International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Optimizing 5G Smart Antenna Design Parameters using Deep Learning

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Submitted: 05/04/2024 **Revised:** 15/05/2024 **Accepted:** 30/05/2024

Abstract: This study focuses on optimizing the design parameters of 5G smart antennas using a deep learning approach, specifically through the implementation of an Artificial Neural Network (ANN) model. The model was trained and validated on a dataset to predict key performance metrics, achieving exceptional accuracy. The results demonstrate a sharp decline in training and validation loss, stabilizing near zero, along with a low Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) like 2.937, 2.764 and 5.2581. Additionally, the $R^2 error$ value is nearly 1, indicating the model's capability in optimizing antenna design.

Keywords*: Deep learning, ANN, 5G antenna, optimization, MSE*

1. Introduction

Communication or data transformation from peer to peer is increasing daily, and the beginning of technologies like 4G and 5G promises transformative improvements in wireless communications, offering enhanced data rates, reduced latency, and increased connectivity for many devices. The smart antenna system is a required component that enables these advancements. These antennas are characterized by their ability to dynamically adjust their parameters to optimize signals' transmission and reception in the 5G network landscape. The optimization of smart antenna design parameters in 5G technology is essential in various environments.

The complexity of modern wireless and adhoc communication systems, which connected with the dynamic and often unpredictable communication environment, has many challenges in designing and optimizing smart antennas and their parameters. Traditional methods for optimizing antenna parameters, which worked on statistical approaches, are increasingly insufficient with dynamic environment. These methods are time-consuming, less adaptable to changing environments, and often fail to control the vast amounts of data generated by 5G networks. Many of the researchers implemented artificial intelligence methods for channel estimation, signal detection, and related tasks in communication systems, with a focus on improving accuracy and performance. For training these neural networks on network data many studies used simulated datasets which are not real are used to train and validate their models, demonstrating significant improvements in estimation accuracy, detection accuracy, and overall system performance compared to traditional methods.

The rapid proliferation of fifth-generation wireless method has revolutionized communication networks, promising unprecedented data rates, ultra-low latency, and massive connectivity. Central to realizing these capabilities are smart antennas, which leverage beam forming and spatial multiplexing to enhance signal quality and network capacity. However, optimizing the design parameters of 5G smart antennas, such as beam width, radiation pattern, gain, and polarization, presents significant challenges due to the complex and dynamic nature of wireless environments.

Traditional methods for antenna design and optimization, like heuristic and iterative algorithms, these approaches struggle to achieve the required balance between computational efficiency and

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performance accuracy and will not provide optimal design. As 5G networks must adapt to various scenarios, including urban, suburban, and rural deployments where the network designs should be changed dynamically, designing antennas capable of maintaining high performance across varying conditions becomes very complex. And should consider more number of parameters likes bandwidth, computational space, and net work size etc. because concerning to the place of deployment these parameters will be changed and designs also changed.

In this context, deep learning has emerged as a powerful tool for addressing optimization challenges in 5G antenna design to provide optimal design options and decrease the computational power of the network. These neural networks' can learn from high-dimensional data, deep learning can provide predictive insights and enable real-time optimization of antenna parameters. Techniques such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs) offer the potential to refine antenna performance by understanding the nonlinear relationships between design variables and operational metrics with these one can achive dynamic designs and reduce the computational power in the updated network.

This paper presents application of deep learning to optimize 5G smart antenna design parameters, aiming to improve key performance indicators such as spectral efficiency, energy efficiency, and coverage, so that it can reduce the computational time of the network. By integrating deep learning models into the design pipeline, the proposed approach that significantly reduces computational complexity while achieving robust performance across diverse operating conditions.

Contributions:

- The proposed ANN model achieved near-zero training and validation losses, indicating highly accurate predictions of 5G smart antenna parameters.
- Low error metrics, including MAE, MSE, and RMSE, demonstrated the model's specific predictive capability.
- The R-squared value was nearly perfect, showcasing the model's ability to explain almost all variability in the design parameters, ensuring robust optimization.

2. Related Work

Machine learning techniques have gained very importance for their ability to optimize multi-parameter systems in 5G antenna design and provide optimal design options. The researchers like Haque et al. [1] applied a machine learning-based gain prediction model for broadband MIMO antenna arrays designed for 5G mm-wave applications. The study showcased how ML models could predict gain with high accuracy, significantly reducing the computational burden associated with traditional methods. Sree et al. [2] proposed deep learning algorithm to optimize a stub-loaded dual-band four-port MIMO antenna for sub-6 GHz 5G and X-band satellite communication applications. These approaches achieved superior performance metrics, including higher gain and reduced error or loss, demonstrating the robustness of ML-driven optimization techniques. To achieve the optimal performance, the optimizer helped to push the performance. But when the number of parameters is increasing this model will get over fitted.

