

Hybridised CNN Approach for Pathloss Modeling: A Comparative Study with Traditional and Machine Learning Based Pathloss Models



A. A. Jimoh*, Z. K. Adeyemo, F. K. Ojo

^{1,2,3}Department of Electronic and Electrical Engineering, Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria



ABSTRACT: This study compares empirical, machine learning-based, and hybridised Convolutional Neural Network (CNN) based-pathloss models. Field measurements of pathloss (dB), altitude (m), latitude, and longitude were measured from 9,217 data points along four major routes covering urban and suburban areas in Ilorin, Kwara State, Nigeria. The hybridized CNN-based pathloss model, integrating the architectural strengths of DenseNet and ResNet, was trained using 70% of the dataset, while 15% each was allocated for evaluation and testing. Training and simulations were performed on Google Colaboratory, leveraging GPU and TPU resources for computational efficiency. The results demonstrate that the hybridized CNN-based pathloss model outperforms empirical models and conventional machine learning approaches, achieving the lowest prediction of Mean Square Error (MSE) and Root Mean Square Error (RMSE) (MSE: 7.35, RMSE: 8.295) and the highest coefficient of determination ($R^2 = 0.80364$). Random Forest and Extreme Gradient Boosting (XGBoost) models followed in performance, while the Transformer model exhibited the highest errors and lowest accuracy. These findings confirm the robustness and accuracy of the hybridized CNN-based pathloss model in enhancing path loss prediction, offering a more reliable approach for mobile network planning and optimization.

KEYWORDS: Hybridised Convolutional Neural Network (CNN), Traditional Pathloss Models, Machine Learning based-Pathloss Models, Training Data and Training Process.

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I. INTRODUCTION

The rapid growth of mobile communication systems has increased the demand for reliable and efficient wireless networks. One of the critical components of wireless network planning is pathloss modelling, which predicts the attenuation of signal strength as it travels from the Base Transceiver Station (BTS) to the user. Accurate path loss modelling ensures reliable communication, optimizes network performance, and reduces interference (Pawar and Venkatesan, 2024). Traditional path loss models, such as the Davidson, COST231-Hata, and ITU-R models, have been used for decades. These models are based on empirical formulas that consider frequency, distance, and terrain type. However, these models have limitations, including their inability to account for complex urban environments, varying terrain types, and dynamic weather conditions (Laptiev *et al.*, 2020). In recent years, Machine Learning (ML) techniques have emerged as a promising approach for pathloss modelling. ML-based models, such as Random Forest (RF) and Extreme Gradient Boosting (XGBoost), can learn complex patterns in data and make predictions based on large datasets. These models have shown improved accuracy and flexibility compared to traditional pathloss models, especially in complex urban environments (Famoriji *et al.*, 2022; Kelif *et al.*, 2014; Zhiwen and Xinping, 2013).

However, ML-based pathloss models also have limitations, including the need for extensive training data, computational complexity, and the risk of overfitting. To address these limitations, researchers have started exploring deep learning techniques, such as Convolutional Neural Networks (CNNs), for path loss modelling (Iyare *et al.*, 2019). CNNs have shown remarkable performance in image classification tasks and have been applied to various fields, including wireless communication systems (Yazici *et al.*, 2024). The use of CNNs for path loss modelling is due to their strong feature extraction capabilities and ability to recognize patterns in data. One key reason is that CNNs can automatically learn complex relationships between environmental factors like frequency, distance, and pathloss without requiring manual feature engineering.

Additionally, their local receptive fields enable them to capture spatial dependencies and correlations in structured input data, including geographical coordinates, elevation data, and building layouts, significantly influencing signal attenuation (Ozkok and Celik, 2022). Another advantage of CNNs is their robustness in handling non-linearities in wireless signal propagation. Since signal pathloss is a subject of diffraction, reflection, and scattering (Jimoh *et al.*, 2022), CNNs are well-suited for modelling these complex interactions compared to traditional statistical models. Furthermore, CNNs offer scalability and generalization, allowing them to be trained on diverse datasets and perform well across different

*Corresponding author: adehameed79@gmail.com

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environments, such as urban, rural, indoor, and outdoor settings, without requiring environment-specific tuning. Lastly, CNNs utilize hierarchical representation learning, where multiple layers progressively extract high-level features from low-level input characteristics, making them efficient in capturing multi-scale dependencies in propagation environments.

This research, therefore, presents a hybridised CNN-based approach for pathloss modelling, which combines the strengths of two CNN variants of DenseNet and ResNet. The hybridization flow chart is presented in Figure 1, which depicts the hybridization of the dense connections layers of the DenseNet to the residual block networks of the ResNet, facilitating the input feature reuse and smooth gradient flow for efficient learning of the hybridised CNN architecture (Gao *et al.*, 2022). Therefore, the hybridised CNN architecture will promote deep network training with reduced vanishing gradient scenarios, enhanced feature extraction and representation, improved training efficiency, and optimal convergence. These complementary strengths of DenseNet and ResNet are envisioned to create a robust CNN architecture capable of learning complex patterns in radio mobile pathloss modelling, improving prediction accuracy and robustness, and optimising mobile network design and performance (Khan *et al.*, 2023). This innovative approach has the potential to revolutionise radio mobile path loss modelling, enabling more accurate predictions and efficient mobile network optimisation (Alhichri *et al.*, 2021). This article is organized as follows: the introduction provides an overview of the study's background, aim, and objectives. The following section gives an overview of the path loss model's development, highlighting the limitations of the earlier and existing path loss models and the potential of CNN-based pathloss models to address these challenges. The methodology section details the data collection process, machine learning techniques, and the hybridised CNN-based pathloss model development process. Following this, the results and discussions section presents the findings and evaluates and validates the model's predictability. Finally, the conclusions summarise the research contributions and suggest directions for future work.

