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Geo-Spatial Disparities and the Internet Divide: A Terrain-Informed Study of Connectivity Challenges in Africa

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ABSTRACT ***Original research paper***

This study investigates the persistent internet connectivity gap across Africa through the lens of geo-spatial environmental development. While global advancements in wireless technologies have narrowed the digital divide in many regions, African nations continue to face signal degradation, high latency, and inconsistent throughput. These challenges are frequently attributed to socio-economic and infrastructural factors. Yet, this article presents a technical perspective, attributing a significant portion of the problem to the poor geo-spatial coordination of both natural and artificial terrain features. Drawing on satellite imagery, propagation modeling, and machine learning techniques, this research highlights how the geo-spatial arrangement of environmental features relative to transceiver systems critically impacts signal reliability. The findings underscore the urgent need for terrain-informed planning in telecommunications infrastructure to foster more inclusive digital growth across the continent.

1. Introduction

Access to fast, reliable internet has become a fundamental requirement for socio-economic growth, digital inclusion, and global competitiveness. Yet, across many African nations, internet connectivity remains uneven and often unreliable, especially in rural and underdeveloped regions(Baccour*et al.*, 2013). While significant investments have been made to expand telecommunication infrastructure, many areas still suffer from weak signals, high latency, and inconsistent data throughput. These shortcomings are typically attributed to a lack of infrastructure, regulatory challenges, or economic constraints. However, a less discussed but equally critical factor lies in the geo-spatial development of the environment itself(Afolabi *et al.*, 2024).The spatial arrangement of natural and artificial terrain features such as hills, buildings, vegetation, and road networks has a significant influence on signal propagation. When these features are poorly coordinated with transceiver positions, signal degradation becomes inevitable. This challenge is particularly acute in many African settings where urban planning is fragmented, and environmental design rarely considers Radio Frequency (RF) transmission dynamics(Awal-Halifa *et al.*, 2017). The result is a persistent signal impairment that worsens the continent's digital divide. Empirical path loss models, widely used in the planning of wireless networks, often fall short in accounting for the complex and diverse terrain patterns found across African landscapes. These models, developed in vastly different environments, fail to generalize accurately to settings with highly irregular spatial structures(Jimoh *et al.*, 2015). This research was inspired by the observed limitations of such models and driven by a desire to develop more accurate, data-driven alternatives tailored to the African context. This study examines how the poor coordination of geo-spatial features contributes to the internet connectivity gap in Africa by leveraging satellite imagery, digital elevation models (DEMs), and hybridized machine learning techniques, specifically,Convolutional Neural Networks (CNNs) to model and predict signal impairments more accurately(Alhichri*et al.*, 2021). Emphasis is placed on identifying which environmental features most significantly affect signal quality and how improved spatial planning could mitigate these issues.

The overarching goal is to provide technical insights that can guide terrain-aware infrastructure planning, enabling better signal coverage, reduced latency, and an improved user experience. This terrain-informed approach to RF planning has the potential to shift the discourse from reactive fixes to proactive design, bridging the connectivity gap through intelligent environmental alignment. The remaining sections of this article are outlined as follows: section two, highlighting the overview of internet signal impairment due to terrain inducement, section three presents the research approach, study focus, and internet service disparity. Section four presented the results and discussion,and section five concluded the article.

2. Overview of Internet Signal Impairment due to Terrain Inducement

The study of internet connectivity challenges in Africa has evolved significantly, with early investigations primarily focusing on infrastructure limitations and mobile network service unavailability. In the early 2000s, most analyses emphasized the lack of physical infrastructure, such as fibre optics and mobile towers, particularly in remote and rural communities (IEEE Communications Society, 2014). Subsequent studies between 2005 and 2010 began to introduce demographic and economic factors as major contributors to the digital divide, emphasizing poverty, low literacy, and limited governmental investment in ICT development(Qaisar *et al.*, 2010). In the midst of 2014, attention shifted to include environmental and spatial dimensions, recognizing that terrain features, such as mountains, valleys, vegetation, and building densities, significantly affect signal coverage and internet accessibility (Kelif *et al.*, 2014).

