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Original scientific paper

MACHINE LEARNING ASSISTED S11 PREDICTION FOR A SLOTTED SQUARE PATCH ANTENNA IN 5.8 GHZ WLAN BAND*

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Abstract. *This article explores machine learning techniques, specifically Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Gaussian Process Regression (GPR), to predict the S11 parameter of a slotted square patch antenna optimized for Wireless Local Area Network (WLAN) operation between 5.6 GHz and 5.85 GHz. The antenna, measuring 30x30x1.6 mm³ and centered at 5.725 GHz, features a coaxial probe feed design with a circular slot within the square patch to enhance bandwidth. These ML methods demonstrate superior efficiency compared to traditional simulation tools, enabling robust exploration of design configurations and accurate prediction of the antenna's electrical and physical characteristics. Notably, Gaussian Process Regression (GPR) consistently reveal lower Mean Squared Error (MSE) and higher R-squared (R^2) values than ANN and SVM, suggesting superior accuracy in modeling the antenna's performance metrics.*

Key words*:* *Machine Learning, mean square error, S11, bandwidth*

1. INTRODUCTION

Machine learning (ML) has achieved huge attention for its capability to automate tasks and provide deep insights across diverse scientific and engineering disciplines. While still developing, ML has notably impacted several industries, including antenna design and optimization. ML has brought forward innovative methods that enhance efficiency, adaptability, and performance in antenna systems. Traditionally, antenna design was heavily

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reliant on complex mathematical models and precise parameter adjustments to achieve optimal performance. This traditional approach involved several steps, including defining the antenna shape and tuning parameters using simulation tools, which, although accurate, required considerable manual effort and iterations. On the other hand, ML techniques streamline the prediction and optimization of antenna parameters, making the process much faster and simpler compared to traditional simulation tools. These methods are remarkably favorable for handling complex antenna designs and high-dimensional parameter spaces. The effectiveness of ML methods [1-2] is affected by factors such as the complexity of the design, the optimization algorithm used, and the level of automation in the ML models. By integrating simulation tools with ML methods, a more comprehensive and efficient approach to antenna optimization can be achieved, improving the overall design evaluation process. This combined approach leverages the strengths of both methodologies, resulting in a more rapid and effective optimization workflow [3-4].

In [5], for analyzing the radiation pattern and estimating antenna's resonant frequency of patch antenna, tunnel-built multi-slot and hole-coupled patch antenna was designed with implementation of Artificial Neural Network (ANN) followed by Genetic algorithm(GA). It predicted that results of GA-coupled a ANN matched with theoretical and experimental results. In [6], with the implementation of Support Vector Regression, a rectangular patch antenna was optimized and when compared to ANN showed high computational competence. In [7], array antenna was suggested and it was observed that by employing Support Vector Machines (SVMs) with a Gaussian Kernel was more proficient at designing antennas with exceptional precision. In [8], the accurate prediction of resonant frequencies for E-shaped compact microstrip antennas (ECMAs) was achieved using two robust techniques, namely the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Support Vector Machine (SVM). The antenna was designed to operate within the UHF band. In [9], a heuristic optimization algorithm called the Fruit Fly Optimization Algorithm (FOA) was proposed and applied in array factor synthesis and horn antenna design. While its utilization for optimizing antenna designs has been limited, it has shown promise in the synthesis of array factor analytical functions. In [10], a machine learning-based technique for optimizing antennas and estimating parameters efficiently was introduced. The Multi-Stage Collaborative Machine Learning model demonstrated exceptional results by combining minimal Normalized Root Mean Squared Error values with reduced computational time. In [11] Gaussian Process Regression (GPR) was employed to optimize various parameters for a multiband microstrip antenna. Slot loading was successfully incorporated to reduce the overall size of the antenna. In [12], a compact MSA with dimensions 33x33mm^2 using GPR covered a frequency range of 0.48 GHz–7.84 GHz. The study explored dependencies related to the antenna's resonant frequency, including material properties, electrical characteristics, the presence of a slot, and patch dimensions. In [13], a miniaturized monopole antenna with a band-notched feature and coplanar feeding was designed and optimized using Machine Learning (ML) algorithms. The antenna exhibited stable radiation characteristics suitable for Ultra-Wideband (UWB) applications, and among the ML algorithms used, K-Nearest Neighbor (KNN) stood out for its excellent prediction accuracy. In [14] a model for antenna classification using Fuzzy Inference Systems (FIS) was introduced with a classification model employing Decision Trees (DT) achieved an impressive accuracy rate of 99%. Furthermore, a geometric parameter estimation model using FIS delivered a Mean Absolute Percentage Error (MAPE) of under 5.8%.

