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EVALUATING THE EFFECTIVENESS OF MACHINE LEARNING MODELS FOR PATH LOSS PREDICTION AT 3.5 GHz WITH FOCUS ON FEATURE PRIORITIZATION

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Abstract

Accurate path loss prediction is vital for efficient resource allocation, interference reduction, and overall network reliability in 5G networks, particularly in the widely deployed mid-band frequency spectrum (such as 3.5 GHz). This study evaluates the effectiveness of machine learning models for path loss prediction at 3.5 GHz with a focus on feature prioritization. A feature selection method, recursive feature elimination, was used to identify significant features from datasets obtained through measurement campaigns, weather stations, 3-D ray tracing, geographical data, and simulations. Out of eighteen features, eleven, including new environmental features, were identified as significant features contributing to path loss. These selected variables were then utilized to optimize and train four common machine learning models (ANN, XGBoost, RF, and k-NN) to evaluate their performance in predicting path loss in a specific urban area called an irregular urban environment. The performance of these models was assessed by comparing their predictions with the measured path loss. The Random Forest model closely matched the measured path loss over the entire path length in both LoS and NLoS scenarios, achieving the lowest MAE of 0.15 dB and RMSE of 0.57 dB in the LoS scenario and 0.62 dB and 1.42 dB in the NLoS scenario, with R2 scores of 0.999995437 and 0.999996828, respectively. This indicates its superior performance in predicting path loss in the urban environment.

1.0 INTRODUCTION

The academic and industrial sectors have recently shown a growing interest in fifth-generation (5G) wireless systems. This heightened attention is driven by 5G's potential to greatly increase data speeds, reduce latency, and accommodate various connected devices, as depicted in Figure 1. According to the consensus reached at the World Radiocommunication Conferences (WRC) and the International Telecommunication Union (ITU), the mid-band frequency spectrum, ranging from 1 to 6 GHz, should be prioritized and adopted for 5G communications [1]. This designation underscores the mid-band's crucial role in balancing coverage and capacity, making it essential for the widespread implementation of 5G technology [2].

The Nigerian Communications Commission (NCC) has designated the mid-band frequency of 3.4-3.8 GHz for the deployment of 5G communication networks, aligning with the globally agreed frequency spectrum for 5G adoption [3]. However, the commun-

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ication network faces several challenges on its mid-band channel, such as path loss.

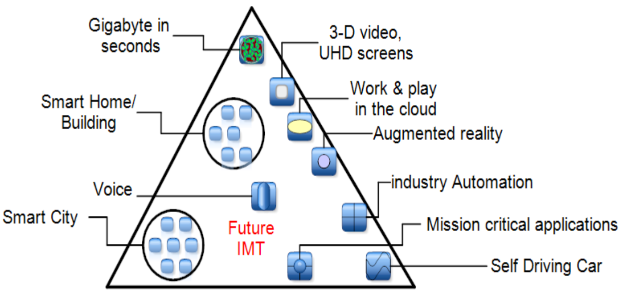

Figure 1: 5G to transform lives

Path loss refers to the reduction in power density of an electromagnetic wave as it travels through a medium or propagates through space. This phenomenon occurs because the energy carried by the electromagnetic wave spreads out as it moves away from its source. Propagation loss is a fundamental concept in the field of wireless communications and is influenced by several factors, including distance, frequency, and the characteristics of the medium through which the wave propagates. Figure 2 illustrates how signal propagation through space causes a reduction in power density and results in propagation loss.

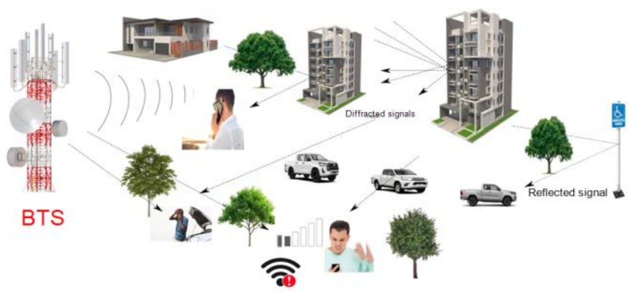

Figure 2: Illustration of signal propagation through space

Propagation path loss is usually mathematically expressed as a function of frequency, speed of wave in free space, and distance, as illustrated in Equation (1) [4]:

$$P_l = 10\log_{10}\left(\left(\frac{4\pi df}{c}\right)^2\right) \quad (1)$$

Where, P_l, d, f, and c represent the free-space path loss, the distance between the receiver, Rx, and the transmitter, Tx, the frequency of operation, and the speed of the wave in free-space [4].

