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Design of 5G Dual Band Antenna and Optimization using Machine Learning Techniques

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Abstract

Objectives: Exploring Machine Learning (ML) application in electromagnetic domain is need of the hour nowadays. This article presents a dual-band antenna for 5G mobile and Wi-Max applications at 2.2 GHz, 3.6 GHz and its optimization using Polynomial Regression (PR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost) ML techniques. **Methods:** Design optimization and Root Mean Square Error (RSME) are obtained. Hyper parameter tuning is applied for better model performance. Antenna design dimensions are obtained from XGBoost techniques which is the better performing model. **Findings:** A novel microstrip antenna of $(0.25\lambda_0 \times 0.32\lambda_0)$mm^2 is proposed on FR-4 substrate using insert line feed. Single unit Complementary Split Ring Resonator (CSRR) is incorporated on the ground plane for dual-band characteristics. The proposed antenna has a return loss of -20.37dB at 2.2GHz and -32.27dB at 3.6 GHz, with a maximum gain of 4.06dBi at 3.6GHz. Full wave High-Frequency Structural Simulator (HFSS) is used for data generation for ML models. After hyper parameter tuning XGBoost model is giving the better performance in case of RSME. Observed values in case of train and test case are [(0.007, 0.068), (0.016, 0.340), (0.761, 4.290), (1.057, 3.575)] & [(0.005, 0.026), (0.010, 0.091), (0.525, 2.626), (0.648, 2.544)] for operating frequency, return loss target variables respectively with and without parametric tuning. **Novelty:** The dimensions obtained from XGBoost model are used for fabrication, and performance comparison of the proposed, ML-based simulated and measured antenna along with various antenna parameters is presented.

Keywords: HFSS, Microstrip Patch Antenna; Machine Learning Algorithm; Polynomial Regression; Random Forest; Extreme Gradient Boost (XG-Boost)

1 Introduction

The antenna is an electromagnetic device that converts an electrical signal to an electromagnetic one and vice versa. Several types of antennas exist, like wire, plane, dish, loop, and strip antennas, etc, in the literature. Among all the available antennas, the Microstrip Patch Antenna (MPA) is unique in its design characteristics and applications. It is compact, low in weight, suitable for a wide variety of frequencies with reasonable polarization facility, and easy to integrate into any electronic circuit with various feeding techniques. Hence, design optimization of MPA is essential for any antenna engineer. Various technologies like massive Multi-Input and Multiple-Output (MIMO), hybrid beam forming, mobile broadband speed, potential application in virtual reality, Internet of Things, and autonomous vehicles are key features in 5G [1]; Millimeter wave (mm-Wave) band supports the 5G designs particularly at 60GHz bands [2]. Compact fractal design, including MIMO structures at 3G, 4G, and 5G, are studied for WLAN, Wi-MAX, ISM, and LTE bands depicted in [3]-[4]. Flexible antenna design using multi-substrate and IOT-based body area networks is a new class of wearable antenna systems. Enhanced radiation characteristics are possible with split ring resonator concepts, which are part of metamaterial, introduced in [5]-[6]. Electrically small reconfigurable antennas at 5G mid-band frequencies are also implemented [7]. Circularly polarized dual-band slotted patch antenna for wireless communications at 2.4GHz and 5GHz for WLAN system is developed in [8]-[9]. A dual band antenna at 2.4GHz and 5.36 GHz using inverted T-slots and probe feeding is designed in [10]-[11]. Antenna optimization has become increasingly important in today's technology landscape, driven by advancements in tools such as MATLAB, electromagnetic simulators, and Scilab etc. Optimization is possible on design and performance parameters of antenna.

ML ability to predict future values of a system attracts the scientific community to apply ML in high-computing electromagnetic applications including antenna design. In [12] authors introduced application of antenna optimization using open ware scilab technology. A comprehensive review of antennae design exploration and optimization using machine learning algorithms is available in [13]. Authors in [14] introduced dimension optimization of microstrip patch antenna at X, Ku bands via Artificial Neural Networks; Fabrication of the antenna from machine learning dimensions and its validation in terms of RMSE is not reported. Christoph Maeurer et al., in [15] reported the dimensional reduction of the antenna with a minimal number of data points, which doubts the model's efficiency. Shilpa Pavithran et al., in [16], explained the 5G antenna design using decision tree and random forest techniques. Higher-order polynomial and extreme gradient boosting techniques to address over fitting issues are not currently explored in the existing literature. Researchers in [17] introduced the application of neural networks in intelligent array antennas. Authors in [18] tried to optimize 5G rectangular patch antenna using decision tree, random forest models but are of single band operation. The design of microwave components in conventional electromagnetic simulators is simple in terms of computational time and resource availability. Simple patch antenna design for WLAN applications at 3.5GHz & 3.6 GHz are available in [19]-[20].

