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Employing Machine Learning Models to Predict Return Loss Precisely in 5G Antenna

Rachit Jain*, Vandana V. Thakare, and Pramod K. Singhal

Abstract—To meet 5G requirements, designing an optimal antenna is challenging due to numerous design factors. Conventional electromagnetic modeling simulators require excessive time and processing power during the antenna design process. Machine learning (ML), an innovative technology, can be used in the domain of antenna design with favorable performance and can resolve problems that the previous conventional methods cannot. The main goal of this work is to create an antenna that operates at 28 GHz, which is a significant 5G band for the 5G futuristic infrastructure revolution, and to predict the return loss of an antenna using some machine learning models like K-Nearest Neighbor (KNN), Extreme Gradient Boosting (XG-Boost), Decision Tree (DT), and Random Forest (RF). On comparing results, all models perform well with over 83% accuracy. However, the Random Forest model predicts return loss with higher accuracy at 90% and lower MSE and MAE values of 1.99 and 0.827, respectively. Moreover, this antenna holds potential for 5G applications and can be efficiently optimized using a machine learning approach, saving valuable time.

1. INTRODUCTION

Antenna design serves as a vital component of any communication system as it is accountable for transmitting as well as accepting signals among two or maybe more parts of the system. Fig. 1 depicts some antenna applications [1]. With the increasing influence of wireless connections, traffic volume has experienced explosive growth [2], often referred to as data traffic explosion. A significant variety of applications are currently migrating from wired to wireless gadgets like cell phones, which seem simpler to handle and use throughout instantaneously; however, this scenario inevitably results in a significant growth in data congestion and a shortage of available bandwidth. As per estimates, the market data rate is anticipated to exceed Gbps or possibly Tbps within the subsequent 10 to 15 years [3, 4]. As a result, we must devise a method that allows antennas to be developed and optimized in less time than needed. Machine learning procedures act as machine's minds, enabling them to gain knowledge and get faster. With more data, more processes are activated, causing the machine to develop and enhance its performance. Unless the predictions somehow do not eventuate, the algorithm is retrained till the desired outcome is reached. It allows the machine learning system to train constantly by itself and provide the best response achievable, which will enhance its accuracy with time. In this case, machine learning may be utilized to optimize or anticipate results in less time than traditional methods. Fig. 2 depicts the various types of machine learning [5].

In paper [6], the authors utilize algorithms based on machine learning for a Yagi antenna that operated on a millimeter wave, where a two-section optimization on the Yagi-Uda antenna is used to produce high gain and wide bandwidth (BW). The Kriging approach is employed as an application framework, and the LOLA-VORONOI specimen maker and error sample selection are used to achieve the best design.

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* Corresponding author: Rachit Jain (rachit2709@gmail.com).
The authors are with the Department of Electronics Engineering, Madhav Institute of Technology & Science, Gwalior, M.P, India.

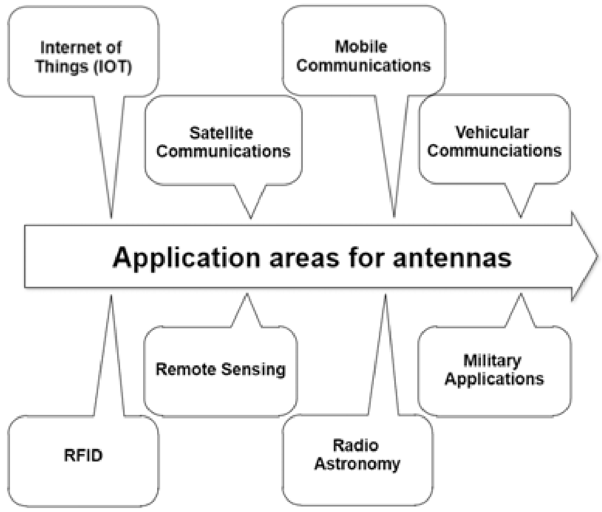


Figure 1. Various fields of antenna.

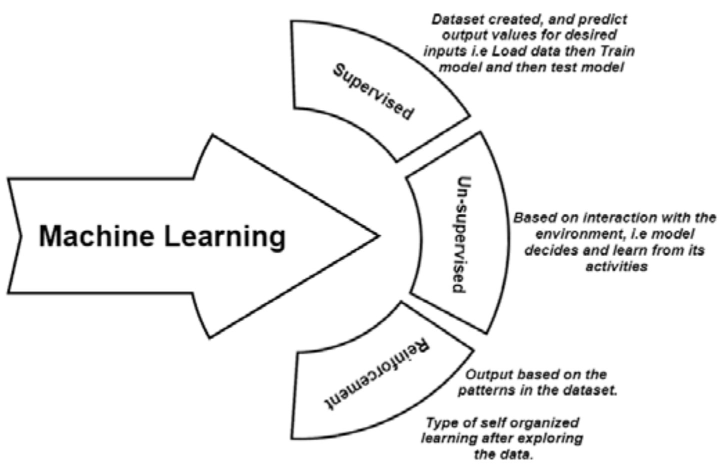


Figure 2. Types of machine learning.

