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Original scientific paper

ENHANCING CIRCULAR MICROSTRIP PATCH ANTENNA PERFORMANCE USING MACHINE LEARNING MODELS

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Abstract. *Machine learning (ML) will be heavily used in the future generation of wireless communication networks. The development of diverse communication-based applications is expected to boost coverage and spectrum efficiency in relation to conventional systems. ML may be employed to develop solutions in a wide range of domains, such as antennas. This article describes the design and optimization of a circular patch antenna. The optimization is done through ML algorithms. Six ML models, Decision Tree, Random Forest, XG-Boost Regression, K-Nearest Neighbour (KNN), Gradient Boosting Regression (GBR), and Light Gradient Boosting Regression (LGBR), were employed in this work to predict the antenna's return loss (S_{11}). The findings show that all of these models work well, with KNN having the highest accuracy in predicting return loss of 98.5%. The antenna design & optimization process can be accelerated with the support of ML. These developments allow designers to push beyond the limits of antenna technology, optimize performance, and offer novel solutions for emerging applications such as 5G, 6G, IoT, and flexible wireless communication systems).*

Key words: *Circular patch antenna, Machine Learning (ML), Return Loss (S_{11}), KNN, Decision Tree, Random Forest, XG Boost, GBR, LGBR*

1. INTRODUCTION

Antennas were originally used only for receiving communications such as radio and television. Antennas are now found in almost every electronic gadget and are extremely important. The need for fast and dependable communication networks has been rising rapidly over the past several years. The employing of ultra-wideband (UWB) antennas is one method that could be used to accomplish this. The frequency range between 3.1 and 10.6 GHz has been designated by the Federal Communications Commission (FCC) for UWB applications [1, 2]. Since then, several researchers have started working on optimized antennas for various UWB applications. For the development and optimization of antennas,

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electromagnetic (EM) simulators such as the High-Frequency Structure Simulator (HFSS) are commonly used. To achieve the desired parameters, the optimization will be done by adjusting the size of various antenna attributes. Usually, the test-and-error approach has been used to carry out the optimization process. That is why the optimizing procedure consumes a lot of time. Traditional antenna design methodologies rely significantly on the practical experiences of designers and electromagnetic (EM) simulation technologies. However, these approaches are time-consuming, computationally expensive, and sometimes produce sub-optimal results. As a result, there is a great demand for more efficient and intelligent methodologies for designing and optimizing antennas for a wide range of applications [3].

Due to the diverse shapes of antennas, exact solutions in finite and closed forms are not available. However, by approximating solutions, valuable insights can be gained for antenna design. Numerical analysis is a widely adopted technique for antenna design. Methods such as finite difference time domain, finite element method electromagnetic, and Method of Moments [4, 5, 6,] are commonly utilized for testing and evaluating antennas. In complex antenna designs, this approach posed challenges in terms of memory usage and CPU requirements due to the size and parameters of the antenna structure. To enhance results and reduce irregularities, ML has emerged as a powerful tool. ML, a branch of artificial intelligence (AI), focuses on extracting information from data and finds significant application in statistical data science [7]

ML-powered solutions boost custom antenna design greatly, giving benefits such as a reduction in time, increased computational performance, lower operational expenses, shorter simulation time, and reduced working hours. The ever-changing demand for multipurpose and compact antennas exposes antenna designers to new problems on a daily basis. ML has enormous promise in tackling these difficulties by building trained models that can rapidly optimize antenna designs to fulfill a variety of objectives. ML enables the establishment of connections between input and output responses by finding undiscovered mathematical relationships inside data, which enables accurate predictions in antenna design. Various types of ML are represented in Fig. 1.

