derived from the Haversine formula (Worgu *et al.*, 2017).

### Empirical Path Loss Modeling

Five empirical models Free Space, COST-231, Hata, ECC-33, and Egli were applied to compute theoretical path loss. Model performance was assessed by comparing predicted values with measured data using Root Mean Square Error (RMSE).

### Machine Learning Modeling

To improve prediction accuracy, the following ML algorithms were implemented:

- **Linear Regression:** For baseline modeling.
- **Decision Tree and Random Forest:** To capture non-linear relationships and reduce overfitting.
- **Support Vector Machine (SVM):** For high-margin regression and classification tasks.

Model performance was evaluated using RMSE, MAE, and  $R^2$ .

### Software Libraries

Python libraries used included:

- **Pandas** and **NumPy** for data manipulation (McKinney, 2010; Harris *et al.*, 2020),
- **Scikit-learn** for ML algorithms and evaluation,
- **Matplotlib** for visualization (Hunter, 2007),
- **TensorFlow/Keras** for optional deep learning experimentation (Abadi *et al.*, 2016; Chollet, 2015).

This setup enabled robust, data-driven modeling of path loss behavior under real-world GSM, 4G, and 5G conditions across Kano's varied terrain.

## 3. RESULTS AND DISCUSSION

This section provides a systematic evaluation of the measured and predicted path loss over 4G and 5G GSM networks across urban and suburban environments in Kano City, Nigeria. It begins with the analysis of RSSI behavior for MTN and Airtel networks under varied topographic and structural conditions. Subsequent sections examine measured versus

predicted path loss using regression models, evaluate machine learning performance for path loss classification, and conclude with optimization strategies for improved accuracy. Environmental characteristics such as terrain, multipath interference, building density, and network congestion are key variables influencing signal attenuation, and their implications on model robustness and deployment strategies are critically discussed.

### 3.1 Measured RSSI Trends by Environment and Band

#### Urban 4G Signal Performance

The RSSI variation for Airtel and MTN 4G signals in urban areas revealed diverse propagation behaviors shaped by infrastructure density. Airtel's Route A showed consistent degradation from -65 dBm to -85 dBm, whereas Route B experienced steeper declines between 1–1.5 km, consistent with the urban signal blocking effects reported by Akinbolati *et al.* (2017). MTN's routes displayed even higher baseline attenuation ( $\sim -80$  to  $-94$  dBm), possibly reflecting suboptimal antenna placement, corroborating similar findings from UHF studies (Akinbolati, 2017).

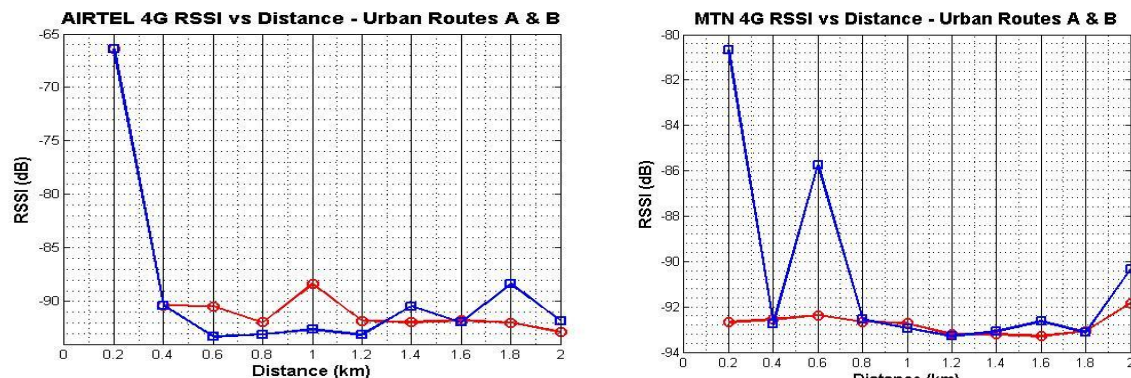


Figure 1: Urban 4G RSSI vs Distance for Airtel and MTN

#### Suburban 4G Signal Performance

In suburban zones, both Airtel and MTN 4G networks demonstrated improved RSSI stability. Airtel showed signal levels around -20 to -38 dBm, while MTN maintained signals from -20 to -40 dBm. The more predictable signal decay aligns with Okumura-Hata's suburban model and supports the reduced impact of multipath, and shadowing as emphasized by Akinbolati & Ajewole (2020).