Frequency reconfigurable antennas have also been a focus area for designing optimal network. So Yahya et al. [3] implemented ML models to optimize the design of compact antennas, enhancing RSSI for long-range 5G applications. Similarly, Babale et al. [4] proposed ML based method for designing planar wideband antennas with tri-band filtering notches for 3G, LTE, and 5G applications. Their approach effectively mitigated interference, improving overall system performance, but concentrated on the very few parameters. Like Yang et al. [5] implemented an optimized model with rapid multi-parameter processing capabilities, which significantly enhanced antenna design efficiency. They observed that how DL-based models could reduce computational time while maintaining high accuracy in parameter optimization. And also how these model can handle high dimensional data, with complex patterns. Yuliana [6] provided a comparative analysis of ML algorithms for predicting 5G coverage. This work identified dominant feature parameters and evaluated the accuracy of different algorithms, emphasizing the importance of feature selection in antenna optimization. Luostari et al. [7] provided an extensive review of ML techniques for optimizing 5G systems, covering areas such as resource allocation, beamforming, and interference management. Deep learning techniques have shown great potential in solving complex problems in antenna design with many parameters. These deep learning models can handle multi dimensional data and provide optimal design patterns. And Gurulakshmi et al. [8] also implemented Hamiltonian deep neural networks optimized using the pelican optimization algorithm for the design of substrate-integrated waveguide antennas. This approach provideds high efficiency and robustness model, by using advanced DL applications in antenna design where they used small number of parameters. And Haque et al. [9] further demonstrated the use of ML for predicting bandwidth and frequency in N77 band 5G antennas. Guntupalli [10] implemented hybrid deep learning models to improve antenna design accuracy. Shakya et al. [11]conducted a detailed comparison of ML algorithms for optimizing antenna design, highlighting the trade-offs between computational complexity and accuracy. Sree and Babu [12] proposed a methodology for optimizing four-port MIMO systems using ML, achieving validated antenna parameters and enhanced performance. Similarly, Jain et al. [13] reviewed ML-driven optimization techniques for wearable and array antennas, identifying key challenges and future directions. Kaushik et al. [14] focused on circularly polarized antennas tailored for 5G communication, employing ML-based optimization techniques to enhance their performance. The work demonstrated the synergy of integrating multiple DL techniques for optimizing gain and bandwidth. Pandi et al. [15] investigated how AI could revolutionize 5G wireless networks by enhancing connectivity and resource allocation. Their study demonstrated the potential of ML-driven optimization in creating smarter and more adaptive networks. Kamble and Nayak [16] extended this concept to array and wearable antennas, presenting a comprehensive overview of ML applications in modern antenna systems. Additionally, Rai et al. [17] optimized wideband MIMO hybrid antennas for n261 5G NR millimeter wave applications using ML, achieving enhanced performance and reliability.

Shrote and Poshattiwar [18] implemented ML techniques to dynamic spectrum sensing method in 5G cognitive radio networks. Their approach improved spectrum utilization and reduced interference, highlighting the role of AI in efficient resource management. Maher Al-Hatim and Al Janaby [19] explored reinforcement learning for beamforming in 5G networks. Their work focused on power-efficient user targeting, showing how AI could dynamically adapt to varying network conditions.

Similarly, Ilyas et al. [20] used EfficientNet-B7 deep learning models to enhance beam forming in massive MIMO systems, achieving energy-efficient and high-performance outcomes.

Comparative analyses of various ML and DL approaches have provided valuable insights into their relative strengths and weaknesses in antenna optimization. By combining ML and DL models with hybrid model also provide optimal frameworks in networks analysis. The study underlined the adaptability of ML approaches in addressing specific communication requirements. Soni et al. [21] proposed an optimized sequence method for sparse channel estimation in a 5G MIMO system to overcome the challenges, and shows and observed that how ML techniques could improve spectral efficiency and signal quality.

