Journal of Science Engineering Technology and Management Science
Volume 02, Issue 04, April 2025 *ISSN: 3049-0952*
www.jsetms.com *DOI:10.63590/jsetms.2025.v02.i04.123-131*

PREDICTIVE PATH LOSS MODELING IN 5G NETWORKS USING MACHINE LEARNING TECHNIQUES

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To Cite this Article

G. Shanmugavel, Nune Pravallika, Kaluvai Yaswini, Naraga Hemapriya, Alahari Venkata Jyothirmayi,“ Predictive Path Loss Modeling In 5g Networks Using Machine Learning Techniques”, Journal of Science Engineering Technology and Management Science, Vol. 02, Issue 04, April 2025,pp: 123-131, DOI: http://doi.org/10.63590/jsetms.2025.v02.i04.pp123-131

Submitted: 09-03-2025 *Accepted: 18-04-2025* *Published: 26-04-2025*

ABSTRACT

The rapid increase in mobile users and data traffic has significantly influenced the evolution of wireless communication systems from 1G to 5G. In real-world urban environments, challenges such as "real call jumps" which lead to rapid signal fluctuations due to reflections and diffractions complicate reliable communication. Moreover, issues like channel propagation errors and overlapping communication paths degrade signal quality, resulting in increased path loss and a higher risk of communication failures.

Currently, communication engineers at Base Stations (BS) and Mobile Switching Centres (MSC) primarily rely on traditional path loss calculation methods that focus on signal properties. However, these conventional techniques are becoming inadequate, particularly with the complexity and high frequency demands of 5G networks. They struggle with challenges such as synchronization errors, increased system complexity, and higher error rates. To address these limitations, a novel solution is proposed: leveraging machine learning to predict path loss more accurately. The foundation of this approach is the development of a "Path Loss Propagation" (PLP) dataset, which will be used to train machine learning models. The key goal is to build a system that can effectively predict future path loss values based on the input features within the PLP dataset. Python has been chosen for implementation due to its powerful ecosystem and rich set of libraries for machine learning. This solution aims to significantly improve the accuracy and efficiency of path loss prediction, ultimately supporting the development of more reliable and resilient wireless communication networks.

Keywords: Path Loss Prediction, 5G Networks, High-Frequency Bands, Mobile Switching Centres, Propagation Loss Estimation.

1. INTRODUCTION

In real-time communication, call jumps manifest as issues arising from path loss, where a call that should ideally occur within visible distance experiences degradation when it transitions into a non-line-of-sight (NLOS) environment. In such cases, when a signal travels from point X to point Y without a clear line-of-sight, the signal fails to propagate properly, resulting in abrupt call jumps that disrupt continuous communication. This degradation emphasizes the importance of maintaining line-of- sight conditions to minimize call jumps and ensure robust connectivity in high- frequency communications. The rapid growth of mobile users and data traffic has driven the evolution of wireless communication systems from 1G to 5G. As the number of users, data rates, and antenna base stations has increased, the demand for reliable and efficient communication has become more pressing. Path loss can occur due to various factors such as noise, AWGN, error channel propagation, and overlapping of communication paths. So, in 5G communication, the deployment of high-frequency bands such as millimeter-wave (mm Wave) significantly increases data rates and supports a larger number of users, which in turn amplifies the challenges associated with path loss. As mobile phone usage surges and more base stations are installed to meet this demand, the inherent propagation issues of high-frequency signals become more pronounced. The limited range and increased attenuation of these signals in NLOS conditions lead to frequent call jumps, underlining the critical need for advanced modelling techniques to predict and mitigate these paths loss issues.