This article introduces machine learning (ML) techniques for optimizing dual-band antenna design. Given the growing demand for efficient antenna solutions, validating the ML-based design through physical fabrication is both timely and essential, further it is rarely available in literature. The study focuses on exploring the potential of ML-driven design and validation of dual-band antennas using open-source Python tools. Specifically, it outlines a design methodology to achieve desired antenna characteristics at 2.2 GHz and 3.6 GHz frequency bands, targeting applications in 5G mobile and WiMAX technologies.

2 Methodology

Antenna optimization using ML with sufficient datasets is the potential alternative to conventional electromagnetic simulators. Introducing powerful ML techniques in conventional electromagnetic solvers is a significant advantage for antenna engineers. Basic design flow procedure of antenna optimization using ML models is mentioned in Figure 1. Data set is the main key for any ML model implementation here in the proposed model data set is created by using the optometric available in HFSS around operating frequency. Post data collection various ML models are verified for better accuracy to obtain antenna dimensions such that proper validation will be achieved.

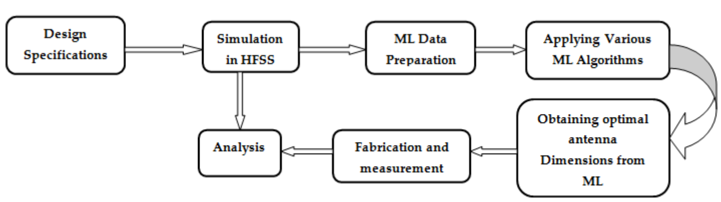

Fig 1. Design flow procedure of antenna optimization

The proposed antenna comprises a rectangular metallic patch over a regular FR-4 substrate with 4.4 relative permittivity and loss tangent of 0.02. The dimensions of the proposed design are mentioned in Table 1, and **eq.1 to eq.5** is used to obtain the mentioned dimensions, where 'w' is width of the metal patch; 'f_0' is the operating frequency in GHz; 'c' is the velocity of light; 'l_{eff}' length of the patch; 'ϵ_r'relative dielectric constant; 'h' height of the substrate; 'ϵ_{reff} 'effective relative dielectric constant. Microstrip insert line feed technique is used for design; the feed line length is adjusted so that it matches the 50Ω line impedance with the port in HFSS. A few basic antenna designs using patch models, and their design equations were discussed in literature. The bare rectangular patch is resonating at a single band at 3.56GHz with return loss of 23.11 dB. A CSRR is etched on the ground plane of the proposed antenna to achieve dual-band character; further CSRR equivalent circuit analysis is available in literature. The uniform CSRR gives dual bands at 2.08GHz & 3.92GHz against the proposed interest of 2.2GHz and 3.8GHz. Non-uniform CSRR is applied per the dimensions mentioned in Table 1 to obtain the required dual band. The proposed non-uniform CSRR results are -20.37dB at 2.2GHz & -32.37dB at 3.6GHz. The Proposed antenna design's top and bottom views are shown in **Figures 2**, where on top surface it is rectangular metal patch and bottom surface has single unit CSRR on ground plane. The return loss comparison in various cases is shown in Figure 3. The dimensions of the antenna and resonance frequency are the target variables. All antenna dimensions are the input variables for the ML optimization, which is explained in the subsequent chapters.