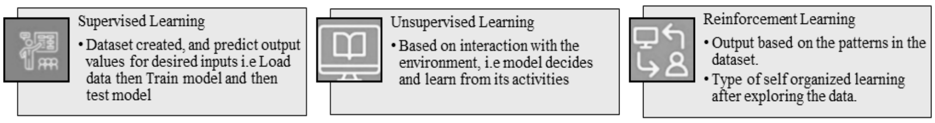


Fig. 1 Types of ML

A Deep Belief Network- Extreme Learning Machine (DBN-ELM) model based on PSO (Particle Swarm Optimization) was proposed by the author [8]. Results demonstrate that the model can rapidly extract samples, minimize the complexity and computational cost imposed by repeated simulations in antenna design, and significantly increase the effectiveness of antenna design. Two UWB antenna designs have been optimized in their work using this approach. The antenna's operational frequency range is from 3.3 to 12.1 GHz. The proposed DBN ELM model offers better prediction abilities and may also be utilized for illustrating more complicated antenna structures.

To optimize antenna design, the article's [9] author recommended applying ML models such as the least absolute shrinkage and selection operator (lasso), artificial neural networks (ANNs), and k-nearest neighbour (kNN) and checking the accuracy of these models, they are applied to a reference double T-shaped monopole antenna. Results from the high-frequency structure simulator (HFSS) are compared with those predicted by these ML techniques. Specifically, ANN and lasso provide more precise predictions as compared to kNN. In the final analysis, proposed by the author, these innovative methods are more effective than the conventional EM simulation optimization technique in designing an optimal antenna design. The findings of this investigation also demonstrate that ML methods possess an opportunity to transform EM simulation methods.

The uses of ML in antenna design are discussed and examined thoroughly in the study [10]. The essential features of ML are covered, including its fundamental idea, how it differs from artificial intelligence and deep learning, learning algorithms, and its numerous applications across a range of technologies, with a particular focus on how it's utilized in antenna design. The analysis contrasts the outcomes of antenna design using ML with those obtained using traditional design techniques. It has been observed that ML will speed up the antenna design process while maintaining high precision, and able to predict antenna performance, with better computing power, and a reduction in the amount of simulations that are required.

The author [11] demonstrates the application of ML techniques to forecast the S_{11} (return loss), which is a very important feature of patch antennas. The results show that S_{11} predictions made using different ML algorithms (Decision Tree, Random Forest, XG Boost, and KNN) are quite precise as well as accurate. It might be helpful in predicting resonant frequency without the need for time-consuming simulations.

The article [12] illustrates the modeling of a microstrip antenna using regression-based ML. The author investigated several effects on the physical and electrical characteristics of the materials employed, the impact of the slot, and the size of the patch on the antenna's resonant frequency. Root mean square error, R square value, and mean absolute error (MAE) are the evaluation criteria used in this work, result shows that performance is extremely similar as predicted by the regression-based ML approach.

In the work [13] author describes the design and optimization of a small Coplanar Waveguide (CPW) fed band-notched monopole antenna. This article's distinctive characteristic is that it offers a method for optimally building an antenna using ML techniques. The antenna design process can be accelerated with the aid of ML. Five methods are used: KNN, XG-Boost Regression, Decision Tree, Random Forest, and Artificial Neural Network (ANN). KNN produces the most precise results out of all the algorithms, with an accuracy rate of as much as 98%. It can estimate the dimensions of the required parameters based on the acquired results, something the High-Frequency Structure Simulator (HFSS) Electromagnetic (EM) simulator was unable to accomplish.

This article analyses the use of ML technology in antenna design optimization. The purpose is to use ML algorithms to predict the return loss (S_{11}) based on various antenna parameters. By doing so, it hopes to eliminate the need for repetitive trial and error-optimization methods. The study employs six different algorithms: Decision Tree, Random Forest, XG-Boost Regression, KNN, GBR, and LGBR. These algorithms were chosen because of their capacity to handle regression tasks involving nonlinear data, which is typically found in the dataset generated by HFSS antenna simulations. After running antenna simulations, the dataset is generated which contains the resonance frequency, diameter of the circular slot of the patch, and diameter of the semi-circular slot of ground and return loss values. The S_{11} values are then predicted using various ML techniques.