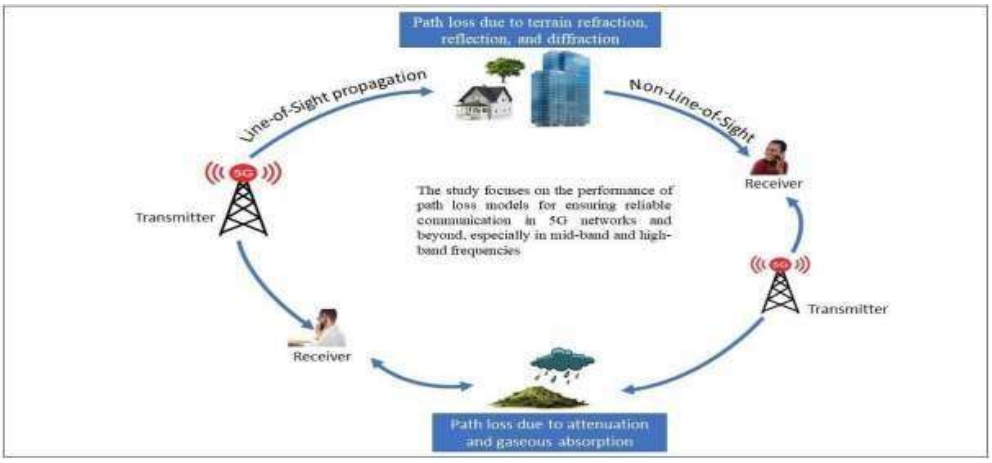

Fig. 1: Performance of Path Loss Models for 5G Communication.

Noise and errors are inherent in the wireless channel, and these propagation issues become more pronounced in complex environments. External factors such as interference, atmospheric conditions, and other noise sources introduce errors into the transmitted signals, compromising data integrity. These issues are further exacerbated by channel propagation challenges, which can lead to distortions in the signal as it travels from one point to another. Moreover, phenomena such as overlapping communication paths and the effects of arrayed waveguide gratings contribute to increased path loss. In scenarios where multiple signals converge or interfere, the effective strength of each individual signal diminishes. This overlapping can result in significant degradation of signal quality, highlighting the importance of precise modelling to predict and mitigate these losses in high-frequency bands.

2. LITERATURE SURVEY

Rayhan, Rakib, et al. [1] (2024) this Non-Orthogonal Multiple Access (NOMA) performance the context of modern wireless cellular communications under various channel conditions. We examined different path loss models and multipath fading effects to evaluate the Bit Error Rate (BER) of NOMA. Additionally, this study was tailored for wireless communications involving multiple users in Rayleigh, Rician, AWGN, and Nakagami fading channels, all of which were considered within the framework of NOMA. To establish connections, ensure equitable user treatment, and achieve efficient spectrum utilization for multiple users across diverse channel scenarios, the Base Station (BS) adopted the NOMA technique.

Rostamikafaki, Zahra, et al. [2] (2024) this intricacies of 5G New Radio (NR) signal propagation, and contrary to most existing literature, focuses on the 3.565 GHz commercial frequency band through extensive ground and airborne measurements. By assessing fundamental cellular network parameters such as Channel Power (CP), Field Strength (FS), Path Loss Exponent (PLE), and Shadow Fading Amplitude (SFA), the purpose of this investigation is to gain a verified and validated insight, in alignment with the 3GPP technical report, into the highly dynamic nature of 5G NR transmissions.

Mako, Serah, Shafrida Sahrani, et al. [3] (2024) this mobile network operators (MNO) in optimizing network performance, improving user experience, and ensuring services, such as voice calls, data transmission, and video streaming, as well as to adhere to quality standards. This approach facilitates capacity planning, resource allocation, and the prompt identification and resolution of network congestion, hardware failures, or security breaches. In this paper, the performance of three MNOs around Papua New Guinea University of Technology (PNGUoT) is examined. The downlink frequency signal was measured and collected using the MST207T spectrum analyzer.

Li, Zihao, Yanhong Kou, et al. [4] (2025) Global Navigation Satellite System (GNSS) is susceptible to signal obstruction in complex environments such as indoors or urban canyons, leading to degraded visibility or even complete failure. As an effective supplement, the 5G system, with its full coverage capabilities and To explore the UL-AOA estimation and UL- AOA-based UE positioning accuracy using 5G Sounding Reference Signal (SRS), we derive the Cramér-Rao Lower Bound (CRLB) for AOA estimation and AOA positioning using planar arrays, and conduct Monte Carlo simulations on angle estimation algorithms, including the beam search, MUltiple SIgnal Classification (MUSIC), Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT), and improved beam space MUSIC for static User Equipment (UE) or pedestrian handheld terminals under Line-of-Sight (LoS) and Non-Line-of- Sight (NLoS) conditions.