In 2017, terrain-induced disparity gained traction as a core determinant of network performance, with several studies linking poor connectivity to poorly coordinated topographical development and land use planning in many African regions(Awal-Halifa *et al.*, 2017). More recently, geo-spatial analysis tools such as GIS and satellite imaging have been employed to study the spatial distribution of broadband infrastructure and identify underserved regions(Sotiroudis*et al.*, 2021). These tools enabled researchers to correlate signal degradation with terrain slope, clutter, and elevation differences, further highlighting how physical geography contributes to Africa's digital exclusion. However, as 4G and 5G deployments expand across the continent, the limitations of traditional infrastructure-centered models become more evident. The increasing demand for real-time connectivity, high-speed data, and smart services requires that environmental and spatial factors be integrated into planning frameworks. In 2022, emerging studies started addressing these challenges by modeling the relationship between topography and signal reachability using artificial intelligence and terrain-influenced datasets(Abdulkarim *et al.*, 2022). These new approaches reveal that connectivity issues are not solely due to a lack of investment but also to the misalignment between signal propagation dynamics and the terrain arrangements surrounding users.

Recent research by (Arnold *et al.*, 2024)emphasizes the importance of spatial planning in broadband network development. Their findings showed that network capacity and reliability significantly improve when terrain-informed deployment strategies are applied.Maurício *et al.*,(2023)explored terrain-aware broadband planning using satellite imagery and found that densely vegetated and hilly regions in Sub-Saharan Africa are disproportionately underserved due to signal attenuation and reflection losses. Sivaz and Aykut, (2024)further introduced a multi-layer GIS model that maps out connectivity disparities by overlaying terrain roughness, population density, and network availability. Their approach has helped to visualize the hidden inequalities in internet access caused by poorly integrated spatial development.

Therefore, a pressing research gap exists in addressing the terrain-induced geospatial internet divide through intelligent modelling frameworks. Most past studies have treated connectivity challenges as either infrastructural or economic, overlooking how land use planning, natural geography, and elevation variance influence broadband deployment success. Moreover, little attention has been paid to modelling the synergistic effect of environmental features and wireless propagation behaviour using data-driven approaches.This study helps to bridge this gap by contributing in three strategic ways:

a. employ satellite images and digital elevation models (DEMs) to develop the 3D geo-spatial distribution of the study area and incorporated the clutter pathloss values to map and understand how terrain features interact with internet infrastructure layouts to affect signal performance.

b. apply ML algorithms such as CNNs and Random Forest to geo-referenced datasets, to identify patterns of digital exclusion and predict potential connectivity failures with terrain as a core input variable.

c. develop policy-supportive outcomes that will be translated into actionable visual maps and guidelines that can assist policymakers and network planners in designing terrain-adaptive internet connectivity strategies, especially in hard-to-reach African communities.

This approach promotes a paradigm shift from conventional network expansion to intelligent and inclusive terrain-sensitive planning, offering long-term solutions to Africa's persistent internet divide.

3. Research Approach

The approach involved the chatting of four interconnected routesspanning urban, suburban, and rural areas of Ilorin, Kwara State, Nigeria. Ilorin is a town in sub-Saharan Africasituated in the north-central region of Nigeria, approximately 300 km inland from the coast of the Atlantic, and lies betweenlatitudes 8°30' N and 8° 40' N and longitudes 4° 30' N and 4° 40' N(Jimoh *et al.*, 2022). The mobile signal strength was captured for four distinct mobile network service providers of MTN, GLO, AIRTEL, and 9MOBILE. The measured signal pathlosses for each of the mobile service providers were estimated using the expression of equation 1 by (Jimoh *et al.*, 2022) to compute the mobile signal path loss values for each of the network providers along each of the field work measurement routes using the field measurement setup of Figure 1.

$$Measured_{PathLoss(dB)} = Transmitter_{Power(dB)} - Receiver_{Power(dB)}$$

Figure 1: Field Measurement Setup.