The equation 1 can be reduced to (2), as;

$$P_L(f) = 20\log_{10}(d) + 20\log_{10}(f) + 92.45 \quad (2)$$

Where, d and f are are the path length in km and the frequency in GHz. Equation (2) can also be presented as in (3).

$$Path\ loss, P_l\ in\ dB = EIRP - R_p \quad (3)$$

Where, $EIRP$ and R_p denote the effective isotropic radiated power and the received power [5] in dBm, of which $EIRP$ is given as;

$$EIRP = P_T + G_T + G_R - C_l - f_{cl} - A_l - A_{fl} \quad (4)$$

Where, G_T, G_R, and P_T indicate the antenna gains for the transmitter and receiver, the transmitting power in dBm, while A_l, f_{cl}, A_{fl}, and C_l denote the losses related to the antenna, feeder cable, antenna filter, connector, respectively [6].

Researchers have shifted from deterministic models to machine learning techniques for wireless channel modeling and path loss prediction. This transition has led to a deeper exploration of machine learning methods, revealing their ability to provide more accurate predictions than traditional deterministic and empirical models. These advancements are particularly notable in complex environments, such as urban areas, where the intricate nature of the surroundings makes precise prediction challenging. Consequently, machine learning models have proven to be highly effective in these scenarios, offering significant improvements in prediction accuracy [7].

This study seeks to assess and compare the accuracy of four widely used machine learning path loss models in predicting path loss in a complex urban environment [6] with irregular street layouts. The main objective is to improve each model's predictive performance by employing the most relevant features, identified through the recursive feature elimination (RFE) method.

Consequently, the key contributions of this paper are as follows:

i. Enhancement of path loss prediction accuracy at 3.5 GHz by identifying and prioritizing key features, leading to more reliable communication performance.
ii. Comparative analysis of four widely used machine learning models, highlighting their strengths and weaknesses in predicting path loss, and offering valuable insights for model selection.
iii. Providing practical guidelines for deploying machine learning models in 5G networks at 3.5 GHz.

The structure of the paper is organized as follows: Section 2 outlines the methodology employed, including the materials used, the measurement campaign architecture, and the data sources for training and testing the models. This section also elaborates on the machine learning models based on feature selection. Section 3 provides a comprehensive presentation of the results and their discussion. Finally, Section 4 offers the concluding remarks.

Numerous studies have sought to determine the most effective approach for path loss prediction, particularly for 5G communications across different scenarios. One such effort involves developing a path loss model derived from measurements collected in the millimeter-wave frequency band in an urban environment [8]. However, to ensure the model's reliability and robustness, it is necessary to test it in more complex settings, such as urban areas. This testing will account for additional factors that contribute to path loss, providing a comprehensive evaluation of the model's stability and accuracy in diverse environments. In another study [9], hyperparameter tuning was adopted to improve the accuracy of a Random Forest (RF) model for predicting path loss using seven features from a measurement campaign dataset. Similarly, a study [10] presented an effective method for improving path loss prediction, comparing the results with two other machine learning models, and revealing the superior performance of the random forest model in path loss prediction.

In [11], an ensemble neural network was used to achieve accurate path loss prediction, with similar methods in [12-14]. In another study [15], data were used from OpenStreetMap to train a machine-learning model focused on enhancing the prediction of cellular coverage in urban areas. Previous studies in [10, 16], however, did not explore the performance of these models in specific scenarios within urban environments, such as irregular urban environments characterized by less organized layouts and infrastructure, featuring a mix of old and modern buildings, and streets arranged more chaotically, as illustrated in Figure 3. The emphasis on this urban environment arises from the unique attenuation characteristics observed between older and modern buildings, as documented in [17] and elaborated on in [18], which highlight higher attenuation levels in modern structures compared to older ones. However, given the unique characteristics of buildings and streets in each urban area, researchers need to focus on improving and assessing the models' suitability for complex and irregular urban environments.