Hammed, Zainab Sh, et al. [5] (2025) This increasing demand for ultra-fast data, high capacity, and low latency in 5G and beyond networks is driving the adoption of millimeter- Wave (mm-Wave) frequencies (3–300GHz), which utilize spatial multiplexing and beamforming for improved performance. However, environmental factors like humidity, temperature, dust, and sandstorms, particularly in the Middle East, pose significant challenges. The parameters of the channel model and how it behaves statistically when exposed to dust and sandstorms have been analyzed using NYUSIM simulator and MATLAB. Wireless communication channels face challenges like time variability, frequency-selective fading, and interference from adjacent subcarriers, making traditional estimation methods less effective.

Tsarov, Roman, Serhii Siden, et al. [6] (2025) This is devoted to the use of 5G networks in the field of telemedicine, namely for the deployment of telemonitoring clusters with a high density of telemedicine sensors and detectors. As part of the study, the possibility of fifth- generation technology for organizing a telemonitoring system was assessed, provided that a guaranteed data transfer rate is ensured, considering the simultaneous connection of many devices and sensors. The assessment was carried out considering that any device within the cluster is a potential source of additional electromagnetic interference and affects other devices. The telemonitoring system based on fifth generation networks was modeled for different initial conditions (distance to the base station, interference power, etc.) under the influence of intra- system interference.

Madusanka, **et al. [7] (2025)** when Local 5G/6G networks operate in locally licensed frequency bands, where incumbent spectrum users exist. Local 5G/6G networks are cellular communication networks operating in geographically restricted areas, deployed by various stakeholders, including Mobile Network Operators, to serve different user groups with different needs. Representative interference scenarios that impact local 5G/6G network deployments are simulated using the SEAMCAT tool, which is used by regulators in Europe for spectrum sharing studies.

Abbaoui, Hind, Salah Eddine EL Aoud, et al. [8] (2025) The proposed antenna features dimensions of 21×23.52× 1.6 mm3, corresponding to electrical measurements of 0.24λ × 0.27λ × 0.026λ. λ represents the free-space wavelength at the resonant frequency of 3.5 GHz. Also, the antenna is printed on a commercially available epoxy substrate with a 4.3 relative permittivity with the ground and radiating patch made of copper of 0.035 mm thickness. In addition, a partial ground structure is used to obtain omnidirectional radiation and miniaturization, while the rectangular slot in the ground greatly enhances the proposed antenna’s bandwidth. After the fabrication and testing of prototypes, the proposed antenna works throughout a frequency range.

4. PROPOSED SYSTEM

Path loss in wireless communication refers to the reduction in power density of an electromagnetic wave as it propagates through space. Machine learning (ML) and deep learning (DL) techniques have emerged as powerful tools to model and predict path loss, especially in complex environments where traditional empirical or deterministic models fall short. ML algorithms, such as decision trees, random forests, and support vector machines, can learn from large datasets of measured path loss values, incorporating features like distance, frequency, terrain type, and obstacles to predict signal attenuation. These models are particularly useful in urban or indoor environments where multipath effects, reflections, and shadowing make path loss highly variable and difficult to model analytically.