Article [7] employs the scenario of designing a metamaterial antenna to demonstrate how machine learning for antenna optimization offers excellent precision and exceptionally high computing performance compared with conventional electromagnetic simulation optimization. When applying machine learning to create an appropriate model for a specific type of antenna, this machine learning model has unrivaled benefits for antenna improvement. The research in this paper reveals that machine learning technology enables autonomous antenna optimization, which is extremely beneficial to the quickly growing 5G and 6G technologies.

Report [8] gives a detailed comprehensive investigation of the performance of a machine learning technique K-Nearest Neighbor (KNN) in predicting the antenna output response of three distinct antenna designs. The different chosen designs have a unique set of design parameters. It has been determined that the number of design variables employed in the training input data has a significant impact on the performance of the machine learning (ML) model. Additionally, it is critical to choose design variables that are identically and equally dispersed.

The authors in [9] present one or more of the primary applications of artificial intelligence (AI) toward antenna design in this paper. The authors examine prior research and implementations for various AI approaches including evolutionary computation, machine learning, & knowledge representation models. Based on the review, popular methods and developing methods have been applied to less complex antenna designs. A wide range of applications from antenna design to antenna optimization is a rapidly expanding research field. Furthermore, potential research paths will concentrate on additional algorithms and machine-learning methods that can be used in antenna design.

A dual-port multiple-input multiple-output (MIMO) antenna with metasurface is constructed in work [10], and several machine learning techniques are employed for optimization. The proposed antenna operates between 26.24 and 27.94 GHz, making it appropriate for 5G communication systems. Specifically, the deep neural network (DNN) and RF algorithms offer good optimization results.

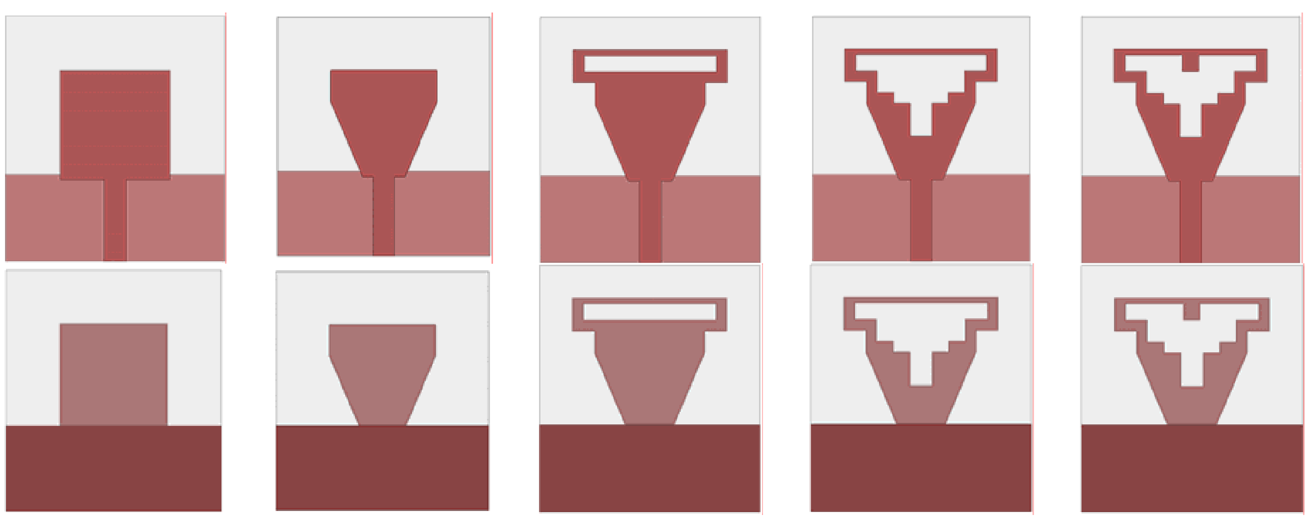
The authors in [11] propose a smart antenna synthesis approach that automatically chooses the appropriate antenna type and provides the best geometric attributes under antenna specifications. It estimates the optimum antenna size attributes by employing a decision tree classifier and a fuzzy inference approach, and it illustrates excellent abilities in parameter prediction with antenna categorization.