This paper aims to address this gap by employing a feature prioritization technique to identify the most significant features from a pool of over fifteen input features, including those previously considered in [9, 16] along with additional new features that significantly influence path loss. By focusing on the most impactful predictors, this approach seeks to enhance the accuracy and reliability of path loss models in complex urban environments.

2.0 MATERIALS AND METHOD

2.1 Study Area

The measurement campaign's study area aimed to capture the received signal strength from a mobile station located in the urban environment of Maitama, a district in the Federal Capital Territory of Nigeria. The mobile site designated as ID FC0125 is in a part of Maitama characterized by a well-planned and modern urban landscape. The architecture here primarily consists of both old and new buildings, with modern materials designed to emphasize vertical expansion. The streets in the vicinity are unsystematically laid out, offering a grid-like pattern that facilitates efficient navigation and urban mobility. These streets are wide, well-maintained, and equipped with modern amenities, including traffic management systems, pedestrian walkways, and landscaping elements such as trees and green spaces, as shown in Figure 3.

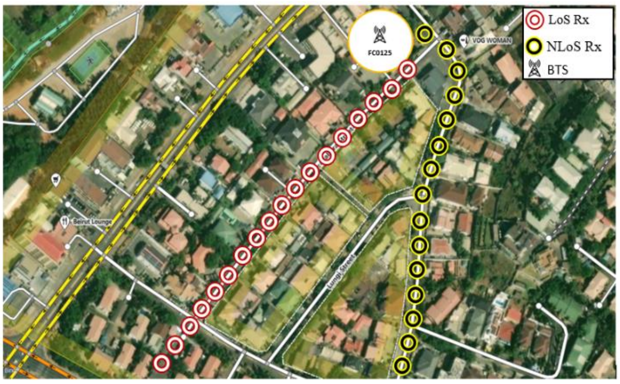

Figure 3: Study area of the urban environment showing the LoS and NLoS scenarios

Table 1 provides the comprehensive technical and geographic parameters of the transmitting base station used in this study.

Table 1: Technical and geographical parameters of the transmitting station

Key Parameters		Cell ID
		FC0125
Technical Parameters	Transmission power (dBm)	10
	Frequency (GHz)	3.5
	Transmitter height (m)	35
	Coverage area (km)	0.71
	Cell radius (mm)	1.2
	Modulation types	16-QAM
	Channel coding techniques	LDPC
	Duplexing method	FDD
	Multiple access method	CDMA

	Handover method	Soft handover
	Antenna type	Sectorial
	Antenna gain (dBi)	20
	Number of antenna ports	16 ports
	Environment	Regular urban
Geographic Parameters	Latitude (°)	9.0853
	Longitude (°)	7.4724

2.2 Data Collection

This section presents the data collection source for the selected models' training and testing.

2.2.1 Measurement Campaign

The measurement campaign was conducted in a unique urban environment using a handheld spectrum analyzer (N9344C, 1 MHz-24 GHz) paired with a HE200 directional antenna. The mobile station with ID FC0125 served as the transmitter, from which measurements were initiated at a reference distance of 10 meters. Subsequent measurements were taken at 50-meter intervals up to 500 meters, moving away from the transmitter, for a total of eleven data points for the purpose of testing the models. Data were collected along two distinct paths: line-of-sight (LoS) and non-line-of-sight (NLoS). The designated paths are visually represented in Figure 3, where the LoS path is marked with a circular shape filled in white and outlined in red, and the NLoS path is marked with a circular shape filled in black and outlined in yellow. The measurements were taken under specific conditions, including varying environmental factors such as temperature and relative humidity, as well as terrain characteristics like building density, street width, and urban infrastructure. Effective isotropic radiated power (EIRP) was calculated using Equation (4) to determine the measured path loss, as outlined in Equation (3). This approach allowed us to gather comprehensive data on signal propagation characteristics in an urban environment, considering varying conditions and distances from the transmitter. Figure 4 provides an illustration of the measurement campaign.