II. OVERVIEW OF PATHLOSS MODEL'S DEVELOPMENT

The development of path loss models has steadily improved and expanded. The Okumura model, developed in 1968 for urban areas, significantly advanced earlier models by considering building height, street width, and frequency (Cheffena *et al.*, 2017). In 1980, the Hata model expanded Okumura's work to suburban and rural areas up to 20 km and introduced parameters like antenna height and terrain characteristics (Elmezughi *et al.*, 2021). The Davidson and COST231-Hata models, developed in 1991, extended the prediction distance of the Hata path loss model beyond 20 km and included terrain roughness and vegetation considerations (Ayadi *et al.*, 2017). In 2001, the ITU-R P.529 model combined elements from previous models and added new factors like clutter and terrain slope. The 2003 Ericsson model

focused on wireless networks and introduced parameters like base station height and urbanisation degree. The Stanford University Interim (SUI) model, developed in 2005 for WiMAX networks, considered terrain roughness, vegetation, and atmospheric conditions (Awal *et al.*, 2017). The IEEE 802.11 model, developed in 2007, built on the SUI model by adding building penetration loss and multipath fading to account for nonlinear path effects. In 2012, the 3rd Generation Partnership Project (3GPP) developed a model incorporating terrain slope, vegetation, and building clutter. In 2023, a 5G path loss model was developed to consider millimeter-wave frequencies and a massive MIMO approach (IEEE Communications Society, 2023). This development briefly highlights that the pathloss model's development is a continuous process of refinement and extension, addressing the limitations of predecessors by expanding frequency ranges, adapting to new environments, incorporating more detailed empirical data, and tailoring to emerging technologies. However, the dynamicity of user environments and the trend toward higher frequency bands with sophisticated access technicalities have challenged the traditional pathloss model's prediction. Therefore, a more robust modeling approach is essential, leveraging artificial intelligence (machine learning) to predict wireless pathloss across multiple frequencies, accurately estimate pathloss across diverse terrains, and accommodate varying trans-receiver separation distances.

Recently, (Sheetal and Mithra, 2024) investigated millimeter wave communication systems, emphasizing the need for accurate pathloss prediction and optimization. They found traditional models less precise, leading to exploring machine learning as an alternative. Deep learning methods were shown to efficiently predict path parameters from large datasets, outperforming traditional methods and highlighting the potential of deep learning in millimetre wave communication systems. Also, vehicle-to-vehicle (V2V) communication was essential in transportation systems (Sagir and Tugcu, 2024) in enhancing traffic efficiency and reducing accident probability. However, accurate pathloss estimation is challenging due to complex propagation environments. The study explores machine learning methods for improving path loss estimation in V2V communication using a large dataset from highway environments in Türkiye. Various algorithms, including Artificial Neural Networks and Random Forest, were compared to traditional empirical approaches, revealing that machine learning methods outperform traditional methods and yield faster results, with Random Forest and Gradient Boosting demonstrating the highest prediction accuracy. Yazici *et al.* (2024) proposed a novel approach to path loss prediction in wireless communication systems using explainable machine learning techniques. Leveraging a public dataset with environmental factors, the research employed Extreme Gradient Boosting (XGBoost) and optimised its parameters through cross-validation. SHAP and LIME were applied to interpret the model's predictions, providing transparency and insights into the relationships between input features and pathloss, enhancing the applicability of machine learning in Radio frequency (RF) planning. Accurate propagation modelling was proposed to be crucial for wireless deployments

and spectrum planning by (Ethier and Châteauvert, 2024). The study suggested a novel approach using environmental information to predict wireless signal propagation, precisely the total obstruction depth along the direct path. This simplified method offers a streamlined and surprisingly accurate solution, providing a practical tool for efficient and effective wireless network planning and addressing the growing demand for high modelling accuracy.

Therefore, a significant research gap exists in applying machine learning-based pathloss models, as previous studies have largely overlooked the potential of hybridising different machine learning algorithms or variants of CNNs to develop a more robust learning and training architecture. This limitation may lead to models failing to fully capture the dynamic variations in mobile user environments, thereby affecting the accuracy and generalizability of path loss predictions. Additionally, most related studies relied on path loss data that was either simulated or measured from a single network system rather than incorporating data from multiple mobile networks. This approach may not accurately represent real-world path loss degradation across different service providers. To address these gaps, this research will contribute in three keyways:

- Development of a hybridised CNN-based pathloss model by integrating CNN variants, the research creates a more efficient and accurate model for path loss prediction, leveraging the strengths of the DenseNet and ResNet architectures.
- Using multi-network field measurement data, instead of relying solely on single-network or simulated data, this research incorporated real-world pathloss measurements from multiple mobile networks such as MTN, GLO, 9Mobile, and Airtel to enhance model reliability.