The integration of ML and DL into broader 5G system optimization to handle multidimensional data and complex parameters to provide better computational methods. Their findings emphasized the transformative impact of ML in improving network efficiency and scalability. Amini [22] addressed resource optimization for fixed wireless access in rural settings using ML [23], overcoming connectivity challenges in underserved areas. Recent works have also explored novel techniques to address emerging challenges in 5G antenna design.

3. Methodology

We implemented an optimized Artificial Neural Network (ANN) to train the normalized data. The model consists of an input layer takes the data with 8 features, and then three hidden layers with 64, 32, and 16 neurons respectively, all three layers are using the ReLU activation function to normalize the data. The output layer is fully connected layer has one neuron with a linear activation function for prediction. In ANN at final layer ADAM optimizer is used to update the weights, and MSE as the loss function, while also tracking MAE as a metric. The training process involves splitting the data into training and test sets, and further splitting the training set into 80% training and 20% validation data. After feature engineering we trained the model for different epochs like 30, 50 and 100, and different batch sizes 6, 16 and 32. But when the model is trained for 100 epochs at a batch size of 32 the model performance is good. Before training the model we did feature engineering in this converted antenna positions to X, Y and Z columns.

3.1 Data set

We manually collected data on eight features, like user position, antenna angle, signal strength, interference, environment conditions, data transmission speed, coverage area, and efficiency. And collected 1000 samples over these features. Figure 1 is a correlation matrix heat map that illustrates the relationships between various metrics related to 5G smart antenna performance. The features include Antenna Angle, Signal Strength, Interference Level, Data Transmission Speed, Coverage Area, and Efficiency. The color intensity in the heat map indicates the strength and direction of the correlations; it is clearly observed that a high positive correlation and blue represents a high negative correlation. Notable observations include:

- A moderate positive correlation between Antenna Angle and Signal Strength is 0.6.
- A strong negative correlation exists between Interference Level and Signal Strength -0.69 and Data Transmission Speed -0.81.
- A moderate positive correlation between Efficiency and Interference Level 0.52.

The figures 2 and 4 show the distribution plots for Signal Strength, Interference Level, Data Transmission Speed, and Coverage Area. These histograms reveal that the values for each metric tend to cluster around specific points, indicating stability and consistency within the observed ranges. The signal strength values are concentrated around distinct levels between -73 and -65 dB, and Data Transmission Speed shows peaks around certain values between 110 and 150 Mbps. Similarly, Interference Level and Coverage Area also exhibit distinct peaks, suggesting that interference and coverage tend to stabilize at certain points. These distribution patterns are crucial for understanding the performance and optimization of 5G smart antenna systems in IoT applications.