Deep learning, a subset of ML, leverages neural networks with multiple layers to capture intricate patterns in the data. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are commonly used for path loss prediction, especially when dealing with spatial or temporal data. For instance, CNNs can process geographic information system (GIS) data or satellite images to account for terrain and building structures, while RNNs can model time-varying channel conditions. DL models excel in scenarios with high-dimensional data and non-linear relationships, often outperforming traditional ML methods. However, they require substantial computational resources and large, high-quality datasets for training. Both ML and DL approaches offer the flexibility to adapt to specific environments, making them invaluable for optimizing network planning, improving coverage, and enhancing the performance of wireless communication systems

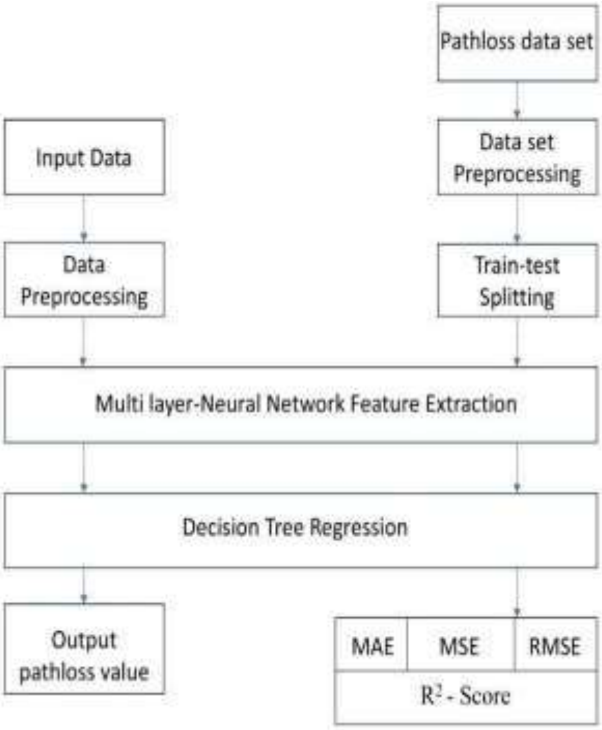

Fig. 2: Proposed System Architecture.

MLNN Feature Extraction

The given diagram represents a deep learning model architecture, specifically a fully connected neural network. It begins with input preprocessed data, which is fed into the first dense layer consisting of 128 neurons with a ReLU activation function. To reduce overfitting and improve generalization, a dropout layer with a high dropout rate of 3.0 is applied. Following this, another dense layer with 64 neurons and ReLU activation is used to extract essential features from the data. Another dropout layer with a lower dropout rate of 0.3 is included to further regulate the model's learning capacity and prevent excessive reliance on specific Next, the network processes the data through another dense layer comprising 32 neurons with ReLU activation, which continues refining feature representations. Finally, a dense output layer with a single neuron is used to generate the final prediction. This type of architecture is well- suited for regression-based tasks, where the output is a continuous value. Given the structured design, this model could be useful in scenarios like signal propagation prediction, path loss estimation in wireless networks, or other numerical forecasting applications.