Improve model generalisation and practical application by providing a more adaptable and scalable solution for mobile network planning, ensuring better accuracy in diverse environments and improving network optimisation strategies.

III. METHODOLOGY

This section presents the systematic approach adopted in this research to develop and evaluate a machine learning-based pathloss prediction model through deep learning techniques, particularly hybridized CNNs; this study aims to improve the accuracy of pathloss modelling for mobile networks. The methodology encompasses data collection, preprocessing, model training, and performance evaluation using real-world measurements. Various computational resources and optimisation strategies were employed to ensure efficient model development. The approach emphasizes comparative and statistical analyses to assess the effectiveness of the proposed model against traditional and machine learning-based pathloss models.

A. Architecture of the developed hybridized CNN approach

The hybridised CNN-based pathloss model integrates the variants of the Densely connected Network (DenseNet121) and Residual Network (ResNet50) of CNN, as depicted in the flow chart of Figure 1. The hybridisation process combines ResNet50 variants, which consists of 50 layers, to extract features from the input data and DenseNet121, comprising 121 layers, to capture dense feature representations. The features from ResNet50 and DenseNet121 are blended using concatenation. We chose concatenation over addition or parallel stacking for the following reasons: concatenation allows us to preserve the feature information from both models without losing any details, increased representation capacity: using concatenating features, we increase the representation capacity of our model, enabling it to capture a wider range of patterns and relationships in the data and concatenation provides flexibility in learning, as the model can learn to weigh the importance of features from each branch during training. The use of concatenation is justified by its ability to effectively combine the strengths of both ResNet50 and DenseNet121. This approach enables our model to pull the residual learning capabilities of ResNet50 and the dense feature representations of DenseNet121, resulting in improved performance (Khan *et al.*, 2023)

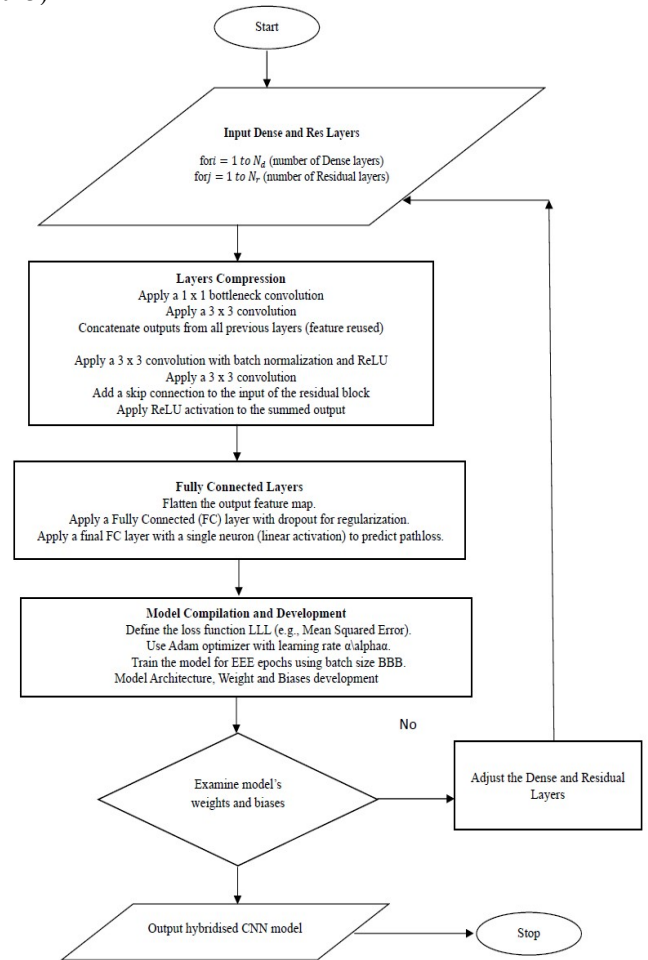


Figure 1: The Flow Chart Architecture of the Developed hybridised CNN based-Pathloss Model.

B. LOCATION DESCRIPTIONS

The study was conducted in Ilorin, Kwara State, Nigeria, located in the country's north-central, approximately 300 kilometres inland from the Atlantic coast. Ilorin lies between latitudes 8°30'N and 8°40'N and longitudes 4°30'E and 4°40'E, with an average elevation of 300 meters above sea level. The city has a tropical savanna climate (Ikueomonisan and Ozebo, 2020), characterized by a wet season (April–October) and a dry season (November–March). The terrain consists of undulating landscapes with occasional rocky outcrops, while the vegetation includes savanna grasslands and deciduous forests

C. DATA COLLECTION AND PREPROCESSING

A driving test was conducted using a licensed professional version of the RantCell application logger installed on an internet-enabled Android phone, as depicted in Figure 2. To minimise the impact of Doppler's effect, the driving test was carried out in a vehicle at an average speed of 40 km/h. The phone's Global Positioning System (GPS) was activated, and each mobile network operator (MTN, GLO, 9Mobile, and Airtel) was sequentially enabled along four measurement routes covering urban and suburban areas. However, all four mobile network services were accessible in all the selected routes, minimizing potential biases related to network availability also, we synchronized data gathering across networks to minimize time-based variability, ensuring that data from different networks was collected under similar conditions.