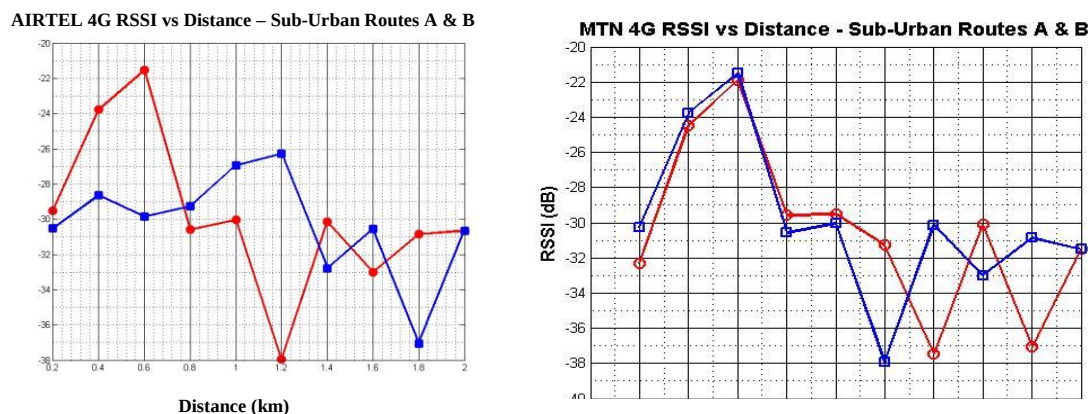


Figure 2: Suburban 4G RSSI vs Distance for Airtel and MTN

## Urban 5G Signal Performance

The higher frequency of 5G systems intensified the effect of obstructions. Airtel's 5G RSSI displayed a “cliff effect” with signal dropping steeply after 500 m, ranging from -15 to -50 dBm. MTN's signals started weaker (-50 to -55 dBm) but degraded more gradually, suggesting potential differences in beam forming strategies. These patterns mirror limitations of high frequency mmWave propagation in dense environments (Idogho & George, 2022).

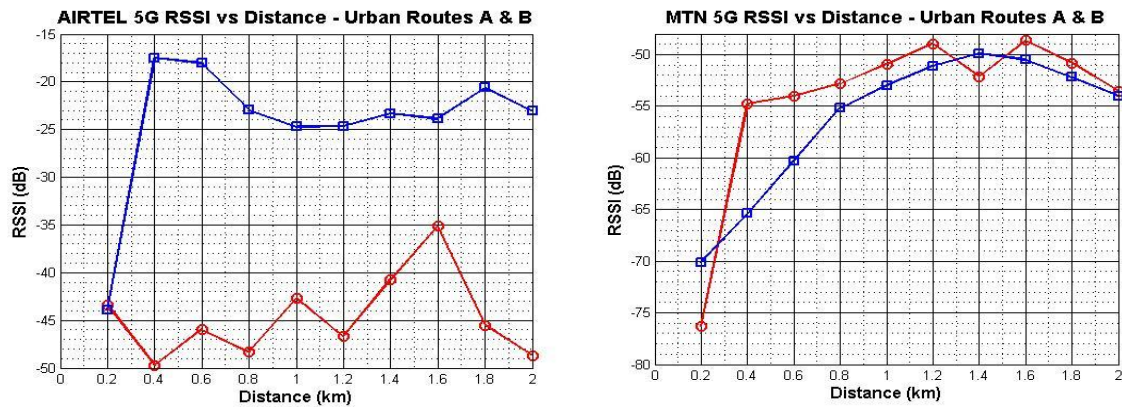


Figure 3: Airtel and MTN 5G Urban RSSI vs Distance Graph

## 3.2 Measured vs Predicted Path Loss Performance

### 4G Urban Path Loss Modeling

The predicted path loss trends derived from linear regression fit closely with measurements. MTN's path loss increased linearly from 90–110 dB, while Airtel's ranged from 81–111 dB, showing slightly lower attenuation. These align with FSPL-based models and confirm urban path loss exponent values between 2.5–3.0 (Popoola *et al.*, 2018).