This paper extensively explores machine learning techniques including SVM, ANN, and GPR to analyze the performance of a slotted square patch antenna by predicting the S11 parameter. Operating within the 5.6 GHz to 5.85 GHz band, the antenna is particularly suitable for IEEE 802.11a (5.725 GHz ∼ 5.825 GHz) applications. For obtaining the dataset, the proposed antenna was designed by employing High Frequency Simulator Structure (HFSS vs.19) and later on the above dataset was used for training and testing the ML models. Section 2 provides a theoretical background on SVM, ANN, and GPR. Section 3 presents both simulated and fabricated models of the suggested antenna, offering insights into simulated and measured results. In Section 4, the effectiveness of SVM, ANN, and GPR in predicting the S11 plot is discussed, evaluated using R-squared scores (R^2) and Mean Squared Error (MSE).

2. Background

Machine learning techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Gaussian Process Regression (GPR) offer substantial benefits over traditional tools like High Frequency Simulator Structure (HFSS), computer simulation technology (CST) etc., especially in their predictive capabilities. These ML methods excel in quickly processing large datasets, detecting patterns, and providing accurate predictions of antenna performance metrics like S11. In contrast, traditional simulation tools typically require more time-consuming iterative processes to achieve similar results.

2.1. Artificial Neural Networks (ANN)

Artificial Neural Networks have demonstrated to be versatile tools with applications spanning across diverse domains. Their ability to learn from data, recognize complex patterns, and formulate predictions makes them a foundational technology in the domain of machine learning. An ANN comprises of interconnected neurons organized into layer, and by adjusting weights and biases in the connections between these neurons information is processed as depicted in Figure 1. In this structure, signals denoted as x_1 to xn originate from signal sources or other neurons, where w_i represents the weight for the ith connection, and θ serves as the threshold (commonly referred to as bias). The relation of input and output [15-17] is related as depicted by equation 1.

$$y = f(\sum(w_i * x_i) - \theta) \quad (1)$$

Here, y is the neuron output, w_i links to the weight connected to the ith linking in the neural network, x_i is the ith point inside the input vector, f relates to activation function, and θ denote neuron threshold value.

2.2. Support Vector Machines (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm designed for both classification and regression tasks. The key aim is to reach peak margin, indicating the distance joining the hyperplane and the nearby support vectors starting in each class. The relationships (linear and non-linear) in data are well managed by SVM [18-19], eased by the use of kernel functions. Recognized for robustness and excellent generalization to new, unseen data, SVMs have garnered widespread application across diverse domains such as image classification, text classification, and bioinformatics, solidifying their status as a versatile cornerstone in the realm of machine learning.

Consider an SVM model, with the input vector x_i and the corresponding desired value y_i from the training data set $\{(x_i , y_i)\}_{i=1}^{P}$ where P is the entire number of data patterns. Support Vector Regression (SVR), a variant of SVM for regression, defines the approximation function f (x) as in equation 2.

$$f(x) = \langle w, d(x) \rangle + b \tag{2}$$

f(x) is a non-linear mapping vector that transforms the input variable x_i into a high-dimensional space. The terms w and b represent the weight vector and bias, respectively, with $\langle\cdot,\cdot\rangle$ denoting the inner product.