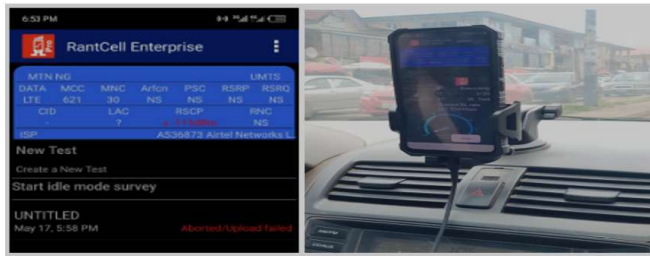


Figure 2: The Field Work Measurement Set-up

D. MEASUREMENT ROUTE DESCRIPTIONS

1. GRA - UNILORIN Route
 - Dual carriageway from the General Post Office through Kwara State Library, Government House, Tanke Junction, and Tipper Garage, ending at the University of Ilorin
 - Features, commercial and residential buildings, state government offices, and private businesses
2. Taiwo – Airport – Otte Route
 - Extends from Taiwo Isale through Queen Elizabeth Roundabout, Ilorin International Airport, to Otte town.
 - Hosts commercial hubs and experiences high vehicular movement

3. Post Office - ARMTI Route
 - Spans from Kwara State Polytechnic, Fate-Zango Roundabout, Maraba, Post Office Flyover, Challenge, Offa Garage Roundabout, through Ganmo-Amayo, to ARMTI
 - Characterized by commercial activities concentrated along the route
4. Emir Palace - KWASU Route
 - Covers B' Division Police Station, Baboko, Agaka, C' Division Police Station, Emir Palace, Gambari, Shao Garage, and Kwara State University, Malete. Features, ancient buildings, and two major markets (Oja Oba and Oja Tuntun) leading to high population density and heavy vehicular movement

E. TRAINING, TESTING, AND MODEL EVALUATION

The collected path loss data and altitude, latitude, and longitude were input features for training the hybridised CNN-based pathloss model. The training and testing processes were executed on Google Colaboratory using its Jupyter Notebook interface.

E1 Computational Resources

- GPUs (Graphics Processing Units): Used to accelerate training by handling parallel matrix computations efficiently.
- TPUs (Tensor Processing Units): Custom-designed by Google for deep learning tasks, optimised for large-scale tensor operations in TensorFlow models.

E2 Data Splitting and Training Process

- The dataset was split into 70% for training, 15% for validation, and 15% for testing.
- The hybridised CNN-based pathloss model was trained using backpropagation and stochastic gradient descent (SGD) with adaptive learning rates.
- The scalar inputs are transformed into 2D tensors to enable effective processing by the CNN architecture. This transformation allows us to leverage the spatial hierarchies and feature extraction capabilities of CNNs.

Transforming the scalar inputs enable the CNN to extract features that capture relationships between the scalar inputs also, the 2D tensor representation is compatible with the CNN architecture, allowing for seamless integration and processing.

The model performance was evaluated and validated using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R² Score to assess prediction accuracy. The error-based metrics formulations are expressed in equations 1 to 8.

Error (E) is the deviation of predicted path loss values from the measured path loss values, as expressed in equation 1. The smaller the numeric error values, the closer the path loss predicted value is to the measured path loss value. This resulted

in a good performance gauge for the hybridised CNN-based path loss model reported by (Fabián, 2021).

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$$\text{Error (E)} = (M_v - P_v) \quad 1$$

where, M_v is the Measured path loss value, P_v is the Predicted path loss value.

- b. Mean error (M_{error}) is the average of the errors spread between the measured path loss values and the predicted path loss values. It helps quantify the average errors in predicted path loss values (McGrath *et al.*, 2020), as expressed in equation 2. (M_{error}) = $\frac{1}{n} \times \sum_{v=0}^n (M_v - P_v)$ 2

Where M_v and P_v are as defined in equation 1.

- c. Absolute mean error ($A_{\text{m-error}}$) measures the average magnitude of the errors between the predicted path loss values and measures path loss values. It is similar to the mean error but takes the absolute value of the differences, making it always positive (Fabián *et al.*, 2021). The mathematical expression is expressed in equation 3.

$$(A_{\text{m-error}}) = \frac{1}{n} \times |\sum_{v=0}^n (M_v - P_v)| \quad 3$$

where n is the number of occurrences, M_v P_v the Measured path loss value, and the Predicted path loss value.

- d. The relative mean error ($R_{\text{m-error}}$) is the quantity used to measure the uncertainty in the pathloss models' prediction values compared to the measured pathloss values (McGrath *et al.*, 2020), as expressed in equation 4.

$$(R_{\text{m-error}}) = \frac{1}{n} \times \sum_{v=1}^n \left(\frac{A_{\text{error}}}{M_{\text{error}}} \right) \quad 4$$

where n is defined in equation 1.