3.1 Geo-Spatial Images' development

The three-dimensional (3D) mean geo-spatial distribution of terrain features along the designated measurement routes was generated using the Google Collaboratory cloud-based Jupyter Notebook environment. This process involved overlaying two-dimensional (2D) satellite imagery of the terrain with elevation data derived from the Digital Elevation Model (DEM). The integration of these data sources enabled the construction of 3D geo-spatial terrain representations for each measurement route, thereby offering a more comprehensive understanding of the geo-spatial structure of the study areas, as illustrated in Figure 2.The close examination of each route's terrain characteristics exhibited distinct patterns of spatial distribution and settlement alignment. The Emir-Kwasu route demonstrated a clustered and irregular terrain distribution, where features appeared to be concentrated in a non-linear formation. This pattern reflects a poorly coordinated settlement layout and a non-linear road network, which could influence the propagation behavior of radio signals in the area.Similarly, the Taiwo-Otte route showed a comparable zigzag arrangement of terrain features, albeit with lower building density and less pronounced clustering. While still indicative of an unstructured settlement pattern, it demonstrated relatively less congestion than the Emir-Kwasu route.In contrast, the GRA-Unilorin route exhibited a more orderly and linear distribution of terrain features. This alignment suggests a well-planned and coordinated urban settlement, which is likely to facilitate better signal propagation and less attenuation due to more predictable structural spacing. Furthermore, the Post Office-ARMTI route revealed a consistent and uniformly distributed terrain pattern. The linearity and homogeneity observed across all sub-routes within this corridor suggest a high degree of replication in the spatial arrangement of features, indicative of a structured settlement plan. These characteristics are essential in evaluating the interaction between geo-spatial configuration and mobile signal behavior. The influence of these varying settlement patterns and terrain arrangements was further examined in Section 4 of the study, which investigates the disparities in mobile network coverage and the emerging connectivity divide. Therefore, understanding these geo-spatial dynamics, provide more effective models that can be developed to mitigate connectivity gaps, particularly in poorly planned or irregularly settled regions.