The rest of this article is organized in the following manner: Section 2 describes the design evolution of the antenna & its analysis. Section 3 shows how to predict return loss using machine learning models. Section 4 analyses performance using results. Lastly, Section 5 summarizes and concludes the paper.

2. ANTENNA STRUCTURE DESIGN & ANALYSIS

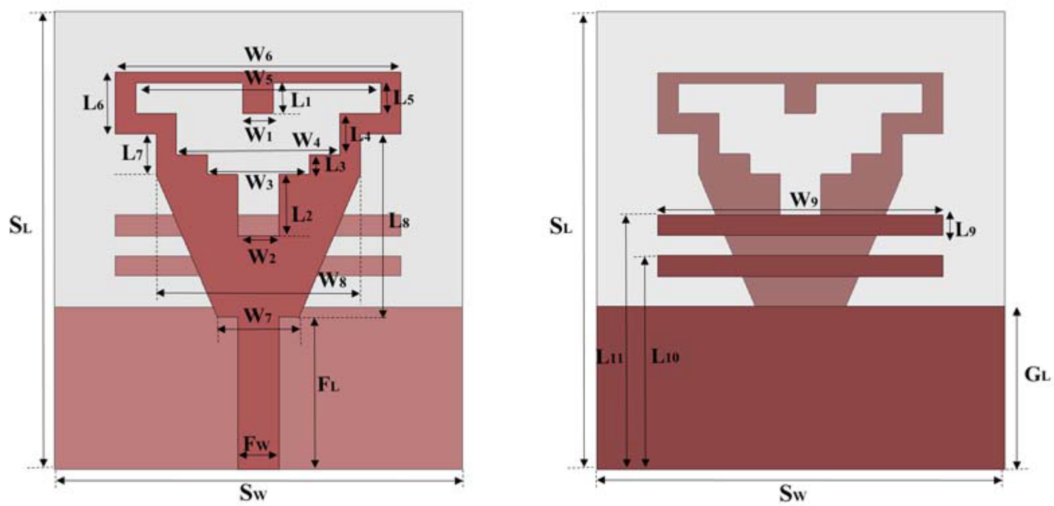
The antenna design evolution is derived in six iterations. The element's intermediate steps are shown in Figs. 3 & 4, and its geometric parameters are listed in Table 1. It is composed of an FR-4 (Flame Retardant and Type 4) substrate, and the dimension is 20 mm × 22.5 mm × 1.6 mm. The thickness of the substrate is 1.6 mm; the dielectric constant is $\varepsilon_r = 4.4$; and the loss tangent is $\tan\delta = 0.02$ for all specified antenna design iterations. The first stage as illustrated in Fig. 3, Ant 1, is a standard square patch antenna. Ant 2 has a tapered bottom portion of the square patch antenna with 3 mm width and 7 mm length on both lower edges to facilitate a seamless transition of current from the transmission line to the radiating patch. Ant 3 is formed with a slot that is 1.5 mm long and 12 mm wide to increase the width of the radiating patch, followed by Ant 4 having multiple slots of 2 mm length by 8 mm width, 1 mm length by 5 mm width, and 3 mm length by 2 mm width which were inserted for better impedance matching, Ant 5 with a 1.5 mm long by 1.5 mm wide strip inserted in the main radiator, and Ant 6 (proposed antenna) with two parasitic strips inserted in the ground plane to tune the antenna and achieve a wider bandwidth.

While comparing the return loss for Ant 1 to Ant 6, as shown in Fig. 5(a), Ant 1 offers wide band characteristics from 25.7 GHz to 30 GHz with a minimum S_{11} of −19 dB at 26.4 GHz and one small



(a) Ant 1 (b) Ant 2 (c) Ant 3 (d) Ant 4 (e) Ant 5

Figure 3. Antenna design steps.