Figure 4: Illustration of the measurement campaign

2.2.2 Weather Station

Weather station data, including temperature and humidity, which affect path loss in radio propagation, were sourced from the Nigerian Meteorological Agency (NiMet) over a span of two years. These parameters are taken into account due to their potential effects on signal propagation, considering environm-ental changes, possible interference, and local variations.

2.2.3 Geographic Data

To obtain geographical data for path loss, the PL5 software tool was utilized to extract information about the study area, including the terrain profile, path length, elevation, and inclination. The process began by launching the PL5 software and importing the geographical map data of the study area from OpenStreetMap.

2.2.4 3D Ray Tracing

WinProp (Altair HyperWorks™) conducted 3D ray tracing to generate a dataset detailing path loss at specific locations, accounting for both transmitted signal effects and environmental factors. This dataset, along with data from the weather station and geographic information, was combined with measurements from the campaign tests to create a dataset comprising eighteen essential features. Additionally, new features were introduced, including the indoor and outdoor distances covered by a direct line connecting the transmitter (Tx) and receiver (Rx), as well as counts of trees and buildings intersected by this line, along with street widths for both Tx and Rx locations. This is depicted in Figure 5.

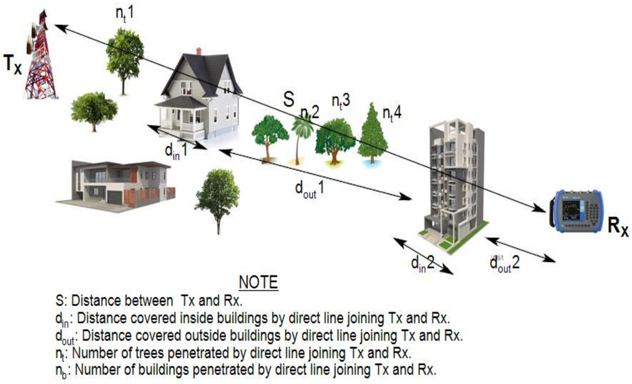

Figure 5: Graphical illustration of supplementary features

The data collected from the measurement campaign, along with the dataset generated from 3D ray tracing, weather station records, and geographic data, were integrated with the newly added novel features to form a dataset containing eighteen significant features.

2.3 Machine Learning Models Based on Feature Selection

The Recursive Feature Elimination (RFE) technique [19, 20], used for feature selection to identify the most crucial features in a dataset, was applied to analyze the eighteen features across 5,310 data points. This process prioritized features that have the greatest impact on path loss within the specific urban environment studied. RFE involves iteratively building models and removing the least significant features until the desired number of key features, based on their importance scores, is attained [20]. A similar methodology was employed in [16] and adopted in [10], although not specifically for the type of environment addressed in this paper.

As a result of this procedure, eleven features were recognized as influential factors affecting path loss, while the remaining seven were systematically removed. These eleven features of the dataset were then used to train the four selected machine learning models, such as the Random Forest (RF) [21], ANN, XGBoost, and k-NN [22]. Following the successful training and testing of the models, their performances were assessed, as depicted in the flowchart in Figure 6.