$$w = \frac{C}{2f_0\sqrt{\varepsilon_r}} \tag{1}$$

$$l_{eff} = \frac{c}{2f_0\sqrt{\varepsilon_{reff}}} \tag{2}$$

$$\varepsilon_{reff} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2}\left[1 + 12\frac{h}{w}\right]^{-1/2} \tag{3}$$

$$\Delta l = \frac{\varepsilon_{reff} + 0.300}{\varepsilon_{reff} - 0.258}\left[\frac{\frac{l}{h} + 0.262}{\frac{l}{h} + 0.813}\right] \tag{4}$$

$$l = l_{eff} - 2\Delta l \tag{5}$$

Table 1. Antenna Design Parameters

Parameter	Value in mm	Parameter	Value in mm
Substrate Length(X)	55	Feed Line arm Length(X-2)	10.425
Substrate Width (Y)	55	CSSRL Length(V1)	15
Patch Length(P-L)	19.41	CSRR Side Height(V2)	5
Patch Width(P-W)	25.35	CSRR Slit Gap(V3)	0.5
Feed Line Length(F-L)	24.5	CSRR arm length(V4)	7.25
Feed Line Insert (F-I)	6	CSRR Width(V5)	0.5
Feed Line Width(F-w)	3	CSRR Height(V6)	2

3 Machine Learning Algorithms

3.1 Introduction to Machine Learning:

Machine Learning (ML), the subset of Artificial Intelligence (AI), is one of the emerging technological solutions for various applications. It uses robust mathematical computation analysis in designing the model interims of input and output variables. It is mainly a data-driven system, where it expects huge data as input, which may be trained or untrained. Based on the type of data given, the type of learning system provides the mathematical model that best suits the given problem in identifying the

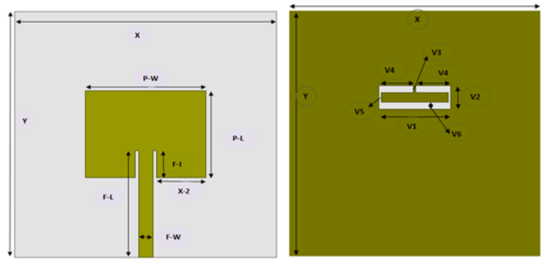

Fig 2. Proposed antenna top and bottom views

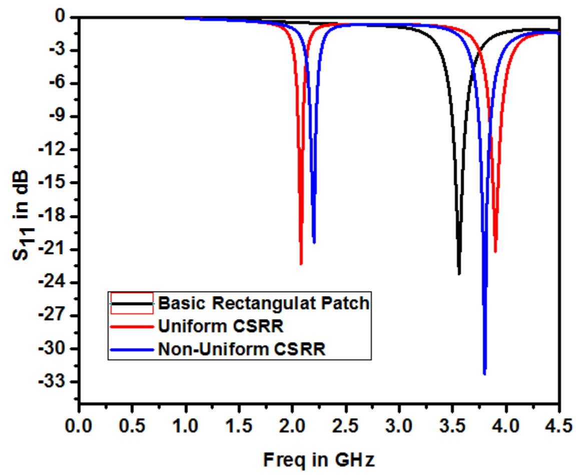

Fig 3. Return loss comparison of proposed antenna

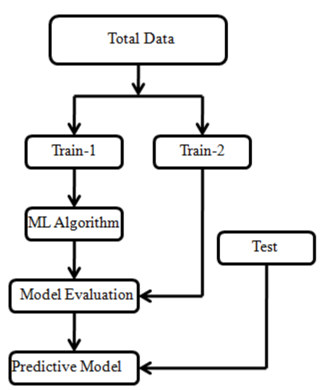

Fig 4. Block Diagram of ML Approach

better solution. There are three central learning systems: supervised, unsupervised, and reinforcement models, based on the type of data available.

The block diagram of the proposed ML model approach is shown in Figure 4. Once the model is obtained, it has to be tested for training and test data sets separately. Parametric validation, feature importance, and model efficiency are crucial for any ML model. Various model validation parameters available in the literature are mentioned in Table 2 for both regression and classification models. Addressing the model accuracy, over fitting, and under fitting problems is challenging for engineers. **Eq.6 to Eq.9** gives mathematical relations to calculate model performance, where 'P_i 'is the probability of the event; 'N' is the total number of records or events here in the data.