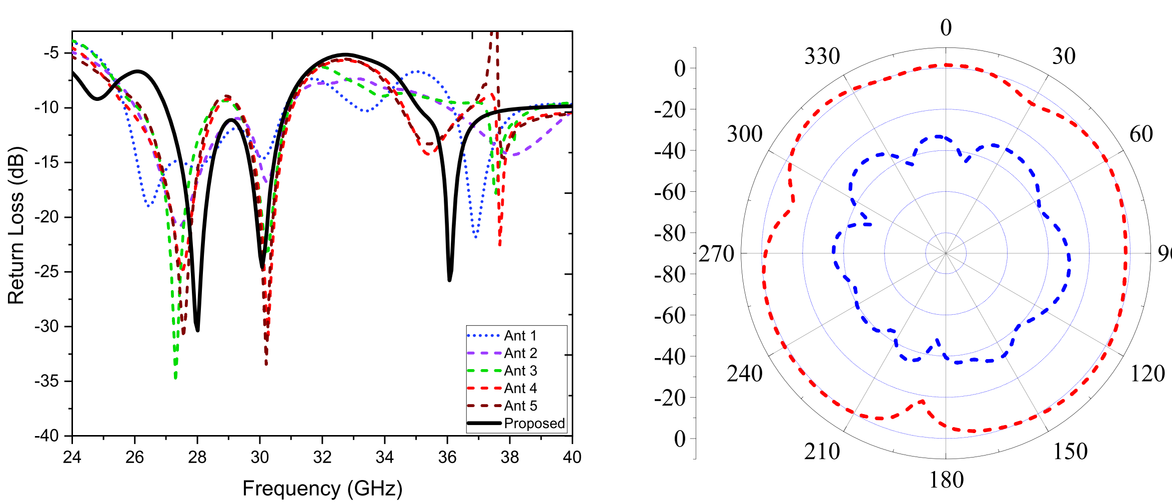


(a) (b)

Figure 4. (a) Front & (b) back view of proposed antenna (Ant 6).

Table 1. Antenna parameters.

Parameter	*Value*	*Parameter*	*Value*	*Parameter*	*Value*
$W_1 = L_5$	1.5 mm	W_7	4 mm	L_{10}	10.5 mm
$W_2 = L_4 = L_7$	2 mm	$W_8 = L_8$	10 mm	L_{11}	12.5 mm
W_3	5 mm	L_1	0.5 to 7.5 mm	F_L	7.5 mm
$W_4 = G_L$	8 mm	L_2	0.5 to 5 mm	F_W	2 mm
W_5	12 mm	$L_3 = L_9$	1 mm	S_L	22.5 mm
$W_6 = W_9$	14 mm	L_6	3 mm	S_W	20 mm



(a) (b)

Figure 5. (a) Comparison of S_{11} for Ant 1, Ant 2, Ant 3, Ant 4, Ant 5 & proposed antenna, (b) radiation pattern of proposed antenna at 28 GHz.

band resonating at 37 GHz with S_{11} of -21 dB; Ant 2 provides band from 26 GHz to 31 GHz with S_{11} of -21 dB resonating at 27.4 GHz; Ant 3 leads to the loss of wideband characteristics, offering dual-band characteristics at 27.28 GHz & 30.2 GHz with S_{11} of -33 dB & -23 dB; Ant 4 gives S_{11} of -25 dB & -30 dB at 27.5 GHz & 30.26 GHz respectively; Ant 5 has return loss of -30 dB at 27.6 GHz & -32 dB at 30.22 GHz. Ant 6 (Proposed antenna with $L1$& $L2$ at 3 mm & 3 mm respectively) has wideband characteristics from 27 GHz to 30.8 GHz resonating at 28 GHz with S_{11} of -30 dB, 30 GHz with S_{11} of -24 dB, also a small band from 35 GHz to 38 GHz resonating at 36 GHz with S_{11} of -25 dB. Fig. 5(b) presents the radiation pattern for the proposed antenna at 28 GHz.

3. PREDICTION OF RETURN LOSS THROUGH MACHINE LEARNING MODELS

The term "return" refers to the bounce-back reflection. Return loss will be the measure of how little the "return" or "reflection" is. Although a minimal amount of signal reflection is required, a major loss on the "reflection" is appropriate. Lower return loss is undesirable and indicates that less energy enters our antenna, and it is measured in dB as indicated in Equation (1) [12] and its signification of values represented in Fig. 6. Evaluating return loss through antenna design is an essential performance measure. Not having higher return loss, an antenna neither accepts radio waves properly nor radiates them. Machine learning approaches are used in this work to predict the return loss of the proposed antenna.

$$S_{11} = 10 \log_{10} \left(\frac{P_{in}}{P_{ref}} \right) \text{dB} \tag{1}$$

where P_{in} — Incident Power, P_{ref} — Reflected Power.

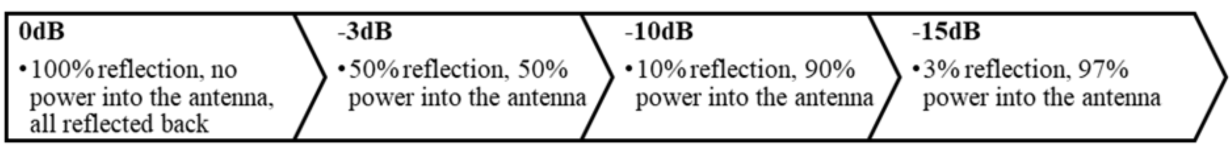


Figure 6. Return loss & its significance.