The rest of the article is organized as follows: Section 2 details the antenna evolution and analysis of the proposed antenna. Section 3 exhibits optimization through the use of ML models. Section 4 evaluates performance using results. Finally, Section 5 presents the conclusions.

2. Evolution and Analysis of UWB Antenna

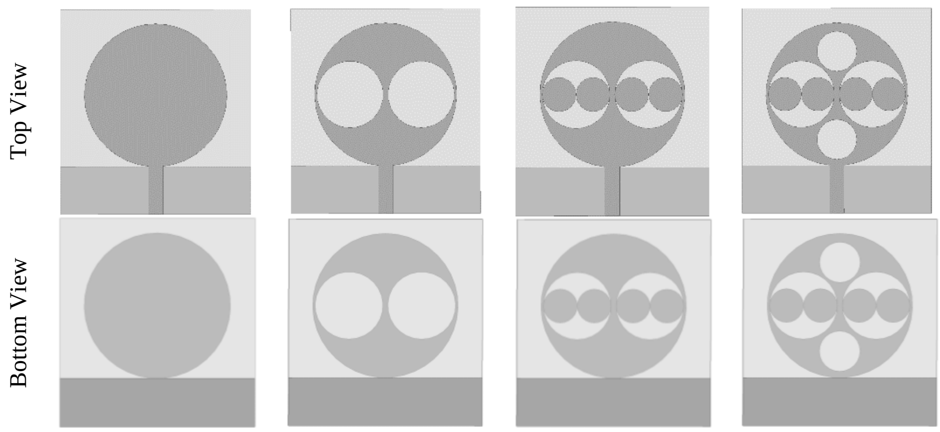
2.1. Antenna Dimensions & Evolution

The antenna design evolution is derived in five iterations, along with the intermediate stages and geometry of the proposed antenna depicted in Figs. 2 and 3, as well as the geometric parameters listed in Table 1. It is composed of FR-4 (Flame Retardant and Type 4) substrate and is 43mm x 40mm x 1.6mm. The thickness of the substrate is 1.6 mm, the dielectric constant is εr = 4.4, and the loss tangent is tan δ = 0.02 for all specified antenna design iterations.

The first stage as illustrated in Fig. 2, Ant 1 is a standard circular patch antenna, the radius of the patch can be calculated using the following equation 1[14].

$$R = \frac{F}{\left\{1 + \frac{2h}{\pi\varepsilon_r F}\left[\ln\left(\frac{\pi F}{2h}\right) + 1.7726\right]\right\}^{1/2}} \tag{1}$$

where, F = 8.791 · 10^9 / (f_r · (ε_r)$^{1/2}$), R = Radius of circular patch, f_r =Resonant frequency, h=Substrate height, ε_r =Dielectric constant of the substrate.



(a) Ant 1 (b) Ant 2 (c) Ant 3 (d) Ant 4

Fig. 2 Antenna Evolution

In Ant 2, two circular slots of diameter 7 mm are formed from the main circular radiating patch of diameter 15 mm to provide for a seamless transition of current from the transmission line to the radiating patch. Ant 3 is formed by four patches of diameter 3.5 mm inside these two slots of 7mm diameter, followed by Ant 4 Additionally, two slots are created on the main patch, one at the top and one at the bottom, whose diameter is varied from 2.4mm to 4mm with a step size of 0.2mm to apply ML algorithms for optimization., Ant 5 A semicircle slot with a diameter ranging from 0.1 to 3mm is produced in the ground plane, which is a defective ground structure (DGS) with dimensions of 10 mm by 40 mm (for optimization).