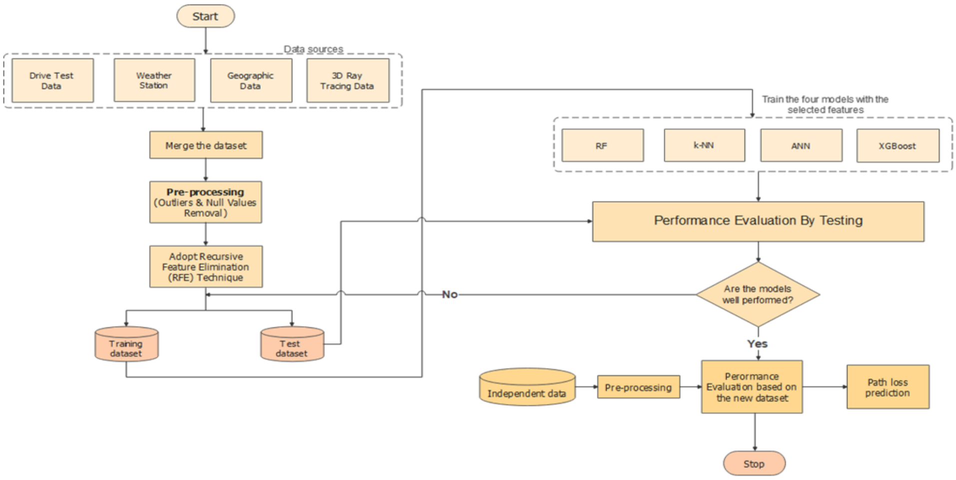

Figure 6: Flowchart of the models' training and testing

2.4 Model Validation

Performance metrics, including mean absolute error (MAE), R2 score, and root mean square error (RMSE) [22, 23], as detailed in equations (5) to (8), were utilized to compare the predicted path loss of the chosen machine learning models with the measured path loss, thereby validating the models' performance.

$$MAE = \frac{1}{N_{test}} \sum_{i=1}^{N_{test}} \left| PL_i^{msd} - PL_i^{pred} \right| \tag{5}$$

$$RMSE = \sqrt{\frac{1}{N_{test}} \sum_{i=1}^{N_{test}} \left(PL_i^{msd} - PL_i^{pred} \right)^2} \tag{6}$$

$$R2 = 1 - \frac{\sum_{i=1}^{N_{test}} \left(PL_i^{msd} - PL_i^{pred} \right)^2}{\sum_{i=1}^{N_{test}} \left(PL_i^{msd} - \overline{PL} \right)^2} \tag{7}$$

$$\overline{PL} = \frac{1}{N_{test}} \sum_{i=1}^{N_{test}} PL_i^{msd} \tag{8}$$

Where, PL_i^{msd} denotes the measured value of path loss , PL_i^{pred} denotes the value, and N_{test} denotes the total number of samples.

3.0 RESULTS AND DISCUSSION

3.1 Measured Received Signal Strength

In the LoS scenario, the RSS exhibited significant fluctuations between 150 and 400 meters, as shown in Figure 7. This fluctuation is primarily attributed to multipath fading, a common issue in urban environments where signals reflect off buildings, vehicles, and other obstacles. These reflections cause multiple copies of the signal to arrive at the receiver with varying delays and phases, leading to constructive and destructive interference.

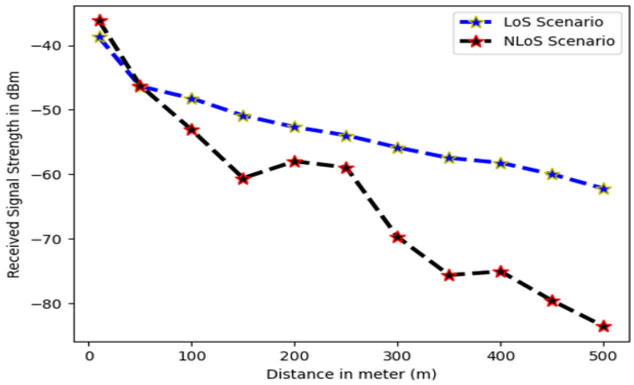

Figure 7: Measured received signal strength

Additionally, the Fresnel zone effect is likely contributing to these fluctuations. The Fresnel zone is the area around the direct path between the transmitter and receiver that must remain relatively clear of obstructions to minimize diffraction and interference.

Given the transmitting antenna height of 30 meters and the complex urban terrain, objects intruding into the Fresnel zone can cause further signal variability.

3.2 Feature Importance

After employing the Recursive Feature Elimination (RFE) technique on the dataset to determine the significance of training features for predicting path loss, eleven features out of the initial eighteen were selected as the most important features for path loss in the examined environment. The other features were systematically removed through iterative processes. Figure 8 displays the importance of these features following the application of RFE.