The Machine Learning models employed in this work are addressed below:

A Decision Tree [13] is a machine-learning model that represents decisions and their possible consequences in a tree-like structure. It is a predictive modeling tool widely used for classification and regression tasks. The entire data set is divided into subsets in a decision tree, and the output will belong to such subset where the input features fall. A split criterion in a decision tree is selected to minimize the difference subset variance as we descend across each branch, and the expected attribute is utilized as the root node, which tends to result in error minimization. Decision Trees are powerful due to their ability to handle non-linearity, feature interactions, and handling missing values.

The random forest algorithm [14] is based on a decision tree algorithm. The decision tree algorithm uses only one tree, whereas the random forest technique uses numerous trees to form a forest. The final prediction is made by pooling predictions from all trees; the mode of the classes for classification or the mean prediction for regression. Also random forest algorithm is referred to as an ensemble technique as it combines results to reach a final result.

XGBoost (Extreme Gradient Boosting) [15] is a powerful machine learning algorithm that belongs to the gradient boosting family. It is designed to optimize predictive performance by sequentially adding weak learners (usually decision trees) to the model while minimizing errors. XGBoost is known for its efficiency, flexibility, and high predictive accuracy.

K-Nearest Neighbors (KNN) [16] is a simple and intuitive machine-learning algorithm used for both classification and regression tasks. It is a non-parametric learning method that makes predictions that depend on the resemblance across the new data point and its neighboring data points in the training dataset.

To predict return loss using machine learning, a data set is created by varying $L1$ and $L2$ lengths and frequency. $L1$ ranges from 0.5 mm to 7.5 mm with a step size of 1 mm; $L2$ ranges from 0.5 mm to 5 mm with a step size of 0.5 mm; and frequency ranges from 11 GHz to 40 GHz with 451 points. With all these design parameters variation in the design and simulation of each antenna is done in HFSS through which return values are generated, and these return loss values created a data set of 36080 values. Further, these are used to apply machine learning models in which the first 80% is used for training the model, and the remaining 20% is used for testing the model. Python is chosen to execute these models due to its versatility, rich libraries, ease of use, and user-friendly nature. It also offers an extensive library that supports machine learning algorithms and their visualization. The flowchart of return loss prediction using machine learning models is shown in Fig. 7.

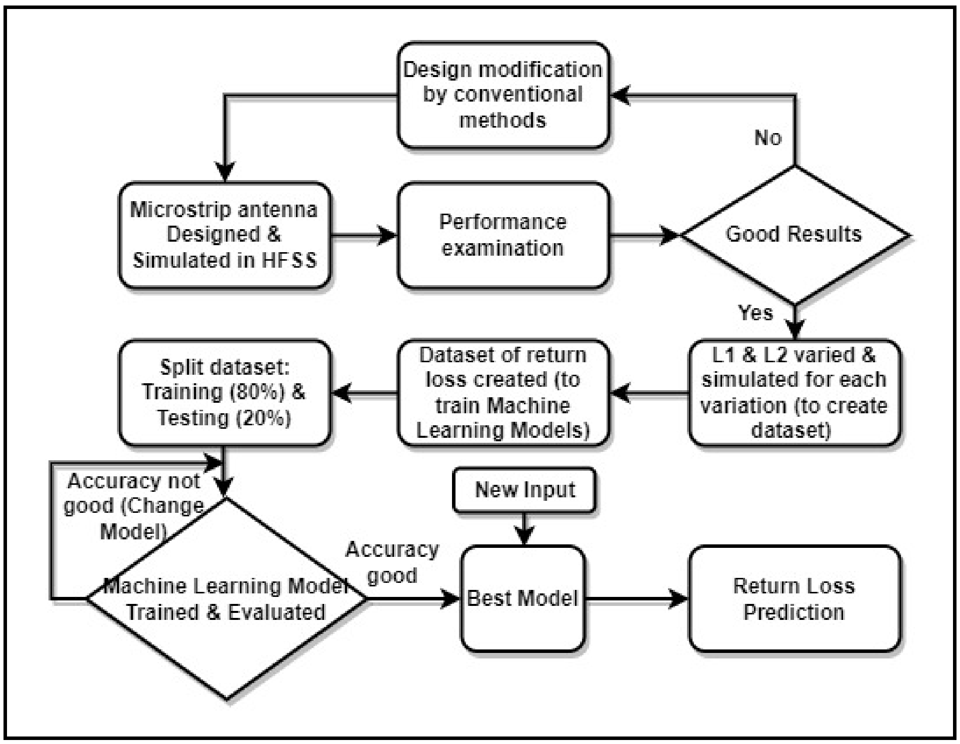


Figure 7. Flowchart of S_{11} prediction using machine learning models.