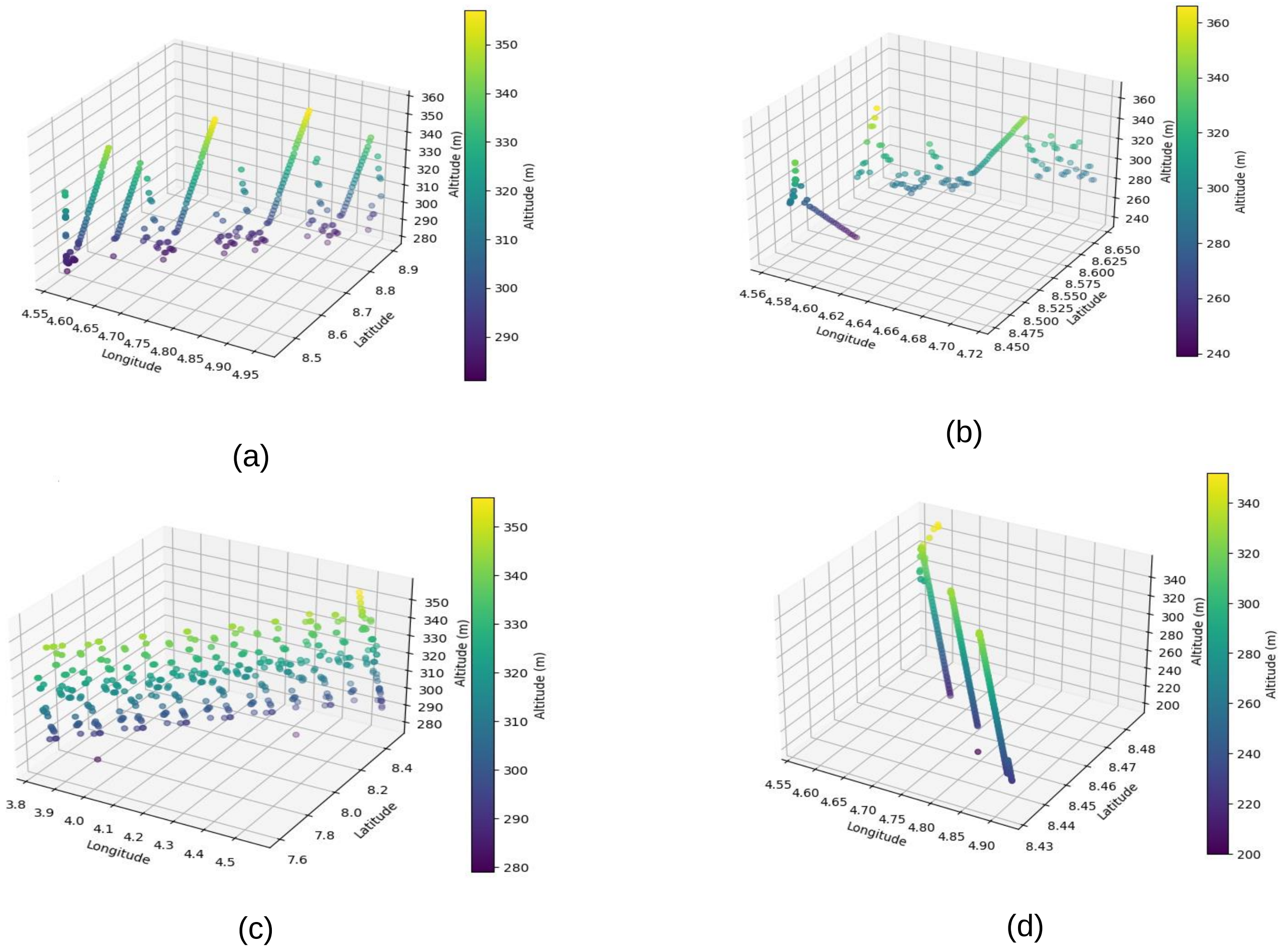

Figure 2: (a) The Geo-Spatial Mean Distribution of the Terrain Features along (a) Emir-Kwasu (b) Taiwo-Otte (c) GRA-Unilorinand (d) Taiwo-Otte Measurement Routes

3.2 Machine Learning Model Training and Input Data

Machine Learning (ML), a subset of Artificial Intelligence (AI), involves the development of computational models that can learn patterns from data and make informed decisions(Badillo *et al.*, 2020). This learning process is enabled by the core architectural components of ML systems, as illustrated in Figure 3. The process begins at the input layer, where raw data is received and significant features are extracted for further processing(Abdollahzadeh *et al.*, 2024). The convolutional layer then captures non-linear features from the data, utilizing pooling operations such as average or max pooling, depending on the configuration. These extracted features are passed to the fully connected layer, where they are combined with weights and biases, and processed through activation functions to generate meaningful outputs(Al-Hakim and Prasetiyo, 2024). The final output layer uses this processed information to produce the model's prediction or decision. In this study, a machine learning framework was trained using 3D geo-spatial mean distributions of terrain profiles alongside measured path loss data collected during field experiments(Qi *et al.*, 2021). The models employed include Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Convolutional Neural Network (CNN)(Ouadah *et al.*, 2022).