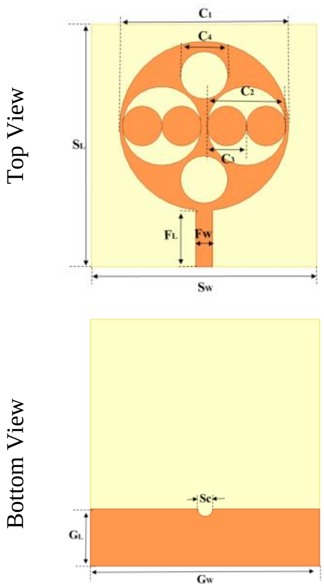


Fig. 3 Geometry of Ant 5 (Proposed Antenna)

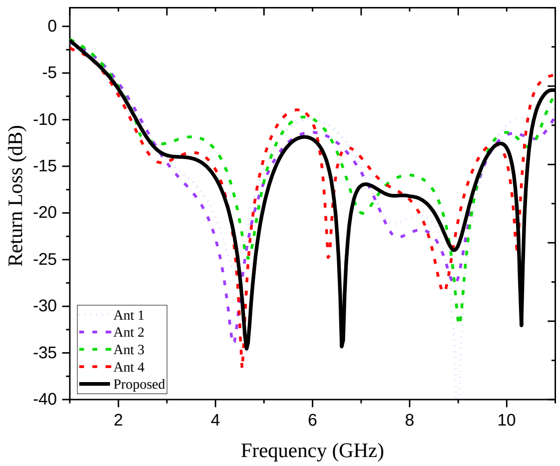


Fig. 4 Comparison of Return Loss for Ant 1, Ant 2, Ant 3, Ant 4 & Ant 5 (Proposed antenna)

Table 1 Antenna Dimensions

Parameters	Symbol	Value	Parameters	Symbol	Value
Diameter of Main Circular Patch	C_1	15mm	Length of Ground	G_L	10mm
Diameter of Circular Slot	C_2	7mm	Width of Ground	G_W	40mm
Diameter of Inner Circle Patch	C_3	3.5mm	Diameter of Semi-Circular Slot at Ground	S_C	1.3mm
Diameter of Top & Bottom Circular Slot	C_4	2.4mm	Substrate Length	S_L	43mm
Feed line width	F_W	3mm	Substrate Width	S_W	40mm
Feed line length	F_L	10mm			

Fig. 4 represents the comparison of Return Loss for Ant 1, Ant 2, Ant 3, Ant 4 & Ant 5 (Proposed antenna). Ant 1 is a simple circular patch antenna having a dual band from 2.4 GHz to 5.8GHz & 6GHz to 10.16GHz, resonating at 4.4GHz & 9GHz with -26dB & -47dB return loss respectively. Further in the next modification i.e. Ant 2, band 2.4 to 10.9GHz, giving ultra-wideband characteristics, resonating at 4.35 GHz & 8.9GHz with -33dB & -27dB return loss. In Ant 3, three bands are there at 4.6GHz, 7GHz, 9GHz with -23dB, -20dB, & -32dB return loss respectively. In Ant 4, 4.6GHz, 7.07GHz & 9.05GHz with -30dB, -24dB & -30dB return loss respectively. In the final design Ant 5 which is the proposed antenna gives ultra wide band from 2.37GHz to 10.56GHz having multiband's resonating at 4.6GHz, 6.6GHz, 9GHz & 10.3GHz with -34.26dB, -34dB, -24dB & -31.46dB return loss respectively.

3. Optimization through Machine Learning Models Methodology

The flowchart of optimizing antenna parameters through ML models is shown in Fig. 5.