To build a non-linear machine, a non-linear mapping vector is created to transform the data into a feature space. Then, a linear model is constructed in this high-dimensional space to perform regression. The weight vectors and biases are determined by minimizing the regression risk function [8] as illustrated in equation 3.

$$\text{Rreg} = C\sum_{i=1}^{P} L_i\left(x_i y_i, f(x_i)\right) + \frac{1}{2}\|w\|^2 \tag{3}$$

Where C represents the regularization parameter, determining the tradeoff between the empirical loss function and model complexity. $L_i(x_i, y_i, f(x_i))$ represents the epsilion sensitive loss function, and $\frac{1}{2}\|w\|^2$ characterizes the modeling complexity.

2.3. Gaussian Process Regression (GPR)

Gaussian Process Regression (GPR) serves as a probabilistic approach in machine learning tailored for regression tasks. Diverging from conventional regression models that yield a single predicted value, GPR distinguishes itself by furnishing a distribution of potential outcomes, thereby supplying valuable uncertainty estimates [20-21]. It is an effective method for performing dynamic inference, offering precise function approximation in high-dimensional spaces based on given datasets, GPR leverages a non-parametric Bayesian approach to address regression problems, using Bayesian inference to portray complex relationships between inputs and outputs. The general formulation for GPR, rooted in Bayesian analysis, is expressed as depicted by equation 4.

$$y=f(x)+\epsilon \tag{4}$$

Here, f represents the function value, y is the observed target value, and ϵ denotes additive noise, which is normally distributed with a mean of zero and a variance of σ_n^2
In matrix form, this can be written as shown below:

$$Y = x^T w + \epsilon \tag{5}$$

where x^T is the input vector and w represents the vector of weights (parameters) of the linear model. The weight vector w follows a Gaussian prior with covariance matrix Σ p is given by equation 6.

$$w \sim N(0, \Sigma\, p)x^T \tag{6}$$

The Bayesian linear model makes inferences based on the posterior distribution over the weights, determined by Bayes' theorem which are predicted by equation 7 and 8.

$$\text{Posterior} = \frac{\text{likelihood x prior}}{\text{marginal likelihood}} \tag{7}$$

$$P(w|y, X) = \frac{p(y|x,w)p(w)}{p(y|X)} \tag{8}$$

3. PROPOSED ANTENNA

3.1. Antenna structure

For this study a slotted square patch antenna is simulated using High Frequency Simulator Structure (HFSS vs.19) software with dimensions Lp and Wp is constructed on an FR4 substrate of height h and is excited using a coaxial probe having impedance of 50Ω. Figures 1(a)–1(c) show the top-view, bottom-view, and side-view of the proposed antenna, respectively. To enhance the performance parameters of the square patch antenna, a circular slot with a radius r_c is incorporated into the radiating patch. The position of circular slot and coaxial probe is optimized to improve the functioning of the patch antenna by broadening its bandwidth and for achieving better impedance matching. Table 1 provides the various dimensions of the patch antenna, and Figure 2 displays the fabricated prototype model.

Table 1 Parameters of the proposed antenna model

Parameters	Values (mm)
Length of ground plane (Lg)	30
Width of Ground plane (Wg)	30
Length of substrate (Ls)	30
Width of substrate (Ws)	30
Patch length (Lp)	11.1
Patch width (Wp)	11.1
Circular Slot radius (r_c)	2
Position of coaxial probe in x-axis (xf)	0
Position of coaxial probe in y-axis (yf)	-2
Position of circular slot on xy plane (x_c, y_c, z_c)	(2,2,1.6)