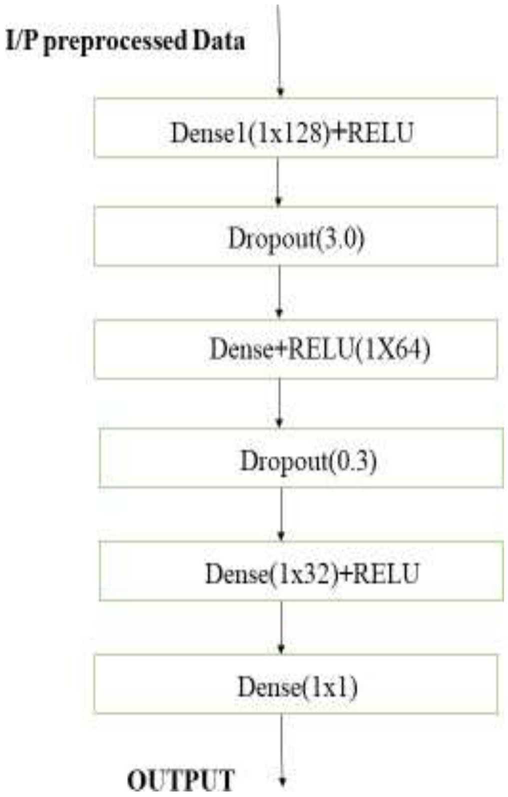

Fig. 3: MLNN Feature Extraction

Decision Tree Regressor

The Decision Tree Regressor operates through a two-phase process: Model Creation (Training) and Model Testing (Prediction). During Model Creation, the algorithm starts by preparing the target variable (Y-Train) and recursively partitions the training data based on feature values, creating nodes and paths that represent decision rules. The algorithm evaluates multiple possible paths and attributes, using measures such as entropy, information gain, and Gini index, to select the best attribute for splitting at each node. This process generates the "best" decision paths that form the tree, and the trained model is saved for later use. During Model Testing, new unseen data (X-test) is mapped onto each path of the trained tree, undergoing multi-level decision analysis to reach a specific leaf node, where the predicted output (Y-pred) is determined. The predicted output can then be compared to the actual true values (Y-true) to evaluate the model's performance and generalization ability.

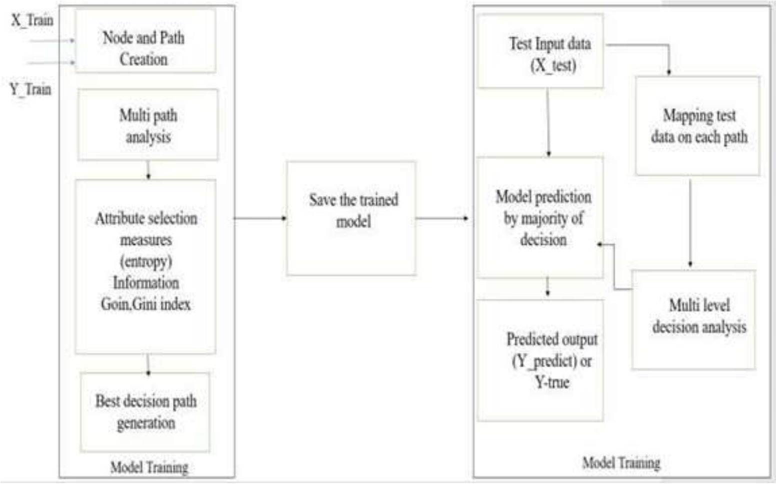

Fig. 4: Decision Tree Regressor

Advantages of MLNN and DTR

Advantages of Multilayer Neural Networks (MLNN)

MLNNs can approximate any continuous function, making them versatile for various tasks. MLNNs can learn and represent complex, non-linear relationships between inputs and outputs. MLNNs can tolerate some level of noise in the training data, making them robust. MLNNs can be parallelized, making them suitable for large-scale computations.

Advantages of Decision Trees Regression (DTR)

DTR models are easy to interpret, as they provide a clear, tree-like structure for decision-making. DTR models can handle categorical variables naturally, without requiring encoding. DTR models are typically fast to train and make predictions, especially for smaller datasets. DTR models can handle missing values in the data, making them robust to incomplete datasets.

4. RESULTS AND DISCUSSION

The fig 5 "Upload Pathloss 5G Data" button allows users to upload the "5G-South Asia" dataset for analysis. It enables seamless access to initiate operations, ensuring the necessary data is available for model training and performance evaluation. This forms the foundation for accurate path loss prediction in 5G high-frequency bands.