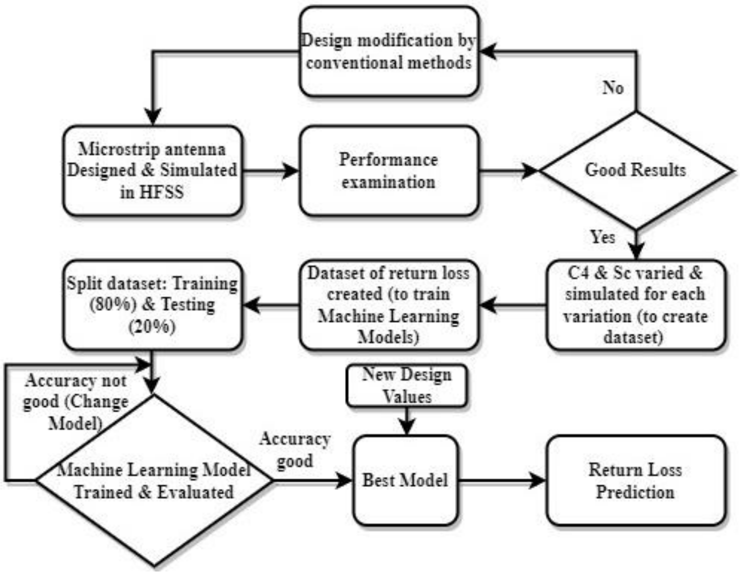
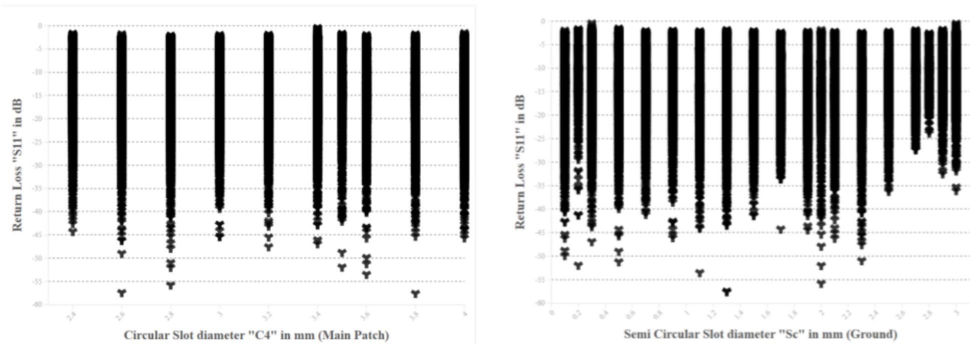


Fig. 5 Methodology Flowchart

The first step represents the design and simulation of an antenna on HFSS, further performance is checked and redesigned if required. The design methodology of the proposed UWB antenna in this work begins with the antenna design modification by conventional methods, in which the first antenna is designed and evaluated on the basis of return loss, and further modifications as mentioned in section 2 until we reach the proposed structure with good results, i.e. multiband along with UWB characteristics. Now in the next step, by varying the diameter of the circular slot (C_4) from 2.4mm to 4mm with a step size of 0.2mm and the semi-circular slot (Sc) varied from 0.1mm to 3mm with a step size of 0.2mm, the dataset is generated. HFSS was used to generate all possibilities that fit within the range of values set for each design parameter. This dataset, which contains 67650 records with 451 columns and 150 rows, is composed of the following features: frequency (Freq in GHz), return loss (S_{11} in dB), circular slot diameter (C_4), and semi-circular diameter (Sc). To apply ML methods, frequency, C_4, Sc will be treated as an independent variable and S_{11} as a dependent variable. The relationship between dependent (S_{11}) and independent variables (C_4, Sc) is shown in Fig. 6.

The next step is to split the dataset into training and test sets. The typical practice is to randomly assign a certain percentage (e.g., 70-80%) of the data to the training and the remaining portion to the test. The randomization helps ensure the representativeness of both. In this work, 80% of the data is used for training. The training dataset is utilized to train ML models. The models learn patterns and relationships between the dependent & independent features during the training process. After training, the ML models are evaluated on the test data set. This allows for assessing their performance on unseen data. The model predictions on the test dataset are compared with the actual values to measure their accuracy and other relevant performance metrics.

Certain models for ML are trained and tested for accuracy and predictability using the dataset produced above. Predictions made with ML take substantially less time and have far smaller margins of error. The best model is chosen based on having the highest R-square score and the lowest MSE value after the ML models have been trained using the dataset collected from the HFSS. Then, using that model, the S_{11} value for this dataset will be predicted. The parameters that produce the lowest S_{11} value will be chosen next.