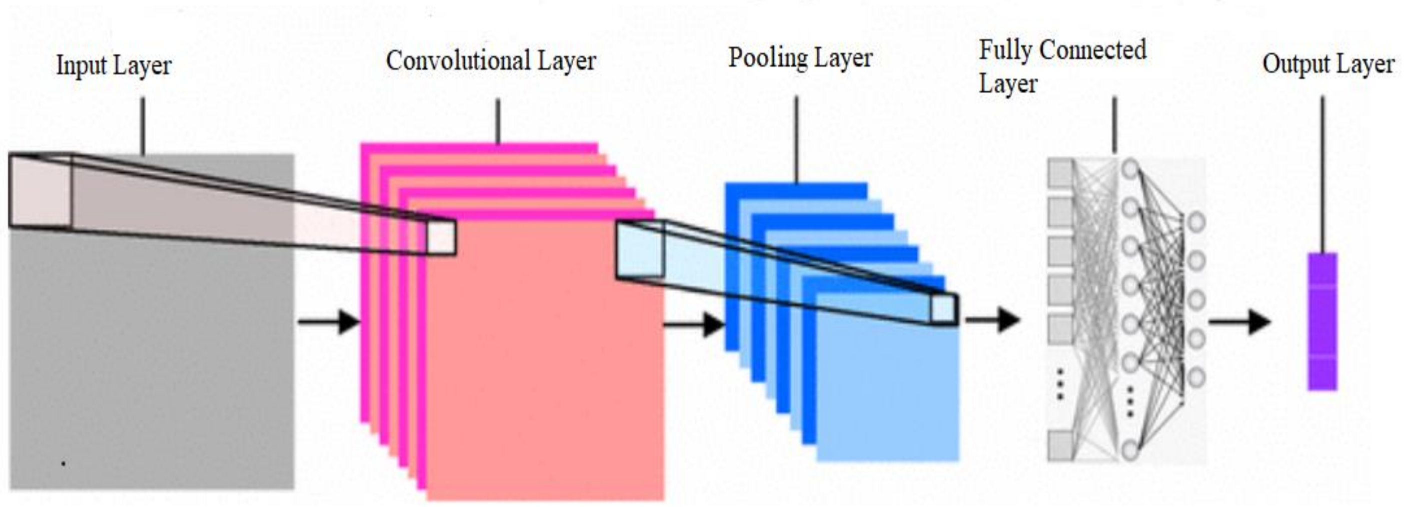

Figure 3: The Basic Architecture of Machine Learning Model

4. Results and Discussions

A significant concentration of data points was observed in Figure 4 between 275 and 325 meters in altitude, where path loss values consistently fall within the range of 60 to 110 dBm.

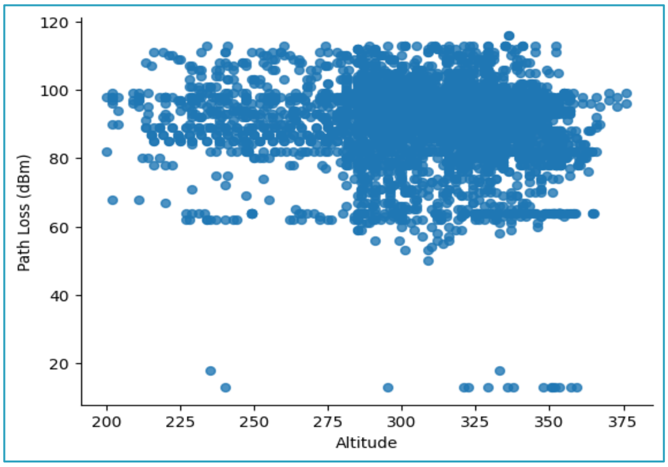

Figure 4: Depiction of Mean Path Loss values again Mean Altitude values across the Field Work Measurement Routes.

This clustering suggests that most of the measurements were taken within mid-altitude zones, which may represent densely populated or commonly traversed areas in the study region. Also, the results indicate no clear linear or strong directional relationship between altitude and path loss.The scatter is widely distributed across altitudes, implying that changes in elevation alone do not significantly influence the variation in signal attenuation. This suggests that altitude may not be the dominant factor affecting signal quality in the studied terrain. There are few outliers exist below 40 dBm, which are unusually low path loss values. These points are predominantly located at higher altitudes (above 300 m), possibly indicating conditions of minimal obstruction or favourable line-of-sight communication. Alternatively, they could be a result of measurement anomalies or specific terrain characteristics such as hilltops or open fields.Unlike what might be expected in highly structured urban or rural areas, the data does not show a predictable increase or decrease in path loss with increasing altitude. This indicates that other environmental factors, such as terrain clutter, vegetation density, structural obstructions, and atmospheric conditionsare likely contributing more significantly to signal attenuation than elevation differences. Therefore, the lack of strong correlation highlights the need for multi-factor analysis in radio signal modelling. Relying on altitude alone would yield imprecise predictions. Therefore, terrain features, building profiles, and weather conditions should be integrated into path loss modelling efforts for more accurate results.