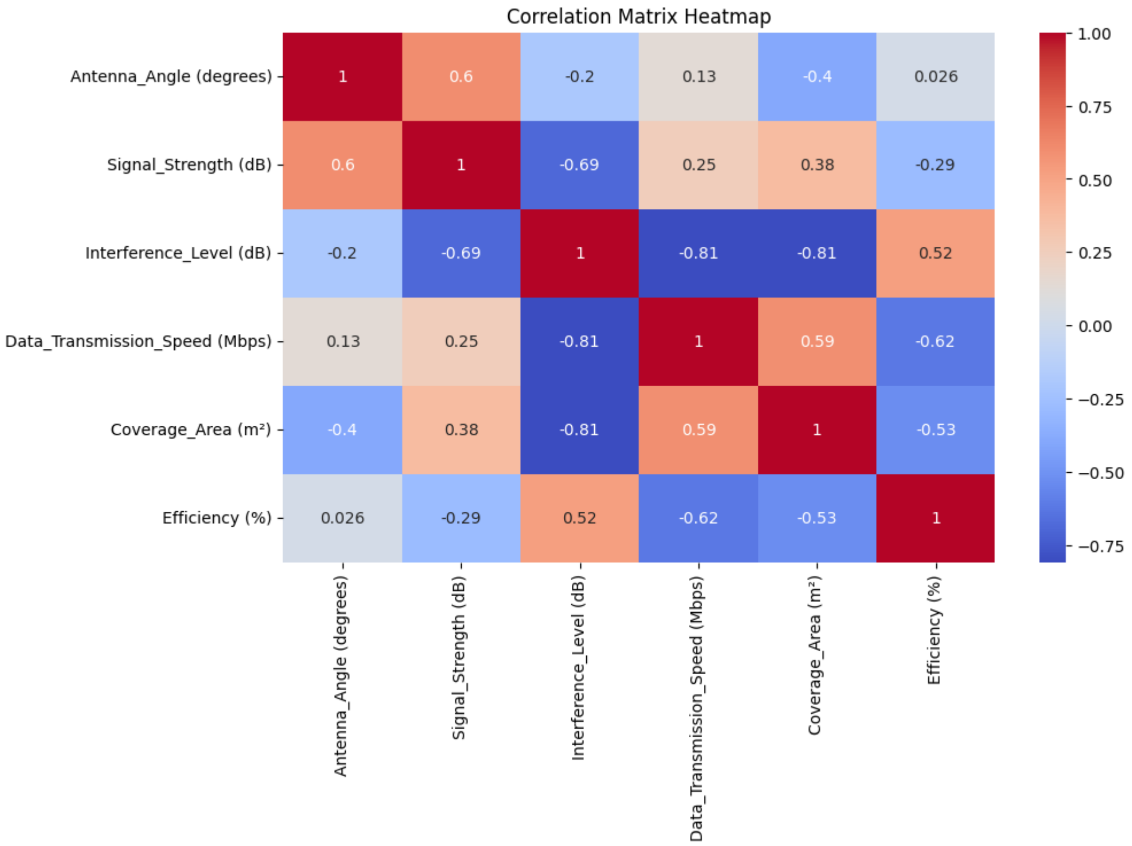

Figure 1 correlation matrix of data

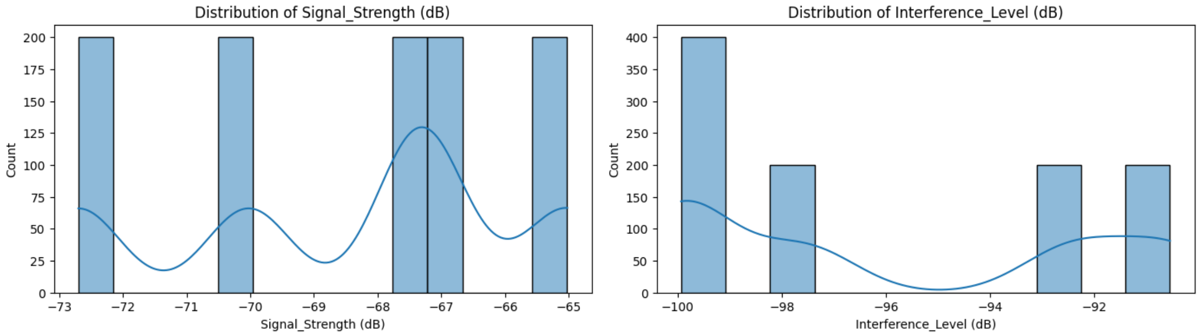

Figure 2 Distribution plot of signal strength and interference level.

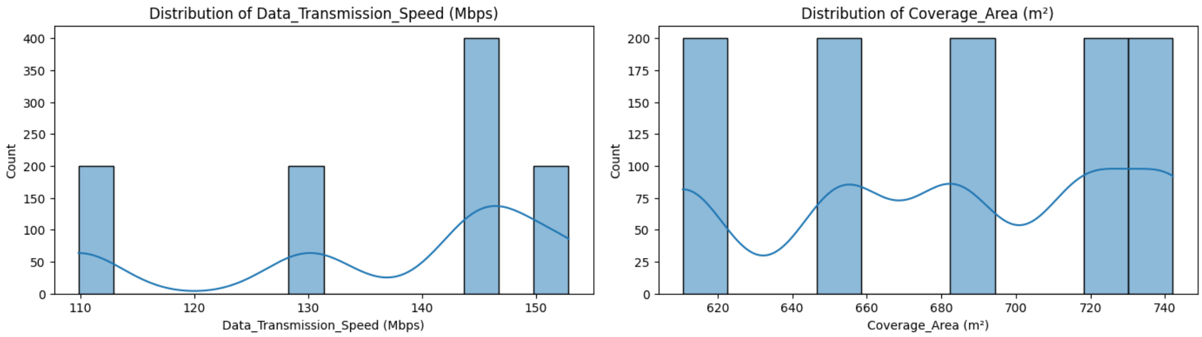

Figure 3 distribution plot of data transmission speed and coverage area.

4. Result analysis

We trained the ANN model for 100 epochs, after normalizing the data, and calculated MSE as loss as shown in Figure 4, the performance of a ANN model over a training period and its predictive accuracy, the Training and Validation Loss (left) and the Training and Validation Mean Absolute Error (MAE) (right) across 100 epochs. Both plots indicate that the model's training and validation losses, as well as MAE, drop sharply and stabilize close to zero, suggesting that the model is well-fitted to the data without significant overfitting.