Table 2. Various ML model validation parameters

Regression	Classification	Recommender System
• Mean Absolute Error • Root Mean Square Error • R-Squared or adjusted R-Squared	• Recall • Precision • F1-Score • Accuracy • Area Under the Curve	• Mean Reciprocal Rank • Root Mean Square Error

$$Gini = 1 - \sum_{i=1}^{N} (P_i)^2 \tag{6}$$

$$Out\ Error = (Desired\ output) - (Predicted\ output) \tag{7}$$

$$Mean\ Square\ Error\ (MSE) = \frac{1}{N}\sum_{i=1}^{N}(Output\ Error)^2 \tag{8}$$

$$Root\ \ Mean\ Square\ Error\ (RSME) = \sqrt{MSE} \tag{9}$$

The sample data set required for ML is collected from HFSS simulator by keeping S_{11} as the target variables and frequency of operation and length, width of the patch as independent variables and all other parameters are kept constant. Next chapter explains the ML model performance of the proposed design.

3.2 Polynomial Regression:

The regression technique is a modified version of the linear regression model to obtain the relation between dependent and independent variables. It converts the original data feature to a polynomial one. Polynomial regression overcomes the limitation of the error function in linear one when we apply it to the non-linear database. Using polynomial regression over linear one in an antenna application is inevitable as the data set is non-linear. Higher-order polynomial helps to reduce the error function. The basic polynomial followed for any application is mentioned in **eq.10**.

$$Y = K_0 + K_1 x + K_2 x^2 + K_3 x^3 + \ldots\ldots\ldots + K_n x^n. \tag{10}$$

Y is the dependent variable; x is the independent variable, and K0, K1, K2, ….Kn coefficients of n_{th} order polynomial.

3.3 Random Forest Algorithm:

It is another supervised learning algorithm applicable to regression and classification techniques. It combines multiple classifications to solve a complex problem and provide a better mathematical model. Random forest algorithms consist of numerous decision trees of various data sets; the more trees there are, the better the model prediction accuracy is in overcoming the over fitting problem. Less training time over large data sets and handling the missing data points gives additional characteristics of random forest. Calculating mean square error and Gini-index is essential in analyzing classification and regression.

3.4 Extreme Gradient Boost (XG-Boost):

XGBoost is a robust greedy algorithm predominantly used to reduce the loss function in the decision tree model. It is applicable for both classification and regression models. Hyper parameter tuning is applied for better model performance by optimizing the model leaning process. Grid and random search is available in open source python. Controlling number of estimators, tree depth, and branches can be trimmed using this tuning process without compromising model performance. Here in this antenna model random search in XGBoost model is applied as part of hyper parameter tuning process such that it reduces the computation requirements with better model performance characteristics in terms of RSME.

4 Antenna Optimization in ML and validation

The main challenge of implementing the ML in antenna design is the availability of data sets. There are multiple variables in the antenna design, such as design parameters and performance parameters. The sample data of 2500 records is collected from the HFSS simulator by keeping return loss (S_{11}) and resonance frequency as the target variables. Out of 2500 records, 80% of data is considered training data, and the remaining 20% is kept for testing purposes randomly. All three models are created in Python language. The following chapters explain the implementation of ML techniques over the prepared data set of the proposed antenna.

4.1 Antenna Parametric Analysis using ML Algorithms

The polynomial regression of order two is applied over the entire data set mentioned, and it is observed that Root Mean Square Error and mean absolute errors were calculated in two modes: one is on the whole model, and the other is on the individual target parameters. The model's efficiency in any ML technique is less on the entire model; hence, it is better to follow the study model performance based on individual output parameters. The RSME of frequency and return loss at both bands in train and test cases is (0.079, 0.076); (4.946, 5.206); (0.299, 0.268); (5.069, 5.210) respectively. After introduction of hyper parametric tuning, it is observed to be (0.043,0.044); (3.669,3.983); (0.134,0.114); (3.584,3.711). The RSME, in Random forest and XGBoost techniques are mentioned in Tables 3 & 4 with and without parametric tuning. Among the three models, parametric tuning is applied on random forest and XGBoost. Here in XGBoost includes all the input parameters relatively better than the RF model.

Patch length and width play a crucial role in design optimization in terms of feature importance further, XGBoost covers all parameters with better matching RSME for train test cases. Figures 5 & 6 indicate the patch length and width optimization concerning all output parameters. Similarly, optimization of the other three input parameters is also available.