- e. Root Mean square error ($RM_{\text{s-error}}$) gives the magnitude of errors between the predicted path loss values and the measured path loss values; the smaller the numeric value of the root mean square error the closer the expected path loss values to the measured path loss values and vice versa (Hodson, 2022). The mathematical expression is as expressed in equation 5.

$$(RM_{\text{s-error}}) = \sqrt{\frac{1}{n} \times \left(\sum_{v=1}^n (E_v - M_{\text{error}(v)})^2 \right)} \quad 5$$

Furthermore, the machine learning metric of Mean Squared Error (MSE) and the coefficient of determination (R-squared) are employed in a regression analysis, where the goal is to predict a continuous output variable based on one or more input features. These metrics will provide insights into the accuracy, precision, and reliability of the hybridised CNN-based pathloss model, helping to identify areas for improvement and optimise its performance.

- f. The Mean Squared Error (MSE) computes the average squared difference between predicted

and actual values. It penalizes more significant errors more heavily than MAE due to squaring (Heydarian *et al.*, 2022)

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad 6$$

where: n is the number of data points, y_i is the actual path loss measured value, $\hat{y}_i$ is the predicted path loss value, and $(y_i - \hat{y}_i)^2$ represents the squared error for each predicted pathloss value. The Lower MSE values indicate better predictions. However, it can amplify the impact of outliers because errors are squared.

- g. The R-squared (R^2) measures how well the model explains the variability of the dependent variable. It ranges from 0 to 1, where 1 indicates perfect fit and 0 indicates poor fit (Deng *et al.*, 2016; Xu *et al.*, 2023).

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \bar{y})^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad 7$$

where n , y_i as defined in equation 6, $\bar{y}$ is the mean of the actual path loss measured value, $\sum_{i=1}^n (y_i - \bar{y})^2$ is the residual sum of squares, and $\sum_{i=1}^n (y_i - \bar{y})^2$ is the total sum of squares. The values range between 0 and 1, where 1 indicates a perfect fit and 0 indicates a poor fit. Tables 1 and 2 summarize the reference BTS for the four measurement routes and the selected hyper-parameter tuning features.

Table 1: The summary of Reference BTS for the four measurement routes
GRA Unilorin Route

Mobile	Alt.(m)	Lat.	Long.	RSRP(dB)	Data
MTN	299	8.48513	4.56636	-74	LTE
Glo	302	8.49997	4.57865	-64	LTE
Airtel	287	8.48887	4.56586	-69	LTE
9Mobile	286	8.48524	4.56606	-76	LTE

Post-Office Armti Routes

Mobile	Alt.(m)	Lat.	Long.	RSRP(dB)	Data
MTN	340	8.45223	4.58196	-80	EDGE
Glo	334	8.45302	4.58098	-61	LTE
Airtel	288	8.49901	4.57336	-75	LTE
9Mobile	330	8.45316	4.56606	-86	LTE

Taiwo Otte Route

Mobile	Alt.(m)	Lat.	Long.	RSRP(dB)	Data
MTN	284	8.49952	4.56169	-50	HSPA+
Glo	340	8.44737	4.50745	-91	LTE
Airtel	294	8.43722	4.49921	-79	LTE
9Mobile	290	8.48381	4.55826	-87	LTE

Emir Kwasu Route

Mobile	Alt.(m)	Lat.	Long.	RSRP(dB)	Data
MTN	248	8.49379	4.56680	-75	HSPA
Glo	278	8.49361	4.56689	-73	LTE
Airtel	323	8.43732	4.49925	-76	LTE
9Mobile	330	8.45316	4.58111	-86	LTE

Table 2: The selected hyper-parameters tuning

No of epoch	200
Batch size	8
Optimiser	Adam optimizer
Number of hidden Layers	17
Dropout Rate	0.5

Pooling Type	Average Pooling
Activation Function	ReLU
Random State	42
Test Size	0.3
Learning Rate	$2e - 5$
Weight decay	0.01
Trainable Parameter	9,217

IV. RESULTS AND DISCUSSION

The mobile signal pathloss variation compared to the altitude variation measured for the four measurement routes under study is presented in Figures 3, 4, 5, and 6, respectively. The routes were carefully mapped to ensure they cover the urban and suburban areas of Ilorin, Kwara State.

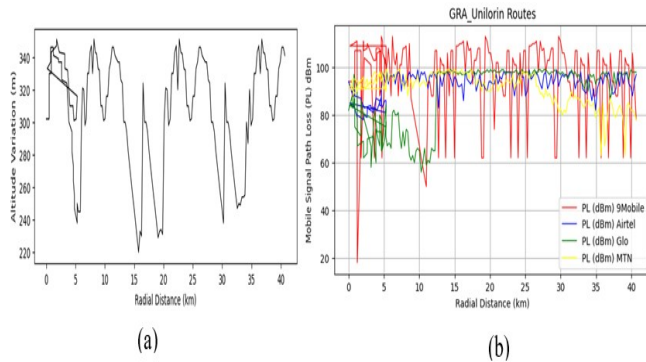


Figure 3: Depiction of GRA to University of Ilorin Routes (a) Measured Altitude variation (b) Mobile Signal Path Loss variation against the Radial Distance

The routes consist of two-lane roads extending 39 km from the Government Residential Area to the University of Ilorin, passing key locations such as Tanke Junction and Tipper Garage. Bungalows, offices, shops, and some suburban residences border the streets. The measured path loss signal varied in pattern with altitude, except for the Airtel signal, which maintained a consistent variation throughout the route.