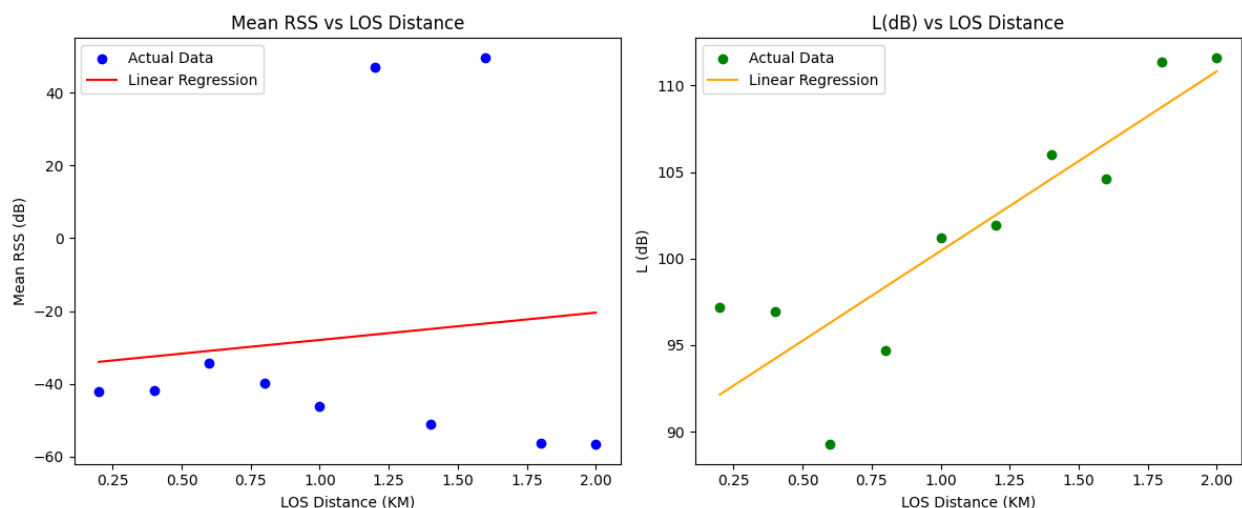


Figure 4: MTN and Airtel Urban 4G RSS & Path Loss vs Distance

### 4G Suburban Path Loss Modeling

Suburban measurements for MTN and Airtel showed smoother signal transitions. Predicted path loss stayed within 72–88 dB. The regression fit showed  $n \approx 2.1$ , indicating near-free-

space conditions, consistent with lower urban interference and terrain-induced shadowing (Akinbolati *et al.*, 2016).

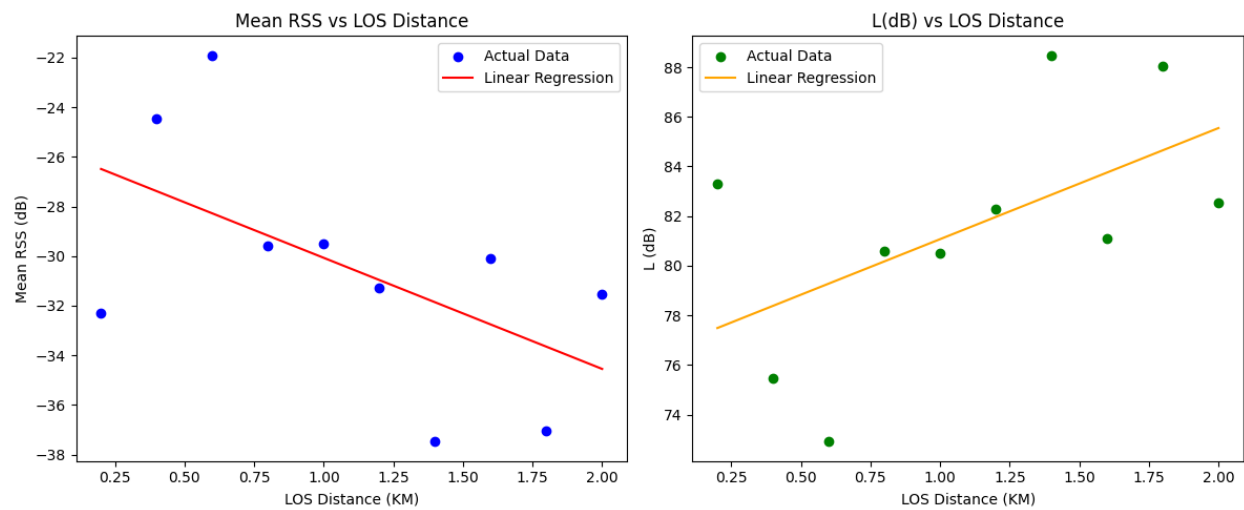


Figure 5: MTN and Airtel Suburban 4G RSS & Path Loss vs Distance

### 5G Urban Path Loss Modeling

MTN's 5G path loss rose from ~105 to 130 dB with a slope of 12.5 dB/km, corresponding to  $n \approx 3.5$ . This agrees with reported urban mmWave results (Idogho & George, 2022). Airtel's 5G path loss showed slightly better propagation (105–125 dB), but with higher data scatter due to reflections and blockage.