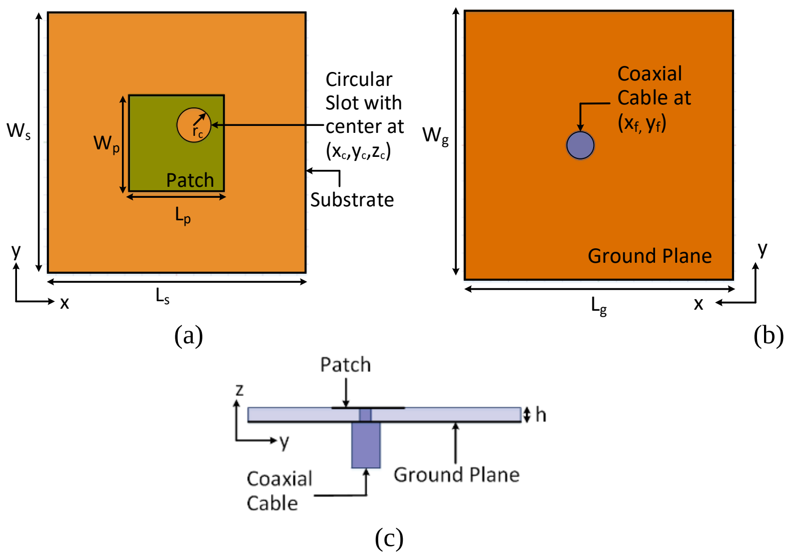
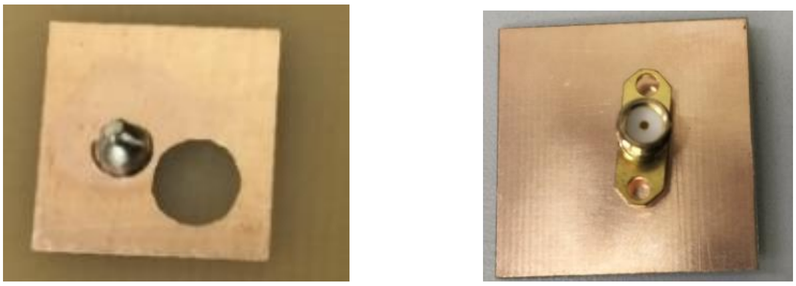


Fig. 1 Proposed Antenna geometry. (a) Top-view (b) bottom-view (c) side-view

Figure 2 illustrate the fabricated prototype of the antenna, with the results of the antenna being measured with the help of vector network analyzer.



(a) (b)

Fig. 2 Fabricated model of proposed Antenna (a) Top view (b) bottom view

3.2. Analysis of simulated and measured results

Figure 3 presents a detailed comparison of the simulated and measured S11 of the antenna across frequencies, showing that the proposed antenna achieves an impedance bandwidth from 5.6 GHz to 5.85 GHz. Figure 4 analyzes the gain versus frequency, indicating a peak gain of 4.2dBi. The strong agreement between measured and simulated results, with minor differences due to fabrication and connection losses, is noteworthy. Figure 5 illustrates the simulated radiation patterns of the proposed antenna in both the E-plane and H-plane at 5.79 GHz.