(a) (b)

Fig. 6 (a) The Relationship between S_{11} and C_4. (b) The Relationship between S_{11} and Sc.

4. Result and Discussion

Common performance metrics used to evaluate the accuracy and efficiency of machine learning models are the MSE (Mean Squared Error), R-Square Value, MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), Fit Time (in seconds), and Prediction Time (in seconds). Table 2 shows the values estimated by several ML algorithms.

The mean squared error (MSE) is calculated as the average squared difference between predictions and actual values, Lower MSE indicates better accuracy, as shown in equation (2). The R-square value of the regression model shows how accurate it is, R-square ranges from 0 to 1, with 1 indicating a perfect fit, as shown in equation (3). The MAE is the average absolute difference between the predicted and actual values. It provides a measure of the model's prediction accuracy without considering the direction of the error, as shown in equation (4). The MAPE is a relative measure of the prediction accuracy and is calculated as the average percentage difference between the predicted and actual values. It is useful for interpreting the prediction errors in terms of their percentage relative to the actual values, as shown in equation (5). Fit Time is the time taken by the machine learning model to learn from the training data and build the internal representation. It indicates the training time required for the model to be ready for predictions. Prediction Time is the time taken by the model to make predictions on new data. It measures the efficiency of the model during the prediction phase [11, 15, 16].

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

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{3}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|(y_i - \hat{y}_i)\right| \tag{4}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(y_i - \hat{y}_i)}{y_i}\right| \cdot 100 \tag{5}$$

where n is the number of data points, y_i is the actual value, $\hat{y}_i$ is the predicted value, $\bar{y}_i$ is the mean of actual values.

Table 2 compares MSE, R-square, MAE, MAPE, Fit Time, and Prediction Time for various models, illustrating that the KNN model has the highest R-square value and the lowest MSE, MAE, MAPE, fit time, and prediction time, implying that it is the most accurate and fastest model among the models compared. Random Forest has the second highest R-square value, however, it takes significantly more time to train and test in comparison to other models. All models have an accuracy of more than 76%, five of them having an accuracy of more than 90% making them extremely useful, and the error is quite low. Because KNN is a non-parametric approach that finds a fixed number of training samples based on feature similarity, it outperforms the other methods [17].

Table 2 Comparison of MSE, R-square, MAE, MAPE, Fit Time & Prediction Time for different models

Model	MSE	R-Square Value	MAE	MAPE	Fit Time (sec)	Prediction Time (sec)
Decision Tree	1.555	0.959	0.506	0.033	0.240	0.012
Random Forest	1.100	0.970	0.478	0.032	12.214	0.583
Gradient Boosting Regression (GBR)	8.739	0.769	1.893	0.132	3.796	0.042
XG Boost Regression	2.782	0.927	0.953	0.065	2.088	0.028
KNN	**0.559**	**0.985**	**0.273**	**0.017**	**0.038**	**0.066**
Light Gradient Boosting Regression (LGBR)	3.782	0.901	1.162	0.080	0.302	0.074

Fig. 7 depicts the association between predicted and actual return loss values for various ML models such as Decision Tree, Random Forest, GBR, XG Boost, KNN and LGBR [17-23] over a frequency range of 1 to 15 GHz. The close correlation indicates that the models learned the patterns and relationships in the data successfully, resulting in reliable predictions of the return loss.