4. RESULT AND DISCUSSION

Although Decision Tree, Random Forest, XG Boost, and KNN can execute effective regression analysis, handle complex relationships in data, and make accurate predictions, these have been selected for use on the dataset to discover relations and predict antenna return loss. The mean absolute error (MAE), mean squared error (MSE), and R-square score will serve as tools to evaluate the various machine learning models [17, 18] implemented in this work.

The MSE, as represented in Equation (2), serves to determine the accuracy of the model based on predictions made across the full training data set. Equation (3) represents R-square which is an excellent way to determine the effectiveness of a machine learning model in predicting observed outcomes. As indicated in Equation (4), the MAE is the mean of the absolute difference between the model prediction and the desired/true value.

$$\text{MSE} = \left[\Sigma(\text{True values} - \text{Predicted values})^2\right]/n \tag{2}$$

$$\text{R-square} = 1 - (\text{SSR}/\text{TSS}) \tag{3}$$

$$\text{MAE} = 1/n * \Sigma(\text{True values} - \text{Predicted values}) \tag{4}$$

where Σ is the summation; n is the total number of data points; true values are the actual values of data points; predicted values are the predicted or forecasted values; SSR is the Sum of Squares of Residuals; TSS is the Total Sum of Squares.

Table 2 shows the MSE, R-square score, and MAE values predicted by several Machine Learning algorithms. In contrast, all models have an accuracy of more than 83%, making them extremely useful, and the error is quite low. The high R-squared value signifies that the Random Forest model captures a substantial portion of the variability in the target variable, resulting in predictions that closely match the actual values. Furthermore, the Random Forest model exhibits the lowest MSE and MAE values among the compared models. The lower MSE value underscores the model's ability to minimize prediction errors, while the lower MAE value confirms that the absolute differences between predicted and actual values are smaller than other models. The Random Forest model demonstrates remarkable predictive capabilities, characterized by its high R-squared value, lower MSE, and lower MAE values. These findings indicate that the Random Forest model is well-suited for accurate predictions and could be a viable alternative for a variety of applications that require precise predictions.

Table 2. Comparison of MSE. R-square & MAE for different machine learning models.

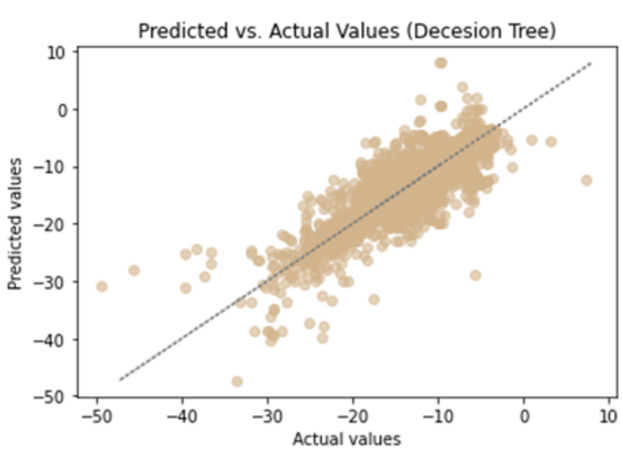
Model	***MSE***	***R-Square***	***MAE***
Decision Tree	3.42	0.831	1.029
Random Forest	1.99	0.901	0.827
XG Boost Regression	2.10	0.892	0.900
KNN	2.696	0.866	1.032

4.1. Predicted and Actual Values of Return Loss

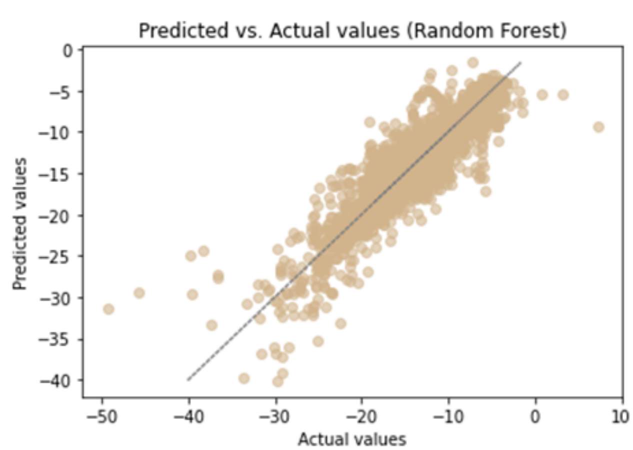
Figure 8 correlates the predicted and actual return loss values for Decision Tree, Random Forest, XG Boost, and KNN between 11 and 40 GHz, respectively, which indicates that the model has been properly trained and that the actual values are very close to the predicted ones.