Table 1 (a, b, c and d): Depicting pathloss value's variation for the four Mobile Service Network along the Field Work Measurement Routes

1(a): Taiwo-Otte Route

Radial Distance (km)	Altitude (m)	9Mobile (dBm)	MTN (dBm)	Glo (dBm)	Airtel (dBm)
0.004306757	291	105	63	109	97
0.472558267	294	105	59	109	98
0.480251747	295	87	63	107	98
1.185014354	301	87	70	107	98
1.191600293	301	100	65	107	97
1.222276342	300	100	74	107	98
1.222276342	300	101	64	102	98
1.999937038	305	101	66	102	98
2.621685457	320	99	75	98	97
2.621685457	320	103	65	93	97
3.200755939	316	103	63	93	98
3.200755939	316	92	66	93	98
3.584492054	316	92	70	102	95
4.136663925	329	90	75	102	98
4.152132028	329	106	69	98	96
4.702082679	329	105	67	86	95
5.534515772	323	111	66	81	97
6.385471433	318	95	73	92	97
6.397142162	319	96	78	98	96
7.095050935	341	96	71	97	96
8.072981983	335	113	71	97	98
8.087889646	335	87	71	85	97
8.340654663	345	87	76	85	98
8.340654663	345	97	74	101	97

1(b): Emir-Kwasu Route

Radial Distance (km)	9Mobile (dBm)	MTN (dBm)	Glo (dBm)	Airtel (dBm)
0.49589001	110	82	96	90
0.49589001	110	82	98	91
0.857268911	88	64	98	88
0.857268911	88	64	91	87
1.758011205	102	64	88	86
1.765303448	102	64	88	83
2.221244786	108	82	88	84
3.169278269	79	82	88	83
3.169278269	79	82	84	83
3.651284066	104	82	84	82
4.023320009	97	80	90	87
4.566066622	97	80	90	83
4.717761618	103	80	91	86
5.123559961	102	80	92	86
5.290314484	94	84	92	81
5.290314484	94	84	96	85
0.172348883	105	82	96	83
0.749594793	109	82	96	84
0.750036741	109	88	96	79
1.198106282	102	82	97	80
1.2235406	102	82	100	78
2.087183721	101	64	100	80
2.101415272	101	64	100	79
2.628683464	103	64	62	83
2.646994312	103	64	102	81
3.52293953	93	86	102	87
3.872885043	112	86	107	87
3.872885043	112	78	101	86
4.39184685	95	78	101	84
4.39184685	95	80	99	84

1(c): GRA-Unilorin Routes

Radial Distance (km)	9Mobile (dBm)	MTN (dBm)	Glo (dBm)	Airtel (dBm)
0.801194365	106	98	82	97
0.801194365	107	97	73	97
1.039617646	62	96	73	97
1.663504938	110	91	84	87
1.795209409	111	90	84	87
2.321458491	111	90	91	89
2.474296772	108	92	67	89
2.462977559	103	92	62	87
2.462681688	103	95	64	87
3.159364428	67	94	60	89
3.319908749	62	94	65	85
3.480499243	58	97	66	87
3.801795385	50	93	56	85
3.962491748	94	94	60	87
4.12321516	94	94	66	89
4.283962684	88	92	59	85
4.44473182	88	96	61	87
4.92714707	62	97	65	87
5.087982494	104	98	65	89
5.248830869	101	98	97	85
5.409690862	101	99	98	87
5.570561681	62	97	98	89
5.731442214	106	98	98	85
5.89233177	88	98	97	87
6.214135287	107	99	98	85
6.375048035	62	99	98	87
6.535967253	109	98	99	89
6.696892605	109	98	98	85
6.857823733	110	99	98	87
7.179701435	111	98	97	85

1(d): Post Office-Armti Routes

Radial Distance (km)	9Mobile (dBm)	MTN (dBm)	Glo (dBm)	Airtel (dBm)
0.857268911	110	88	73	106
0.857268911	88	80	73	103
1.758011205	88	92	73	113
1.765303448	102	90	73	89
2.221244786	102	91	89	107
3.169278269	108	91	93	111
3.169278269	79	92	93	108
3.651284066	79	79	97	104
4.566066622	97	88	97	116
4.717761618	97	91	97	102
5.290314484	102	92	94	101
5.290314484	94	90	92	97
6.404426976	90	91	83	93
6.819182366	91	88	82	93
7.032188214	92	88	83	90
7.689960978	93	92	85	93
7.914604182	93	82	91	90
8.141570717	94	90	91	93
8.370671777	94	87	88	90
8.601736503	95	89	89	93
8.834610997	95	82	70	90
9.305244206	96	94	78	90
9.542761914	96	90	80	93
10.02167792	97	92	77	93
10.26289502	98	91	76	90
10.50517719	98	89	75	93
10.74845231	99	93	74	90
10.99265453	99	91	98	93