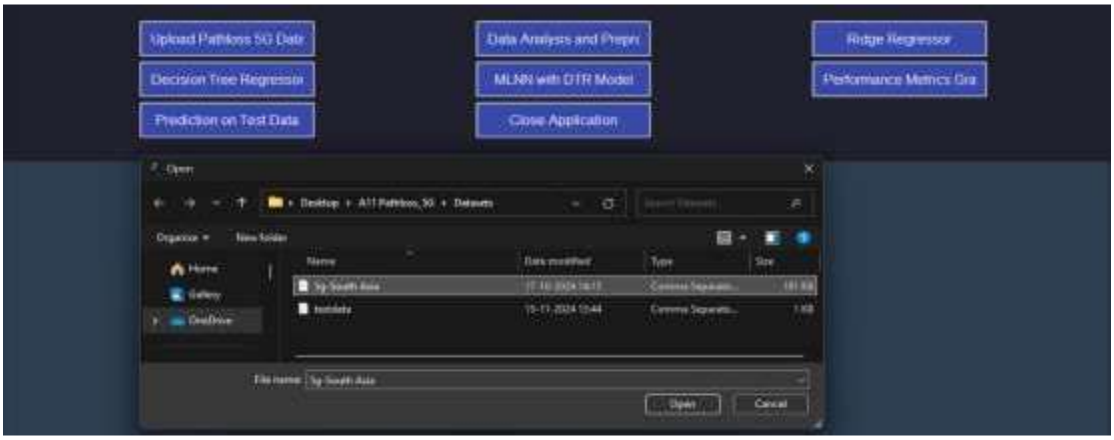

Fig 5: Dataset uploading.

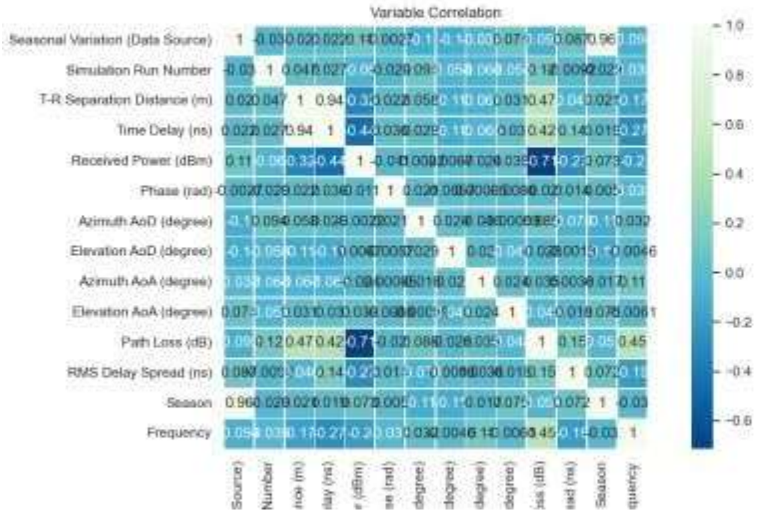

Fig. 6: variable correlation

The image 6 After clicking the "Data Analysis and Preprocessing" button, the application generates a correlation heatmap that visualizes relationships between features like Path Loss, Received Power, Separation Distance, and Time Delay. Correlation values range from -1 to 1, indicating negative, positive, or no correlation. A negative correlation between Path Loss and Received Power shows that as path loss increases, received power decreases. Conversely, a positive correlation between Separation Distance and Path Loss highlights the impact of distance on.

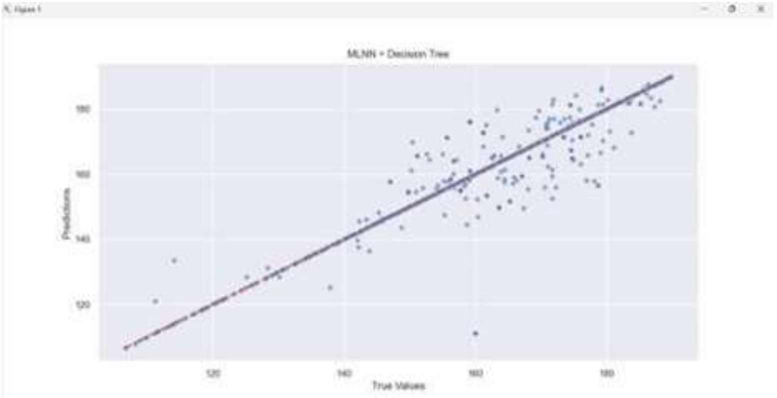

Fig. 7: MLNN with DTR Model Graph.

The fig 7 graph represents the performance of the MLNN with DTR model, showing predicted values against true values. The red dashed line indicates the ideal fit, representing perfect predictions. The close proximity of the blue scatter points to the red line signifies high accuracy with minimal path loss estimation errors. Compared to previous models, the reduced spread of points around the line suggests fewer prediction errors. This highlights the model's effectiveness in capturing complex patterns and providing accurate path loss predictions for 5G high-frequency bands.