4.2. Predicted and Simulated Values of Return Loss for Random New Variation in Antenna Design

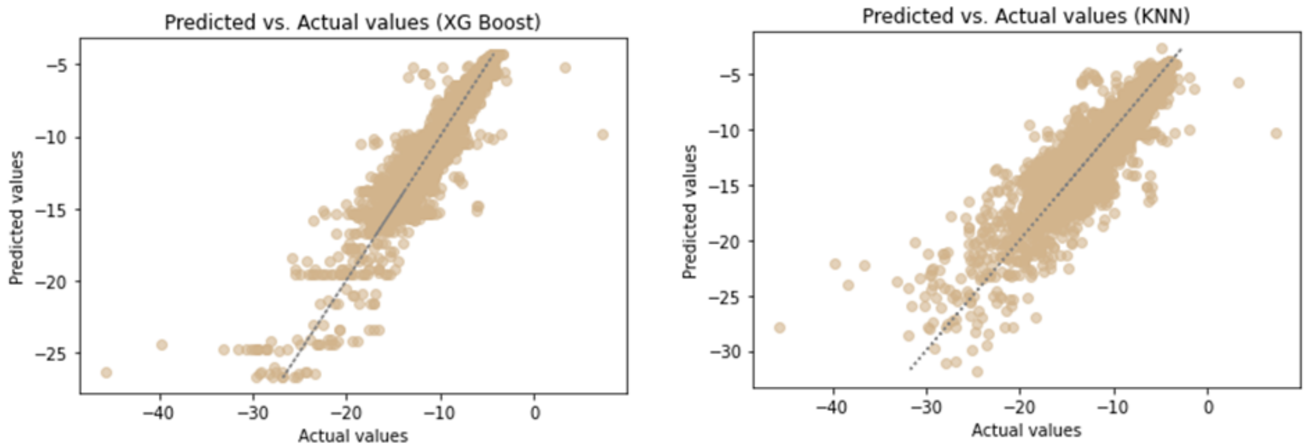
Table 3 compares the return loss predicted by various machine learning models for the new variation in the antenna design, creating 4 new designs randomly, which is also simulated on HFSS whose return loss graph is shown in Fig. 9(b), and further making comparisons randomly at 28 GHz, 30 GHz, 32 GHz, and 38 GHz for all new variations. Its graphical view is shown in Fig. 9(a), and this represents that the model is well-trained and predicts values precisely.



(a)

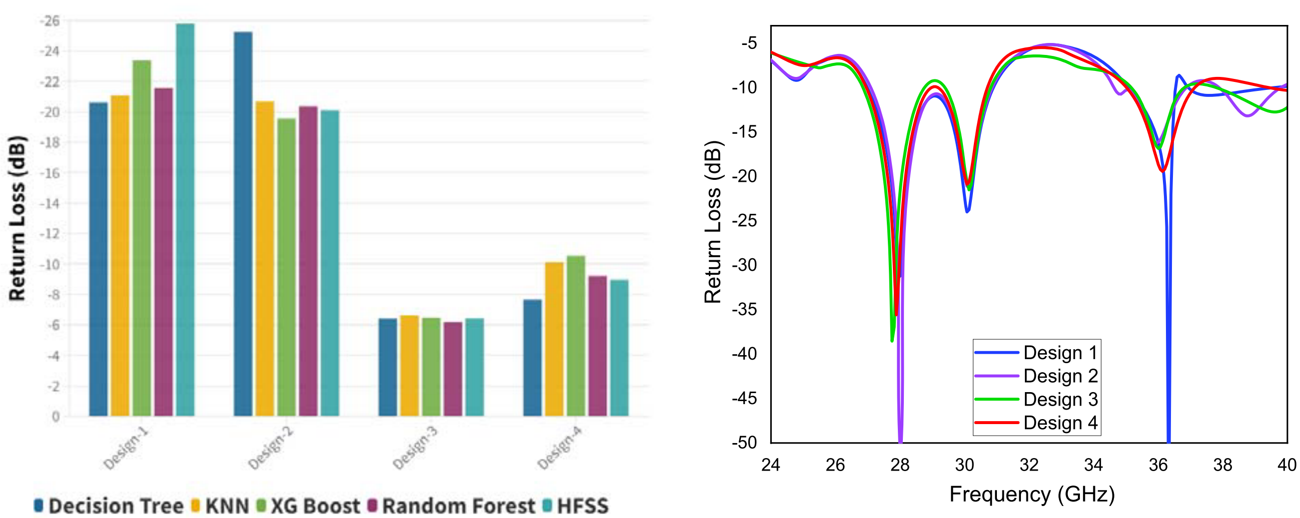


(b)



(c) (d)

Figure 8. Actual values versus predictions by (a) decision tree, (b) random forest, (c) XG boost & (d) KNN.