Table 3. Root Mean Square Error without hyper parametric tuning

Target Parameter	XGB-Train	XGB-Test	RF-Train	RF-Test	Poly-Train	Poly-Test
F-1	0.007	0.068	0.028	0.052	0.079	0.076
S11-1	0.761	4.290	1.425	4.339	4.946	5.026
F-2	0.016	0.340	0.098	0.306	0.299	0.268
S11-2	1.057	3.575	1.485	3.852	5.069	5.210

Table 4. Root Mean Square Error with hyper parametric tuning

Target Parameter	XGB-Train	XGB-Test	RF-Train	RF-Test	Poly-Train	Poly-Test
F-1	0.005	0.026	0.012	0.023	0.043	0.044
S11-1	0.525	2.626	0.826	2.553	3.669	3.983
F-2	0.010	0.091	0.030	0.091	0.134	0.114
S11-2	0.648	2.554	0.936	2.569	3.584	3.711

4.2 ML model validation

Among all three ML models used to optimize the proposed antenna in XGBoost post hyper parametric tuning RSME is in close agreement in train & test cases. Hence, the proposed antenna dimensions are optimized through XGBoost. The obtained patch length, width, CSRR slit gap, CSRR height, and width are 19.38mm, 23.56mm, 0.69 mm,2.1mm, and 0.67mm against 19.41, 24.35, 0.5, 2 & 0.5, respectively. Dimension optimization is observed without compromising the frequency and return

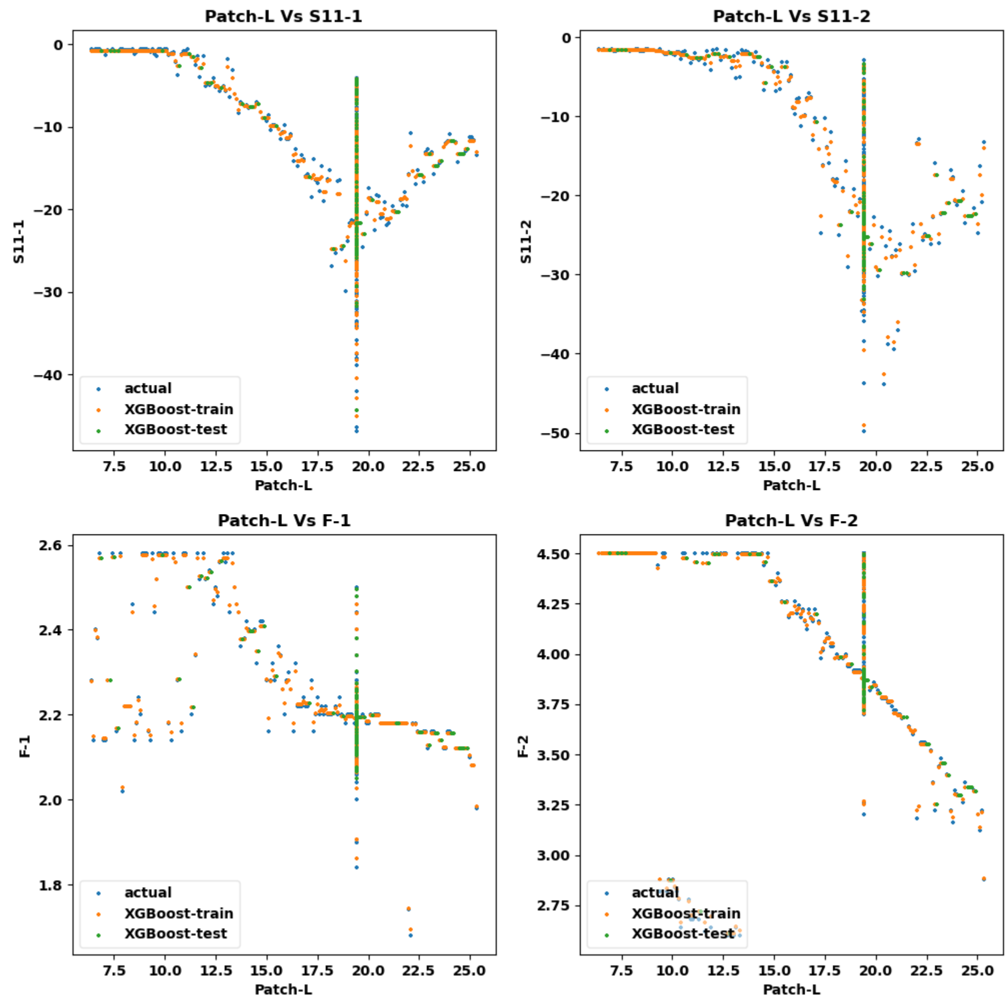

Fig 5. Patch Length optimization in XGBoost

loss values. The antenna dimension from the XGBoost technique is used for fabrication due to its low error rate. The real-time fabricated and tested antenna from ML dimensions is shown in Figure 7. The simulated return loss and gains of the proposed design from the ML model are compared with the measured one, which are shown in Figures 8 & 9. It is observed that fabricated and simulated results are in good agreement.