The Figure 5 and 6 further confirm the model's accuracy. The Distribution of Prediction Errors plot shows the frequency of prediction errors clustered around two points, with a majority of errors being very close to zero, indicating high prediction accuracy. The final plot, depicting Actual vs. Predicted Data Transmission Speed, reveals a nearly perfect linear relationship along the diagonal, highlighting the model's precise predictions matching the actual data points closely.

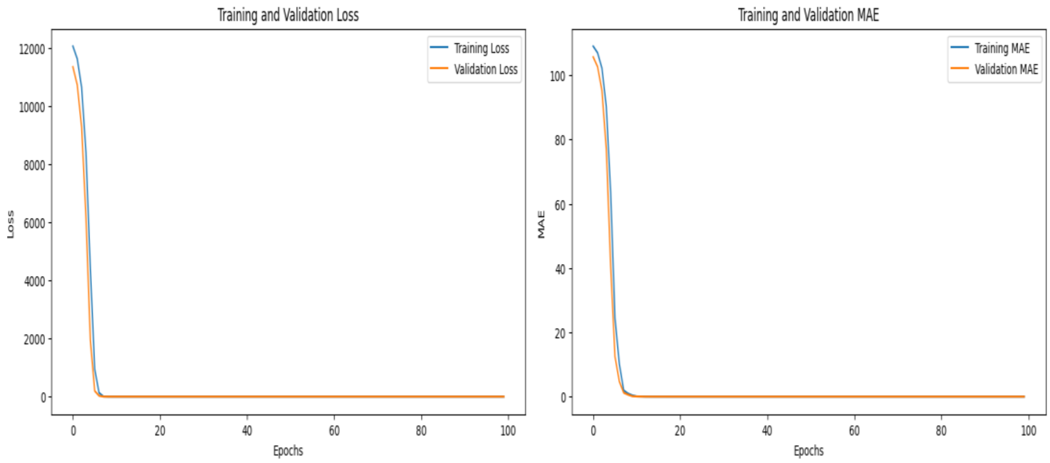

Figure 4 Training performance of ANN model

Table 1 error of ANN model

Result of ANN model	
MAE	2.9373168217716674e-06
MSE	2.7648638586952323e-11
RMSE	5.258197234070394e-06
R^2	0.9999999999998468

Table 1 presents the error metrics for the ANN model, demonstrating its exceptional performance. The MAE is 2.9373e-06, indicating that the model's predictions are almost optimal and same as the actual values by a minimal amount. The MSE is 2.7649e-11, and the RMSE is 5.2582e-06, illustrating the model's high accuracy with minimal error variance. The R-squared (R^2) value is nearly 1 (0.9999999999998468), indicating that the model explains almost all the variability in the target data points, confirming the models is near-perfect fit and predictive power compare to the other model.

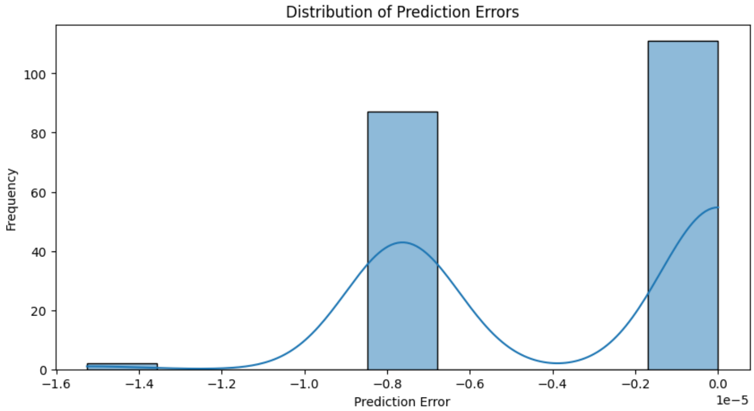

Figure 5 Prediction error of proposed model

From figure 7 and 8 it is observed that, the performance of proposed model is illustrated. The figure 8 represents the feature importance of various parameters based on permutation importance, indicating that "Antenna_Angle (degrees)" and "Interference_Level (dB)" are the most significant features influencing the model's predictions. The figure 7 illustrates a residual plot, showing the predicted values and the actual values. The residuals appear to be close to zero for most of the predicted values, suggesting that the model predictions are fairly accurate. However, there are a few points with larger residuals, indicating some discrepancies between the model predictions and the actual outcomes (true values).