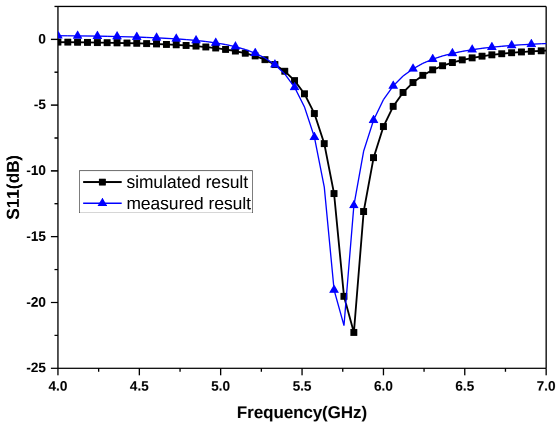


Fig. 3 S11 versus frequency (simulated, measured) of Proposed Antenna

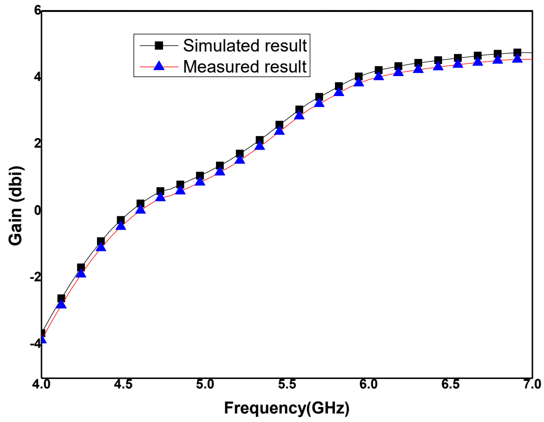


Fig. 4 Gain versus frequency (simulated and measured) of Proposed Antenna

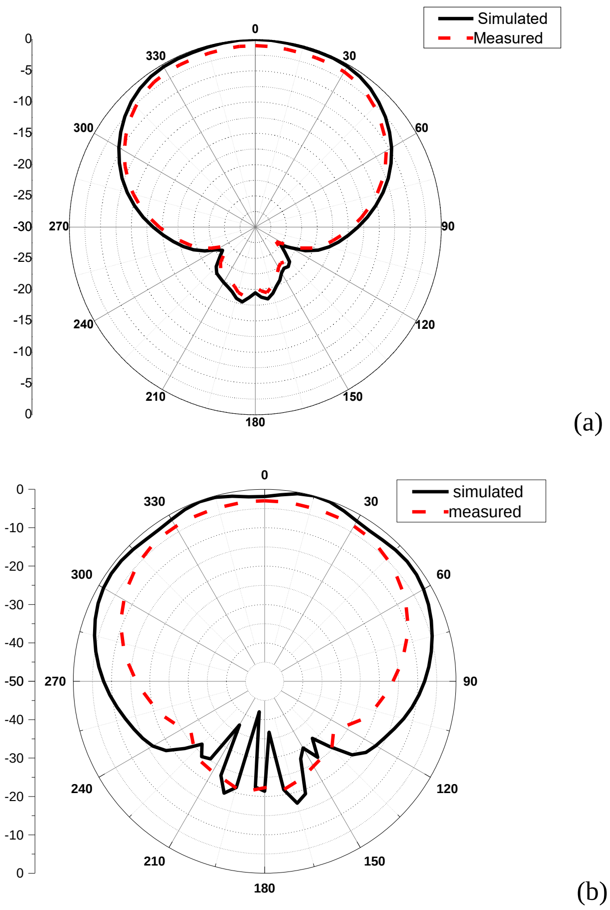


Fig. 5 Radiation pattern (simulated and measured) at 5.79 GHz of the proposed antenna

4. IMPLEMENTAION AND DISCUSSION USING ML TECHNIQUES

This section throws insights about machine learning algorithms being employed to predict S11 of slotted patch antenna. Initially, the dataset is loaded and then divided into a training set (80%) and a test set (20%), following standard practices. The training set is employed to train three ML models (ANN, SVM,GPR) with various parameters. Once the model is trained, predictions are made using the test set. Finally, the Mean Squared Error (MSE) and the R-squared (R^2) score are calculated to assess the model's accuracy by comparing the predicted results with the actual data.

4.1. Data set

The dataset used for prediction was obtained by designing the proposed antenna using HFSS simulator in which the variation of S11 with frequency in the range of 4 GHz to 10 GHz was observed. The performance parameters of the envisioned antenna are subject to analysis across various slot size (r_c), patch length (Lp), feed position in y direction (yf) and ground plane length(Lg) and its width (Wg) and their effect on S11 is observed. In total 14700 records was collected which comprised of 2100 rows and 7 columns. The dataset include the independent features (f, Lp, Lg, Wg, rc, yf) and the corresponding S11 values Each one of the 2,100 rows represents a distinct combination of the independent parameters along with the corresponding S11 values across the range of frequencies. The dataset comprised of six independent variables (f, Lp, Lg, Wg, rc, yf) forming the first six columns, with S11 as the dependent variable in the last column. The independent variables were sampled across the relevant range during simulations as depicted in Table 2 to capture the S11 behavior as the independent features (f, Lp, Lg, Wg, rc, yf) and the corresponding S11 values.are generated utilizing the High frequency structural simulator (HFSS vs.19).