Table 1 presents the field measurement data, which reveal significant signal variation along the Emir-Kwasu and Taiwo-Otte routes. These fluctuations in mobile signal strength are primarily attributed to the clustered and poorly coordinated settlement patterns of terrain features along these routes. In contrast, the Post Office–ARMTI route exhibited relatively moderate signal path loss variation, while the GRA–Unilorin route showed minimal variation in signal strength. The reduced variations observed along these routes can be linked to the well-organized and uniformly distributed terrain features, which promote more consistent signal propagation along the measurement paths.

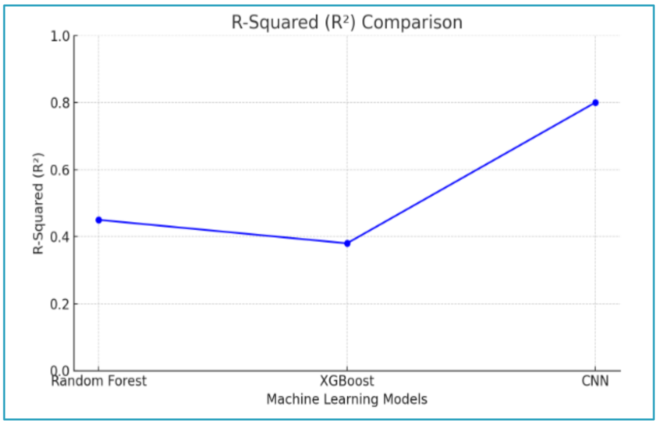

Figure 5: The Coefficient of Determination of Fit of a Regression Model.

The CNN model demonstrates the highest R-squared (R^2) value among the evaluated machine learning models, indicating its superior predictive accuracy and better fit to the training data. With an R^2 value close to 0.80, CNN effectively captures the underlying patterns in the input data, making it the most reliable model for path loss prediction in this study.In comparison, the XGBoost model shows a moderate performance with an R^2 value of approximately 0.38, suggesting that while it performs reasonably well, its ability to generalize from the training data is limited compared to CNN. The Random Forest model follows closely with an R^2 of around 0.45, reflecting a slightly better performance than XGBoost but still significantly lower than CNN.Finally, the trend observed in the line graph confirms that CNN outperforms both XGBoost and Random Forest, making it the most suitable model for terrain-informed radio signal prediction tasks in the given context.

5. Conclusions and Recommendations

This study has demonstrated that the internet connectivity gap in Africa extends beyond infrastructural and economic limitations, revealing a critical but often overlooked factor of terrain-induced geo-spatial disparities. Through the integration of satellite imagery, digital elevation models, and machine learning techniques, it has been shown that the spatial arrangement of natural and artificial features significantly influences signal propagation, quality, and coverage reliability. Irregular terrain features, poor settlement planning, and uncoordinated infrastructure development contribute heavily to signal attenuation, latency, and digital exclusion in many parts of the continent. Among the models tested, Convolutional Neural Networks (CNNs) proved most effective in capturing the complex relationship between terrain and signal quality, outperforming Random Forest and XGBoost models in prediction accuracy. This finding supports the argument for adopting data-driven, terrain-aware planning approaches in broadband infrastructure deployment.

To close the internet divide in Africa, policymakers, urban planners, and telecommunication service providers must prioritize terrain-informed strategies in network expansion. This includes the use of geo-spatial analytics and machine learning models for predictive signal coverage mapping, proactive infrastructure placement, and inclusive access designespecially in underserved rural and topographically challenging areas.In essence, bridging Africa's digital divide requires more than just laying fiber or erecting base stations; it demands an intelligent coordination between technology and terrain. By shifting toward terrain-sensitive and data-driven broadband planning, Africa can take a decisive step toward achieving digital equity and sustainable connectivity for all.

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