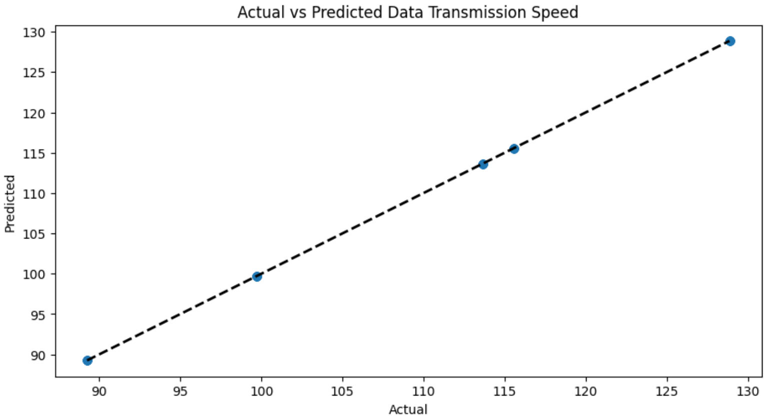

Figure 6 Actual vs predicted on test data of proposed model

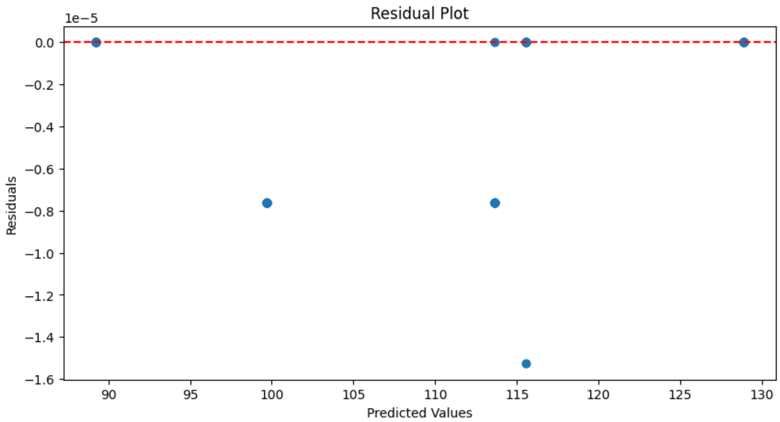

Figure 7 predicted values of residual plot

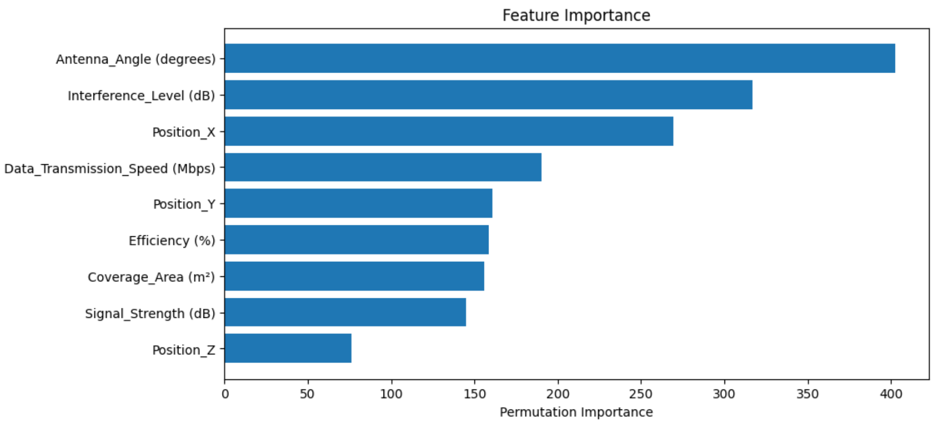

Figure 8 feature importance plot

5. Conclusion

The results of the ANN model underscore its effectiveness in optimizing 5G smart antenna design parameters with high precision. The error metrics, including a MAE of 2.9373e-06, MSE of 2.7649e-11, and RMSE of 5.2582e-06, alongside an R-squared value close to 1, demonstrate the model's excellent performance. Visualization of the training and validation metrics, prediction error distribution, and the close alignment of actual vs. predicted data transmission speeds further validate the robustness and reliability of the ANN approach. This study highlights the potential of deep learning techniques in advancing 5G technology through precise and efficient antenna design optimization.

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