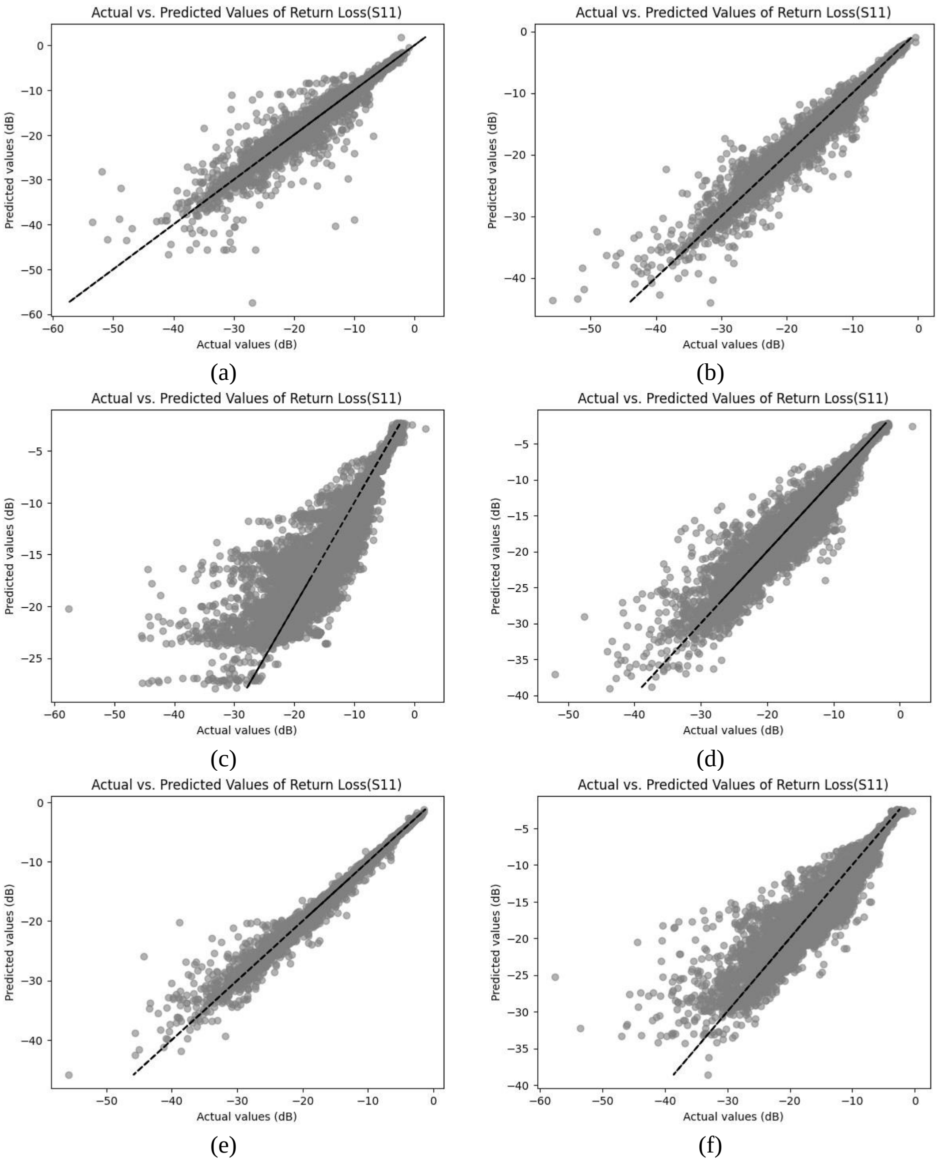


Fig. 7 Association between predicted and actual return loss values for (a) Decision Tree. (b) Random Forest. (c) GBR. (d) XG Boost. (e) KNN. (f) LGBR.

The most accurate prediction is provided by KNN. It performs better because it is a versatile non-parametric algorithm that can handle complex or unfamiliar data sets. Its adaptability enables it to adapt to changing datasets by accommodating new or modified data points, eliminating the need for complete model retraining. S_{11} is now optimized with the help of the ML approach. When the circular slot is 3.8 mm and the semi-circular slot is 1.3 mm, predicted using ML approach, it gives us the minimum value for S_{11}. Using these optimized values for S_{11} and simulating on HFSS with C4=3.8 mm and Sc=1.3 mm, the results are excellent, saving a significant amount of time. UWB band of 2.37GHz to 10.72GHz having three bands resonating at 4.51GHz, 7.1GHz & 8.87GHz with return loss values of -43 dB, -42.29dB, -57.68dB respectively, and one small band at 10.4GHz with return loss of -13.6dB. Hence, comparing the return loss of the proposed design (Ant 5) using the conventional approach and the optimized design using the ML approach with optimized dimensions of C_4=3.8 mm and Sc=1.3 mm is shown in Fig. 8. This illustrates that by employing this approach, minimum values of return loss may be estimated for a particular band, which is quite time-consuming if the conventional approach is followed.