5 Results and Discussion

The proposed dual-band antenna at 2.2GHz & 3.6GHz over an FR-4 substrate of 1.6mm thickness with 4.4 dielectric constant values is designed. Return loss of -20.37dB & -32.27dB and maximum gain of 4.06dBi obtained from HFSS with inset feed and 50Ω Impedance match. A single complementary split ring resonator is slotted on the ground plane for the dual-band operation, and non-uniformity is introduced in the dimension of the CSRR for frequency shifting from 3.8 to 3.6GHz. The design optimization of the proposed antenna is performed using three powerful machine learning techniques: Polynomial Regression, Random Forest, and Extreme gradient boost by choosing the return loss& resonance frequencies of both bands as its target variables. HFSS is used for data collection in training and test data sets for all three machine learning techniques. The root mean square error is calculated in all three models as model performance metrics; further hyper parameter tuning was applied to reduce the error percentage. Basic simulation and dimensions obtained from the ML model are used for fabrication so that validation can be performed. The XGBoost technique performance is used to obtain the proposed antenna's dimensions.

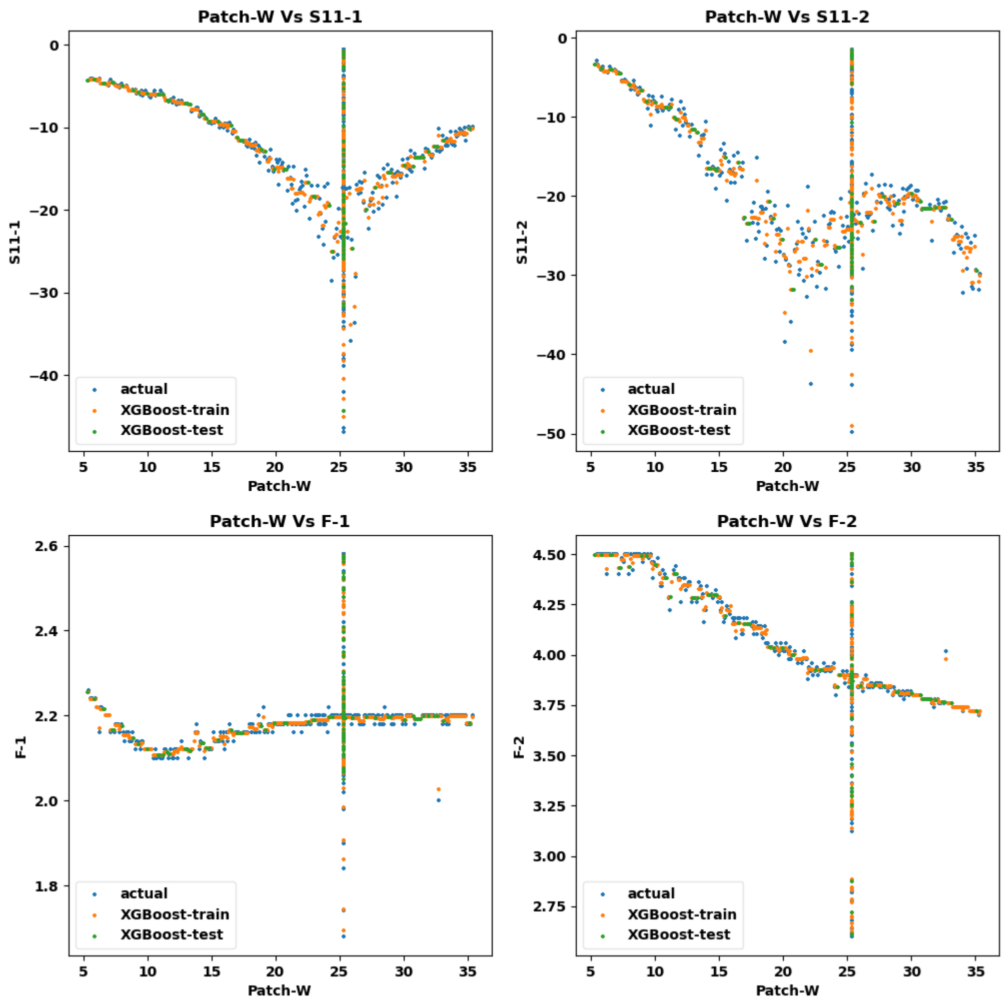

Fig 6. Patch Width optimization using XGBoost

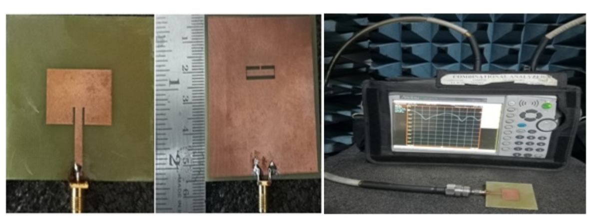

Fig 7. Fabricated Antenna top, bottom views along with test bed return loss

ML modeled antenna, the basic proposed one, and measured performances are observed to match in return loss. The return loss and gain comparison in all three cases is mentioned in Figure 8 & 9. Figure 10 explain the current distribution on the top and bottom surfaces of the proposed antenna at 3.6GHz and 2.2GHz, respectively. Further, the bandwidth obtained at the 2.2GHz band is 110MHz in measured result, which is a little high compared to the ML simulated and Proposed one, i.e., 95MHz & 85 MHz, respectively. The increase in the bandwidth is due to a change in the dimensions of the CSRR slot after the ML optimization. Radiation 3D pattern is mentioned in Figure 11 and feature importance of various antenna design parameters evaluated from Random forest and XGBoost models is mentioned in Figure 12. Clearly it is observed that metal patch length