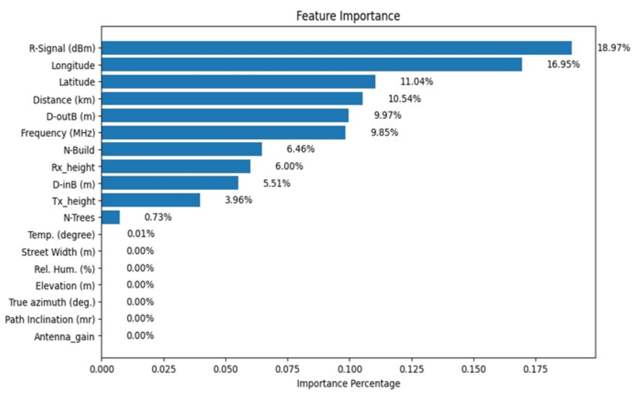

Figure 8: Feature importance map

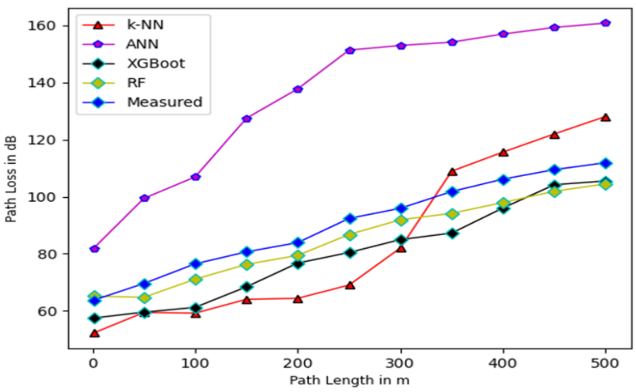

Figure 9: Comparison of path loss predictions in the LoS scenario

3.3 Path Loss Prediction

As seen in Figure 9, the Random Forest (RF) model stands out, closely matching the measured path loss in the LoS scenario across the entire path length. The XGBoost model also performs well, though not as precisely as the RF model, with a noticeable tendency to overpredict path loss around the 410-meter mark. Conversely, the Artificial Neural Network (ANN) model consistently overestimates path loss throughout the entire path. The k-Nearest Neighbors (k-NN) model exhibits a unique pattern, initially underestimating path loss up to about 300 meters before beginning to overpredict. Despite this variability, the k-NN model shows relatively good accuracy over shorter distances, especially up to 150 meters.

As shown in Figure 10, the Random Forest (RF) model [24] model demonstrates remarkable performance. However, there are some inconsistencies in its predictions, highlighting areas for potential improveement. The next best-performing model in this scenario is the XGBoost model, although it is not as consistent as it is in the line-of-sight (LoS) scenario. In contrast, the ANN model consistently overestimates in this scenario. Similarly, the kNN model exhibits a pattern similar to that of the ANN model.

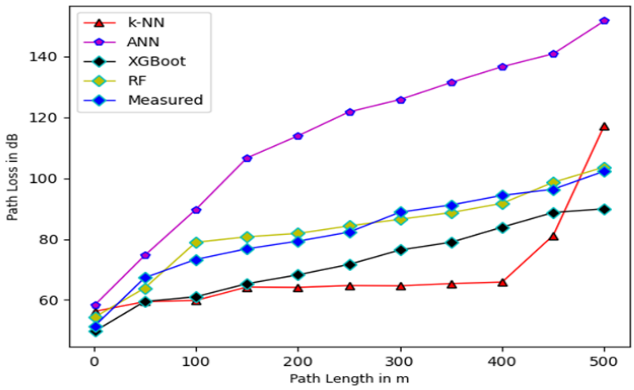

Figure 10: Comparison of path loss predictions in the NLoS scenario

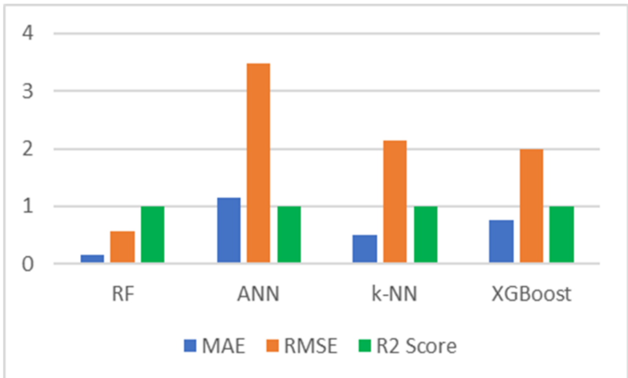

Figure 11: Models' performances in the LoS scenario

3.4 Validation of the Models

The validation results reveal that the Random Forest (RF) model exhibits the lowest MAE and RMSE values of 0.15 dB and 0.57 dB, along with an R2 score closer to 1 (0.999995475), as presented in Figure 11. These metrics indicate the RF model's superior accuracy compared to the other models, underscoring its effectiveness in predicting path loss in the LoS scenario. This superior performance highlights the RF model's robustness and reliability, making it the most effective among the models evaluated for accurate path loss prediction in LoS conditions.