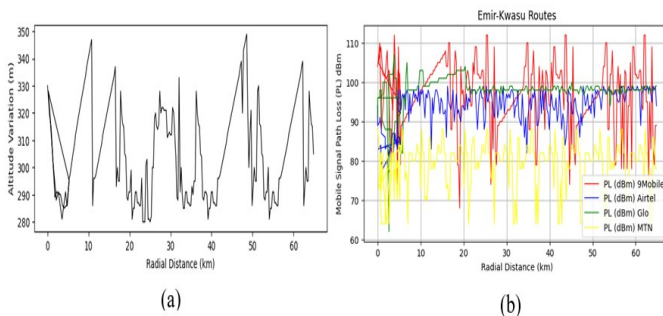


Figure 4: Depiction of Emir Palace to Kwasu Maletе Routes (a) Measured Altitude variation (b) Mobile Signal Path Loss variation against the Radial Distance.

This dual carriageway stretches from B' Division Police Station in Surulere, past Emir Palace, to Kwara State University in Maletе. Bordered by historic buildings, it experiences heavy traffic due to its proximity to Oja Tuntun and Oja Oba markets. Signal measurements were conducted over approximately 60 km of the route. The MTN mobile network showed the highest variations in signal strength, while the Airtel mobile network and the route's altitude were also notably varied.

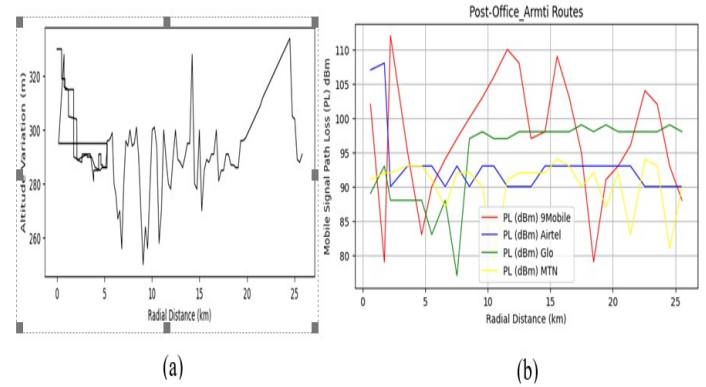


Figure 5: Depiction of Post-Office to Armti Ilorin Routes (a) Measured Altitude variation (b) Mobile Signal Path Loss variation against the Radial Distance.

This dual carriageway extends from Kwara State Polytechnic, through the General Post Office, to ARMTI, passing several key locations. The route is marked by significant commercial activity. Signal measurements were conducted over approximately 40 km of the path. The Airtel mobile network signal maintained a relatively consistent strength, while the signals of other mobile networks varied significantly with the altitude along the route.

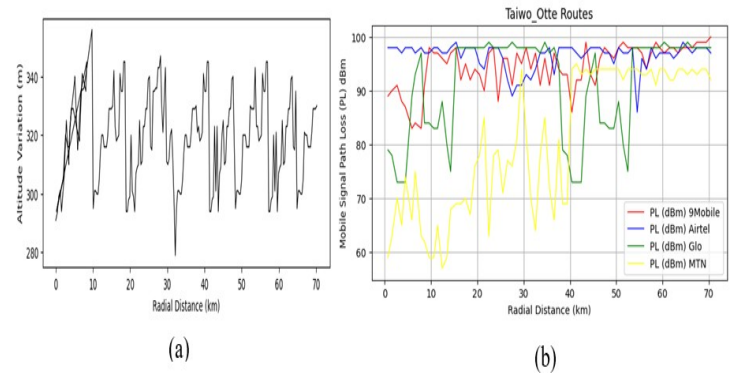


Figure 6: Taiwo Road to Otte Town Ilorin Routes (a) Measured Altitude variation (b) Mobile Signal Path Loss variation against the Radial Distance.

This two-lane road stretches from Taiwo Isale to Otte town, passing key landmarks such as the Queen Elizabeth Roundabout and Ilorin International Airport. It is a bustling

commercial hub with heavy traffic during work hours. The altitude varies significantly along the route. The 9Mobile network exhibited substantial path loss, while Glo and MTN showed moderate signal path losses. In contrast, the Airtel mobile network maintained a consistent signal path loss of approximately 35 km of the route's span.