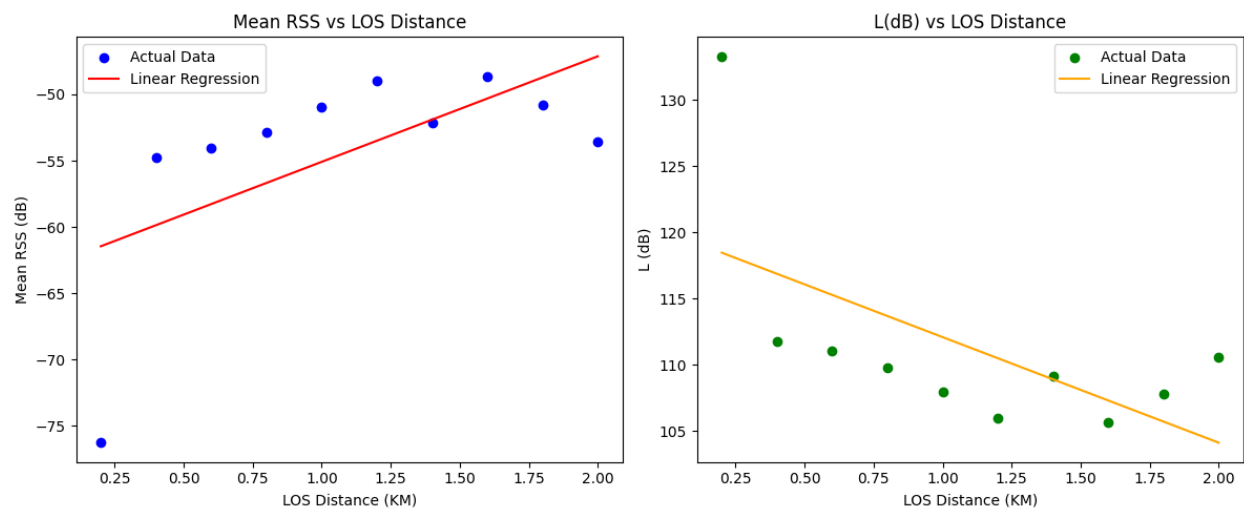


Figure 6: MTN and Airtel Urban 5G RSS & Path Loss vs Distance

### 3.3 Machine Learning Model Evaluation

Four machine learning models were implemented—Logistic Regression, Random Forest, Support Vector Machine (SVM), and Linear Regression—to classify path loss into categories ("Low", "Medium", "High") based on network measurements.