As shown in Figure 12, the results indicate that the Random Forest (RF) model consistently outperforms other machine learning models in non-line-of-sight (NLoS) scenarios, reinforcing findings in existing literature that highlight RF's strength in handling complex datasets. While the differences in mean absolute error (MAE) and root mean square error (RMSE) are less significant in NLoS conditions compared to line-of-sight (LoS) scenarios, the RF model still achieves the highest accuracy overall. This aligns with prior studies that emphasize the robustness and reliability of RF in predicting path loss, particularly in challenging environments character-rized by obstructions and variable signal conditions.

The RF model's effectiveness in both LoS and NLoS scenarios suggests its versatility and adaptability to different urban environments, making it a compelling choice for practical applications in 5G network planning and optimization. Such consistent performance is crucial in real-world implementations, where signal conditions can vary widely due to factors like urban density, building materials, and environm-ental elements. Overall, these results contribute to the growing body of literature that advocates for the use of RF in telecommunications, particularly in developing reliable path loss models that enhance network performance and coverage.

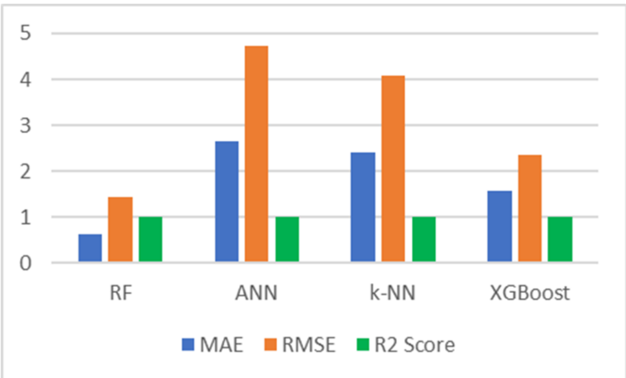

Figure 12: Models' performances in the NLoS scenario

Potential biases in the data collection process may affect the model's predictive accuracy due to variability in factors such as building density, terrain types, and urban infrastructure. Limited diversity in data collection locations could restrict the generalizability of the findings. Additionally, while the Random Forest model performed well in both LoS and NLoS scenarios, its effectiveness may vary in urban environments that differ significantly from the study area, particularly in regions with unique geographical features. These limitations suggest that caution should be exercised when applying the model to new areas without further validation.

4.0 CONCLUSION

This paper presents a comprehensive performance evaluation of four widely used machine learning models—k-NN, ANN, RF, and XGBoost—for path loss prediction at 3.5 GHz in a complex urban environment with irregular street layouts. The primary objective was to enhance the predictive accuracy of each model by employing the most relevant features identified through the recursive feature elimination (RFE) method. Among the models assessed, the Random Forest model demonstrated the highest accuracy, closely matching the measured path loss across the entire path length in both line-of-sight (LoS) and non-line-of-sight (NLoS) scenarios. Specifically, the Random Forest model achieved the lowest mean absolute error (MAE) of 0.15 dB and root mean square error (RMSE) of 0.57 dB in the LoS scenario, and 0.62 dB and 1.42 dB in the NLoS scenario, with R2 scores of 0.999995437 and 0.999996828, respectively.

These results underscore the effectiveness of the Random Forest model, particularly when feature prioritization is applied, in predicting path loss in challenging urban environments. This study's findings, particularly the superior performance of the Random Forest (RF) model, can significantly influence future 5G deployment strategies in urban environments. By demonstrating the RF model's reliability and accuracy, network operators can utilize this model to optimize the placement of infrastructure such as base stations, small cells, and repeaters. This ensures better coverage and signal quality, even in challenging environments with high building density or obstructed signal paths. Future research could benefit from expanding the dataset, incorporating more diverse urban environments, and evaluating a broader range of machine learning techniques to enhance the robustness and applicability of the findings.

5.0 ACKNOWLEDGEMENT

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