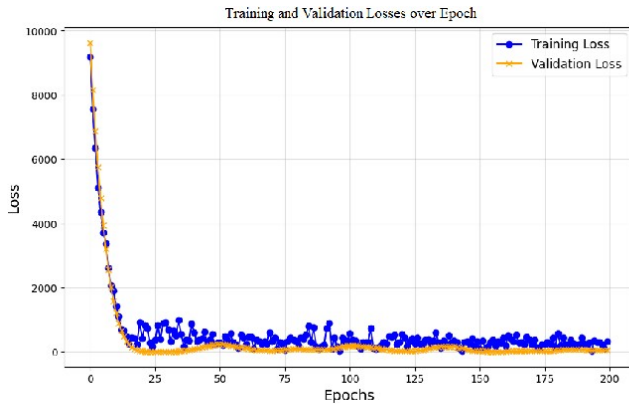


Figure 7: The hybridized CNN Improved Path Loss Model's Training Loss over Epochs

The model shows steady improvement in performance throughout training. At epoch 50, batch size of 2, ReLU activation function, pooling average and 2 hidden layers, the MAE and MSE values were 25.15 and 34.43, respectively, indicating slow progress, while the R-squared value remains negative at -6.01, suggesting room for improvement. Training time per step was 549 ms, reflecting optimisation in efficiency. By epoch 75, batch size of 4, ReLU activation function, pooling average and 10 hidden layers, the MAE slightly increase to 26.45 and MSE decreases to 30.14, showing reduced prediction error, though the R-squared value remains negative at -5.3. At epoch 100, batch size of 6, ReLU activation function, pooling average and 12 hidden layers MAE reduces to 20.27 and MSE to 26.76, slightly improving R-squared to -5.1, indicating an average model fit. Epochs 125 and 150 demonstrate significant progress, with MAE falling to 15.01 at epoch 125 and 9.021 at epoch 150, while MSE drops to 20.14 and 18.54, respectively. R-squared improves from -1.6 to -0.1, signaling approaching convergence with the batch size at 7 and the hidden layers maintain at 12. At epoch 200, batch size of 8, ReLU activation function, pooling average and 17 hidden layers the model achieves optimal performance, with MAE reduced to 2.08, MSE to 7.35, and R-squared reaching 0.8, indicating a firm fit. Although training time increases to 593 ms, the model now shows robust generalisation. These specifics choice of architecture was therefore chosen to achieve optimal learning and prevent overfitting, at which point the learning process was discontinued.

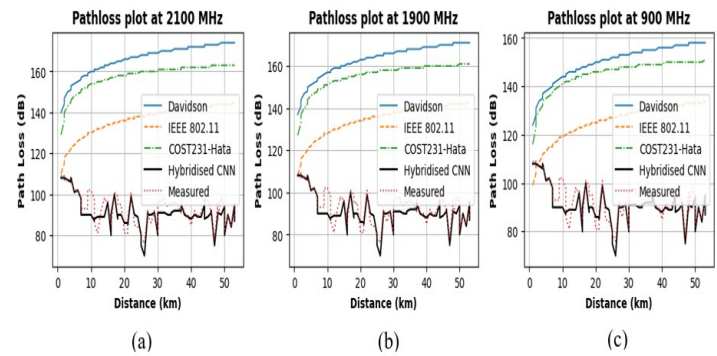


Figure 8: Comparison of the Measured Hybrid CNN and the Traditional Path Loss Models' Values at (a) 2100 MHz, (b) 1900 MHz, and (c) 900 MHz Bands

Figure 8 compares the mobile signal measured path loss against the predicted pathloss values from the hybridised CNN-based and traditional models. A significant deviation was observed in the conventional model's predictions from the measured path loss values, whereas the hybridised CNN-based pathloss closely mirrored the actual measurements. This observation aligns with the Absolute and Root Mean Square Error values obtained, as depicted in Figure 9.

The Comparison of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for Path Loss Models under Study

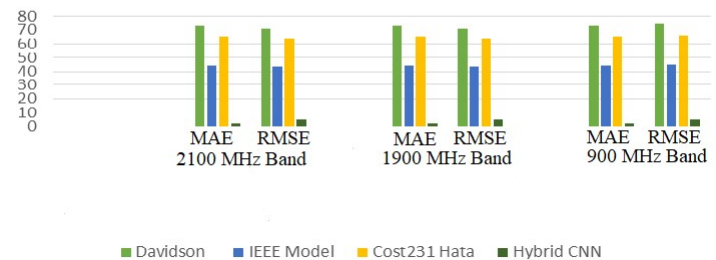


Figure 9: The Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

The graph in Figure 9 illustrates the MAE and RMSE comparison of the hybridised CNN-based path loss model against the traditional pathloss models under study across three different mobile operation bands: 900 MHz, 1900 MHz, and 2100 MHz, respectively. This comparison shows that the hybridised CNN-based pathloss model shows very little drift from the actual or measured pathloss, unlike the traditional frequency-dependent pathloss models, which depicted a high drifting.