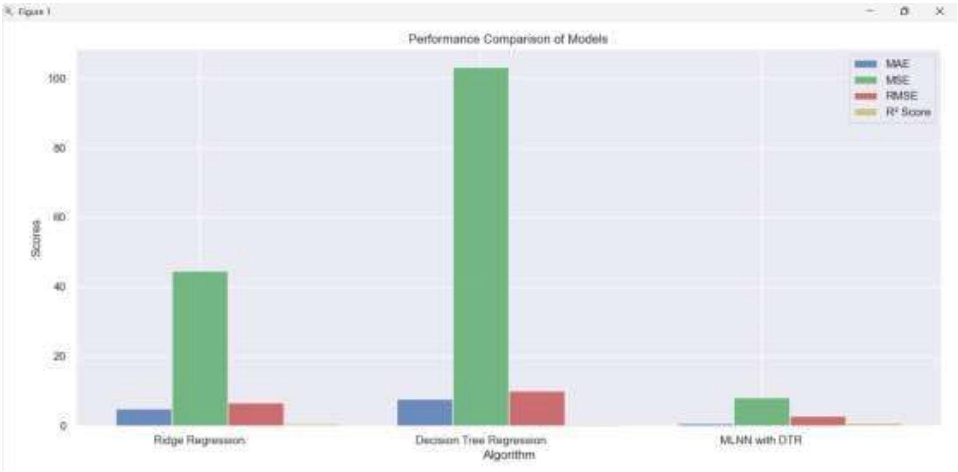

Fig. 8: Performance Comparison of Models.

The fig 8 "Performance Comparison of Models" graph evaluates Ridge Regressor, Decision Tree Regressor, and MLNN with DTR using MAE, MSE, RMSE, and R² metrics. The Decision Tree Regressor shows poor generalization with higher errors, while the Ridge Regressor performs moderately well. The MLNN with DTR outperforms both, with the lowest errors and highest R² score, making it the most accurate for 5G path loss prediction.

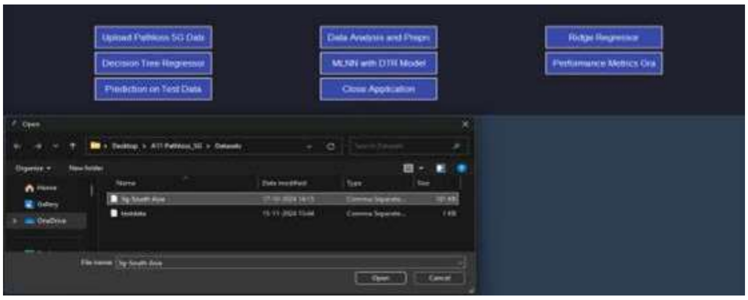

Fig. 9: Prediction on Test Data

The fig 9 "Prediction on Test Data" feature allows users to upload a test dataset to evaluate path loss predictions for 5G high-frequency bands. It uses models like Ridge Regressor, Decision Tree Regressor, or MLNN with DTR. Predictions are compared with actual values to calculate MAE, MSE, RMSE, and R² scores. This helps assess model accuracy and effectiveness. The insights support network optimization in real-world scenarios.

5. CONCLUSION

The rapid growth of mobile users and data traffic has highlighted the need for more accurate and efficient path loss prediction in wireless communication systems. Traditional methods have proven inadequate, especially with the advent of 5G and its higher frequency bands. To address this challenge, a novel approach utilizing machine learning for path loss prediction has been proposed. By creating a comprehensive "Path Loss Propagation" (PLP) dataset and leveraging Python's extensive machine learning libraries, this solution aims to enhance the accuracy and efficiency of path loss prediction. Ultimately, this approach has the potential to lead to more robust and reliable wireless communication networks, paving the way for improved network performance and user experience. Improving path loss prediction and optimizing network planning, 5G networks can achieve higher reliability, better coverage, and enhanced data rates. This ensures efficient resource utilization, reduces network congestion, and supports emerging applications like autonomous vehicles, smart cities, and industrial automation. Overall, accurate path loss modeling plays a critical role in realizing the full potential of 5G technology.

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