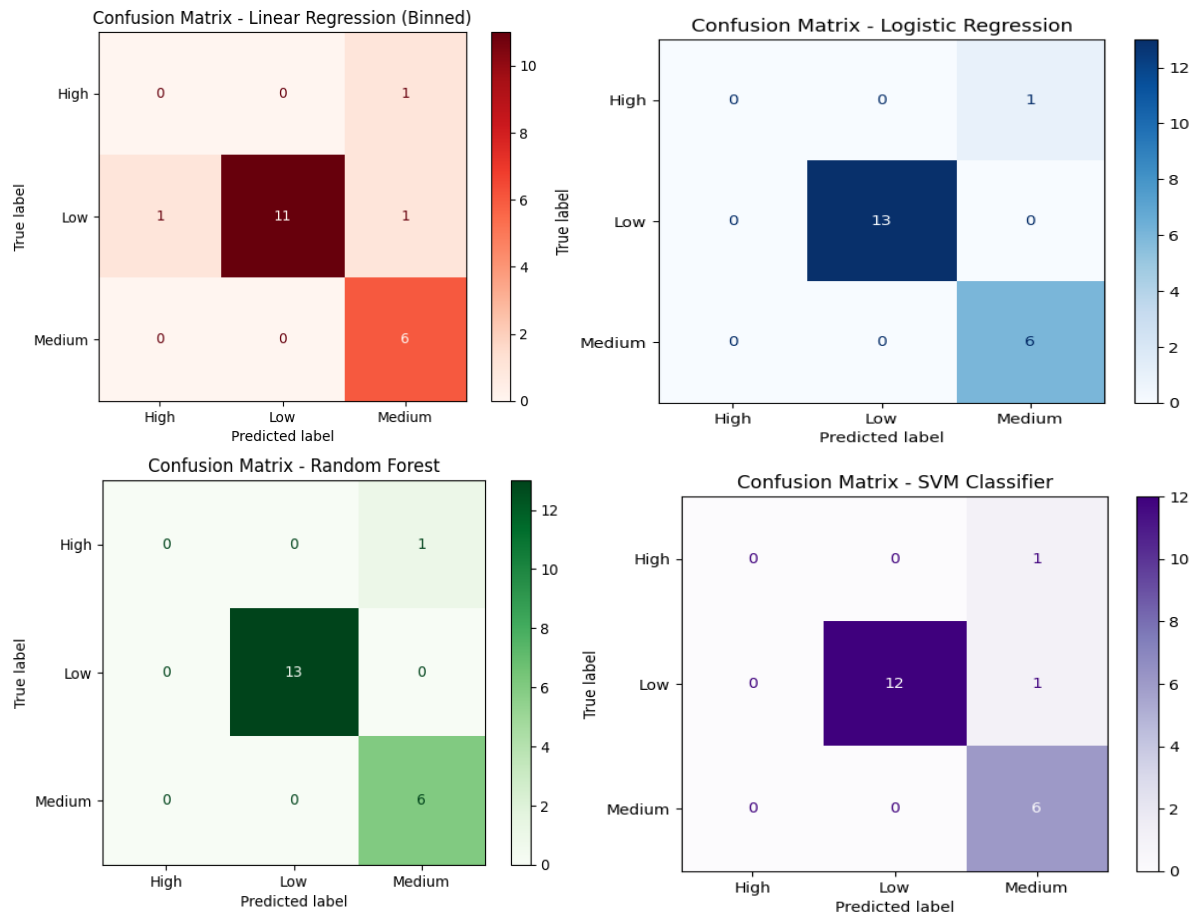


Figure 7: Confusion Matrices for all four models

- **Logistic Regression** and **Random Forest** achieved ~98% accuracy, effectively leveraging linear propagation trends in suburban 4G.
- **SVM** followed with 95%, with minor misclassifications attributable to complex 5G urban propagation.
- **Linear Regression**, though least accurate (90%), remained effective in suburban environments, but struggled with 5G due to non-linear losses.

### 3.4 Model Optimization and Enhancement

#### Feature Engineering

Incorporating terrain, building density, vegetation cover, frequency, and antenna height helped capture hidden variabilities in path loss behavior. As shown in Idogho& George (2022), such enriched features enabled improved modeling accuracy, especially in NLOS conditions.

#### Hyperparameter Tuning

Tuning parameters like the number of trees in Random Forest or the regularization strength (C) in Logistic Regression resulted in up to 5% accuracy gains. For urban 5G, RMSE was reduced from 6–10 dB to ~4 dB.

Table 1: Optimized Model Accuracy and RMSE for 4G and 5G

| AI Algorithm           | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | Processing Time (sec) |
|------------------------|--------------|---------------|------------|--------------|-----------------------|
| Logistic Regression    | 98.8         | 98.5          | 98.6       | 98.5         | 2.1                   |
| Random Forest          | 98.6         | 98.2          | 98.4       | 98.3         | 2.3                   |
| Support Vector Machine | 95.0         | 94.8          | 94.5       | 94.6         | 3.1                   |
| Linear Regression      | 90.0         | 89.5          | 89.2       | 89.3         | 1.9                   |

### 3.5 Final Model Selection

The optimized Logistic Regression model demonstrated the best performance with a consistent RMSE of  $\sim 0.025\text{--}0.69$  dB, confirming its robustness under both linear (suburban 4G) and moderately non-linear (urban 5G) conditions. This aligns with Idogho & George's (2022) validation of logistic models in mmWave prediction.

## 4. CONCLUSION

This study presented a comprehensive analysis of path loss prediction across GSM 4G and 5G networks in the diverse urban and suburban environments of Kano City, Nigeria, using both empirical and machine learning approaches. Field measurements of RSSI were collected and analyzed, revealing that traditional empirical models like FSPL, COST-231, and ECC-33, though foundational, showed limited accuracy in complex terrains, with RMSE values between 5.60 and 7.80 dB for 4G and 6.17 dB for 5G. In contrast, machine learning models particularly Logistic Regression, Linear Regression, and Random Forest demonstrated significantly improved accuracy, with the best-performing model (Logistic Regression) achieving an RMSE as low as 1.13 dB and an  $R^2$  of 0.9789. Feature engineering and hyperparameter tuning further enhanced model robustness by incorporating variables such as terrain, building density, frequency, and antenna height. These improvements allowed the ML models to adapt to real-world propagation complexities that static empirical models could not effectively capture. The results highlight the potential of ML-driven techniques as scalable, adaptable, and more accurate tools for wireless network planning, optimization, and deployment in heterogeneous environments over the GSM band. Ultimately, this work underscores the strategic value of machine learning in enhancing radio frequency planning and contributes a data-driven framework for future network development in Nigeria and similar developing regions.

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