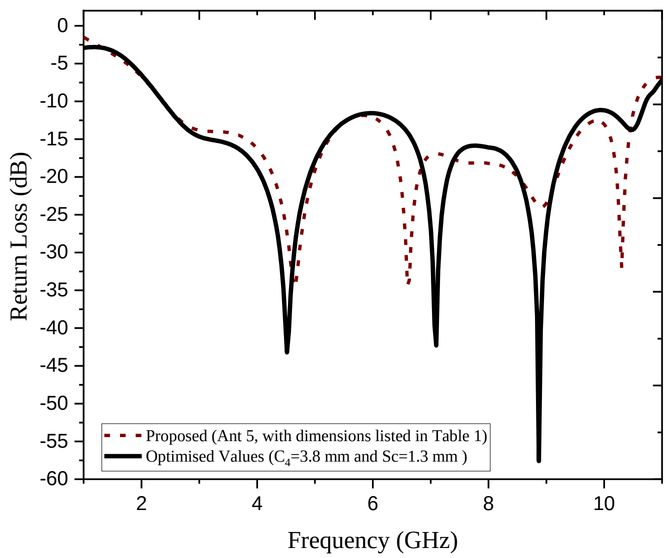


Fig. 8 Comparison of return loss for proposed design using conventional approach and optimized design using ML

To evaluate the accuracy of the KNN model, new random design values C_4=4.2mm and Sc=1.3mm are being prepared and also fabricated as shown in Fig. 9. The return loss comparison of predicted values from KNN, simulated values from HFSS, and measured values obtained from fabricated prototype antenna is shown in Fig. 10. The close relationship demonstrates that the models generate accurate evaluations of return loss. As compared to conventional design approaches, this approach can save significant time and effort.

Fig. 8 Fabricated Antenna

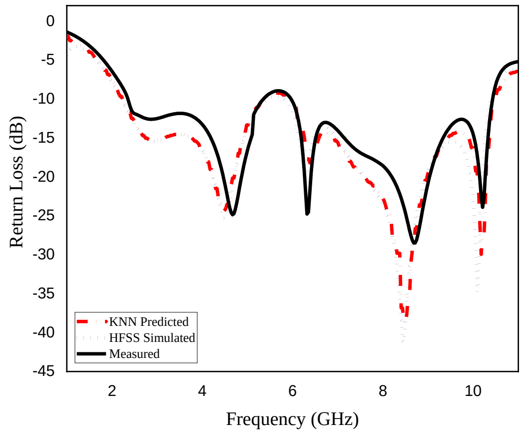


Fig. 9 Return Loss comparison of predicted values from KNN, simulated values from HFSS, and the fabricated prototype

5. CONCLUSION

In this work, a circular patch antenna is first designed and subsequently optimized using the ML technique. After antenna optimization with ML algorithms and testing, the frequency range is confirmed to be 2.37GHz to 10.72GHz, which is suitable for Ultra-Wideband (UWB) applications. The six ML algorithms were used in this work Decision Tree, KNN, Random Forest, GBR, LGBR, and XG-Boost Regression. With an accuracy rate of up to 98.5%, KNN produces the best results. It performs better than traditional EM simulators. ML-powered antenna design is an innovative approach that will continue to define the future of antenna technology, designers can use it to solve design challenges, increase performance, and accelerate the development of revolutionary antenna systems. The ongoing improvement of ML techniques will surely contribute to the future of 3D antenna design, allowing for the creation of highly efficient, compact, and flexible antennas for a wide range of applications.

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