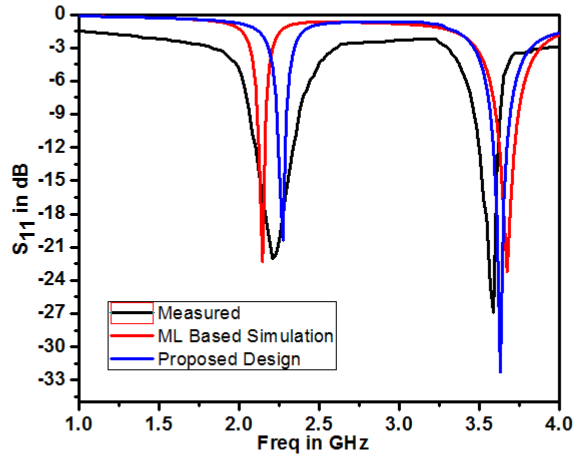

Fig 8. Returns loss validation

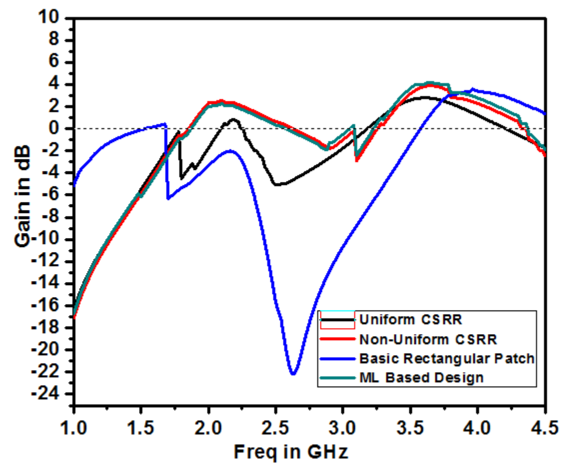

Fig 9. Gain Comparison of the proposed antenna

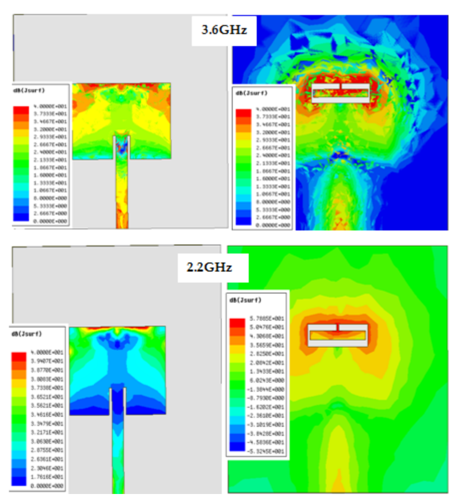

Fig 10. Current distributions on top & bottom surfaces at 3.6 & 2.2GHz Frequency

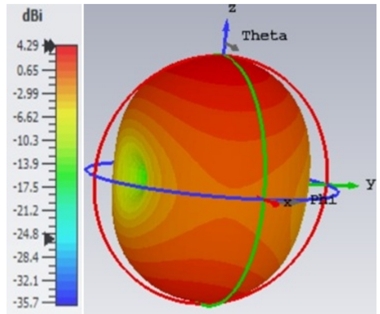

Fig 11. 3D Radiation pattern of the proposed antenna

&width are playing important role further XGBoost model is considering large number of parameters than random forest while calculating the model performance. Performance comparison with existing literature is mentioned in Table 5.

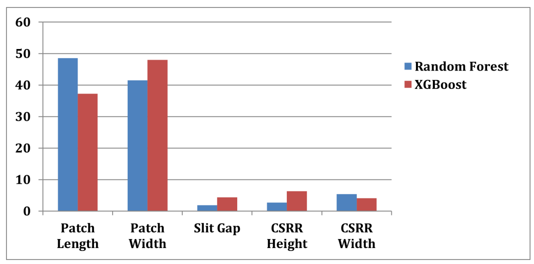

Fig 12. Feature Importance of proposed antenna design

Table 5. Performance comparison with the existing literature

Ref. No	Machine Learning Model	Validation of ML Model
(14)	Regression model	ML Validation and Fabrication are not available
(15)	Decision Tree and Random Forest	ML Validation and Fabrication are not available
(16)	Decision Tree, Random Forest, XGBosst	ML Validation and Fabrication are not available
(?)	Decision Tree, Random Forest, XGBoost	ML validation and ML-based fabrication are available with single band of operation
Present Work	Polynomial Regression, Random Forest, and XGBosst.	ML Validation with fabrication results with dual band operation and hyper parametric tuning

6 Conclusions

In this study, a dual-band microstrip patch antenna operating at 2.2 GHz and 3.6 GHz was designed and optimized using three advanced machine learning techniques: Polynomial Regression, Random Forest, and XGBoost. To address over fitting and under fitting issues, hyper parameter tuning was applied to the XGBoost model, resulting in enhanced predictive performance. The antenna is based on a rectangular patch with a complementary non-uniform split ring resonator (CSRR) integrated into the ground plane to achieve dual-band behavior. Among the models evaluated, the XGBoost model outperformed others in terms of root mean square error (RMSE) and was used to build a multi-target optimization model for predicting key antenna dimensions. The antenna was fabricated on an FR-4 substrate with a size of 55×55 mm^2, and optimized physical parameters including a patch length of 19.41 mm, patch width of 23.35 mm, CSRR height of 2 mm, slit gap of 0.5 mm, and CSRR width of 0.5 mm. The final predicted values from XGBoost—19.38 mm, 23.56 mm, 2.1 mm, 0.69 mm, and 0.67 mm were used in the last simulation and fabrication stage. The proposed antenna achieved return losses of –20.37 dB at 2.2 GHz and –32.27 dB at 3.6 GHz, with a peak gain of 4.06 dB and linear polarization. The machine learning models were trained using a dataset of over 2,500 records generated from HFSS simulations, and the predicted results showed close agreement with simulation and measurement, confirming the effectiveness and novelty of this data-driven design approach. However, the study has some limitations, including the use of FR-4, which introduces dielectric losses and limits efficiency at higher frequencies, and the dependency of the ML model on dataset quality, which may not fully account for real-world fabrication tolerances. Additionally, the models would require retraining for different antenna structures or materials. Future work may explore using low-loss substrates such as Rogers, applying deep learning models for improved non-linear predictions, extending the approach to multi-band or reconfigurable antennas, and conducting real-time testing in practical 5G and WiMAX environments to validate the antenna's robustness and real-world applicability.

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