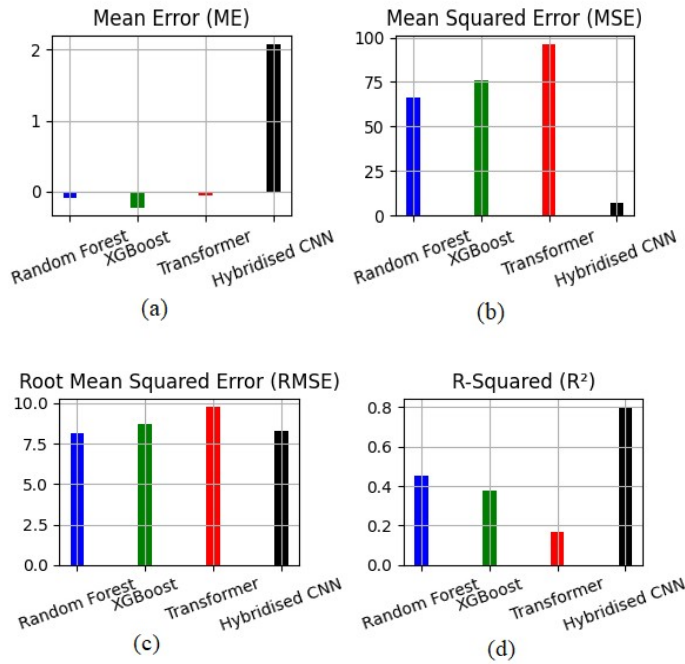


Figure 10: The Graphical of Metrics Comparison of (a) the Mean Error (b) Mean Square Error (c) Root Mean Squared Error and (d) R-Squared of the hybridised CNN and other Machine Learning Based Path Loss Models

The results show that the hybridised CNN-based pathloss model outperforms all other models, achieving the lowest error values (MSE: 7.35, RMSE: 8.295) and the highest R^2 (0.80364) (Heydarian *et al.*, 2022; Hodson, 2022; Xu *et al.*, 2023), making it the most accurate. Random Forest follows with moderate performance, reporting an R^2 of 0.4556 and RMSE of 8.1635. XGBoost performs slightly worse, with an R^2 of 0.3782 and an RMSE of 8.7243. The transformer model is the least effective, exhibiting the highest errors (MSE: 96.0593, RMSE: 9.8010) and the lowest R^2 (0.1683), which indicates poor predictive power. These results highlight the superior performance of the hybridised CNN-based pathloss model in path loss prediction compared to other machine learning models.

V. CONCLUSION

This study presented a hybridized Convolutional Neural Network (CNN) Approach for Path Loss Modeling, comparing its performance against traditional and machine learning-based models. The results demonstrate that altitude variations significantly influence mobile signal propagation along different routes in Ilorin, Kwara State. These variations highlight the need for mobile network vendors to conduct onsite assessments and strategically position Base Transceiver Stations (BTS) to mitigate signal degradation caused by obstructions such as high-rise buildings. The model training process emphasized the importance of well-organized training data in achieving rapid convergence. Although training was initially scheduled for 200 epochs, the loss function stabilized

between 20 and 25 epochs, demonstrating the efficiency of the hybridized CNN approach. The hybridised CNN-based-pathloss model outperformed traditional frequency-dependent pathloss models when tested at 900 MHz, 1900 MHz, and 2100 MHz, confirming its robustness across multiple frequency bands.

Furthermore, a comparative evaluation with other machine learning-based models, including Random Forest, XGBoost, and Transformers, established the superiority of the hybridized CNN-based path loss model. While Random Forest and XGBoost provided moderate predictive accuracy, the Transformer model exhibited the least effectiveness and had higher errors. In contrast, the hybridised CNN-based path loss model delivered the most accurate pathloss predictions, proving its effectiveness in diverse mobile environments. Ultimately, this study successfully developed a hybridized CNN-based path loss model incorporating multi-network system path loss data, achieving improved accuracy and generalizability compared to existing models. The findings reinforce the practical applicability of hybridized deep learning architectures for optimizing mobile network planning and performance in real-world scenarios.

FUTURE WORK

The following areas are identified as potential improvements for future research, considering cost-effectiveness, technical advancements, and enhanced pathloss model development:

- **Open Access to Path Loss Data:** Mobile network providers are encouraged to make empirical pathloss data publicly available to researchers. This would significantly reduce the high costs of field measurement campaigns requiring specialized radio signal measurement tools. For instance, in this research, the RantCell professional version used for data logging required a costly subscription in US dollars. Providing accessible datasets would facilitate large-scale model training and validation.
- **Integration of 3D Environmental Features:** Terrain features significantly influence mobile signal propagation, often leading to increased pathloss in obstructed environments. Future research can explore incorporating 3D spatial data of mobile user environments as additional input features in CNN-based pathloss models. By leveraging LiDAR-generated terrain maps or satellite imagery, a more profound correlation between environmental obstructions and pathloss variations can be established. This integration could enhance model performance, leading to more context-aware and geographically adaptive pathloss predictions.
- **A potential future direction for this research** could involve collecting data from diverse environments over extended periods. This would enable the capture of more comprehensive patterns and increase the

generalizability of the findings, providing a more robust understanding of the phenomena under study.

These improvements would further optimise CNN-based path loss modelling, making it more scalable, cost-effective, and applicable in real-world telecommunication scenarios.

AUTHOR CONTRIBUTIONS

A. A. Jimoh: Conceptualization, Software, Validation, Writing – original draft. **Z. K. Adeyemo:** Conceptualization, Methodology, Supervision. **and F. K. Ojo:** Writing – review & editing.

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