(a) (b)

Figure 9. (a) Comparison of predicted return loss: Machine learning models versus HFSS, (b) return loss values for design 1, 2, 3 & 4.

Table 3. Comparison of S_{11} predicted by machine learning models and simulated on HFSS.

Source	***Design-1***	***Design-2***	***Design-3***	***Design-4***
	$L_1 = 3\,\text{mm}$, $L_2 = 2\,\text{mm}$	$L_1 = 2.5\,\text{mm}$, $L_2 = 3\,\text{mm}$	$L_1 = 4.5\,\text{mm}$, $L_2 = 4\,\text{mm}$	$L_1 = 5\,\text{mm}$, $L_2 = 1\,\text{mm}$
	S_{11} *at Frequency 28 GHz*	S_{11} *at Frequency 30 GHz*	S_{11} *at Frequency 32 GHz*	S_{11} *at Frequency 38 GHz*
Decision Tree	-20.62	-25.23	-6.42	-7.65
Random Forest	-21.56	-20.36	-6.20	-9.22
XG Boost	-23.37	-19.56	-6.49	-10.55
KNN	-21.09	-20.67	-6.62	-10.12
HFSS	-25.79	-20.10	-6.43	-8.96

4.3. Summary of Research Papers Using Machine Learning in Antenna Design

Table 4 summarises several research papers that address the use of machine learning in antenna design.

Table 4. Comparison of the various ML approaches employed in the papers.

Paper	***Year***	***ML Algorithm***	***Antenna Type***	***Frequency Range***	***Key Findings***
[6]	2021	Kriging Model	Microstrip Yagi-uda Antenna	24–30 GHz	Utilizing machine learning (ML) approaches to find the optimum design as a suitable solution.
[7]	2021	Fully connected multilayer perceptron	Dual T-shaped antenna	7–8 GHz, 12–13.5 GHz	ML for antenna optimization showcases good accuracy and remarkably high computational efficiency.
[13]	2021	DT & RF	MSA	2–10 GHz	The prepared model facilitates the design and optimization of structures for the desired frequency, resulting in reduced time and enhanced ease of implementation
[20]	2021	GPR	Square Patch Antenna	0.48–7.84 GHz	Reliable resonant frequency prediction for square patch MSA using GPR.
[19]	2022	DT, RF, XGBoost, KNN & ANN	UWB Antenna	2.9 to 21.6 GHz	Accurate return loss prediction using KNN
[10]	2022	DT, KNN, RF, XGBoost & DNN	DRA	26.24–27.94 GHz	Accurate S_{11} predictions were attained using DT, KNN, RF, and XGBoost, with DNN displaying superior performance.
[11]	2023	Fuzzy inference system & DT classifier	MSA, Horn, Helical antenna	2.4–5 3–27 GHz 1–6 GHz	Demonstrates excellent parameter prediction capability alongside antenna categorization.
Proposed Work		DT, RF, XGBoost & KNN	5G Antenna	27–30 GHz, 35–38 GHz	Return loss acquired by various machine learning algorithms is quite accurate and precise with high R-squared and low errors for 5G antenna.

5. CONCLUSION

In this work, the performance analysis of a 5G patch antenna & the prediction of return loss using Machine Learning models are investigated. The proposed antenna exhibits wideband characteristics from 27 GHz to 30.8 GHz resonating at 28 GHz with a return loss of −30 dB, at 30 GHz with a return loss of −24 dB, also a small band from 35 GHz to 38 GHz resonating at 36 GHz with a return loss of −25 dB. HFSS is used to model the proposed antenna design, to create a data set & to obtain results. The results show that the predictions of return loss acquired by various machine learning algorithms are quite accurate and deliver results in a short time frame. This would assist in correctly determining the return loss for a certain resonant frequency without the need for complex simulations saving significant time and expense. When comparing Machine Learning models, Random Forest produces better accurate results with an R-square value of 0.901 and smaller MSE and MAE values of 1.99 and 0.827, respectively. Furthermore, this antenna may be employed for 5G applications and optimized in less time using a machine learning approach, because its return loss can be anticipated easily based on which variation is needed.

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