Table 2 Sampling strategies

Parameters	Range	Step size	Total data samples
Length of patch (Lp)	11.0 mm≤ Lp≤11.2 mm	0.1 mm	2100 with 80% on training and 20% on testing
Length of ground plane (Lg)	27.0 mm≤Lg≤32.0 mm	1.0 mm	
Width of ground plane (Wg)	27.0 mm≤Lg≤32.0 mm	1.0 mm	
Radius of circular slot (rc)	1.0 mm≤rs≤4.0 mm	1.0 mm	
Feed distance in y-axis direction (yf)	-1≤rf≤-4	1.0 mm	
Frequency (f)	4 GHz≤f≤10 GHz	0.06 GHz	

4.2. Preprocessing and sampling of data

The dataset generated from the High-Frequency Structure Simulator (HFSS) required initial preprocessing to ensure it was structured correctly for machine learning applications. This involved organizing the dataset so that each data sample occupied a row, with each feature represented in its own column. The dataset included six independent features—frequency (f), Length of Patch(Lp), Length of Ground Plane (L)g, Width of Ground Plane (Wg), Radius of Circular Slot (rc)and Feed Distance in the y-axis y with the S11 parameter as the dependent variable in the seventh column. Following preprocessing, the data was split into training and testing sets. Specifically, 80% of the data was allocated for training the model, while the remaining 20% was set aside for testing. This split is crucial for evaluating the model's performance, as testing helps determine how well the model can generalize to new, unseen data [22-23]. The testing phase also plays a significant role in identifying issues such as overfitting or underfitting, which may necessitate exploring alternative models to achieve better results.

Figure 6 illustrates the steps taken during the preprocessing and sampling stages of the dataset.

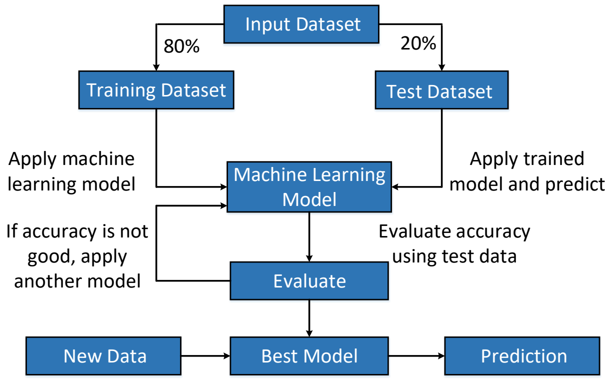


Fig. 6 Basic flowchart of implementation

4.3. Training of SVM, ANN, and GPR algorithm

Three machine learning algorithms -SVM, ANN, and GPR are trained on the dataset to find the relationship between antenna parameters and performance metrics. After being trained, these models can be deployed for predicting the performance of various antenna configurations. The architecture of above three techniques along with their S11 prediction are illustrated in this section.

(a) ANN architecture

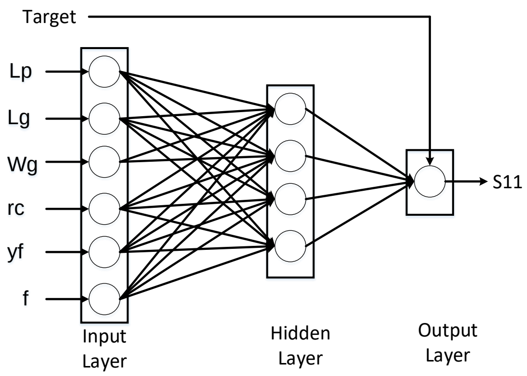


Fig. 7 ANN architecture

Figure 7 highlights an Artificial Neural Network (ANN) model designed to predict S11 values from a set of input features. This model features an input layer with 6 attributes: frequency, lp, ls, lw, yf, and r1. It includes one hidden layer, consisting of 128 neurons activated by the rectified linear Unit (ReLU) function. The output layer is a solitary neuron tailored for regression tasks, specifically predicting S11 values. The model's performance was evaluated employing Mean Squared Error (MSE) and the R-squared score (R^2). While no specific targets for MSE or R^2 were set, the objective was to achieve a low MSE and a high R^2, reflecting improved performance. Training utilized the Adam optimizer with a learning rate of 0.001, and the MSE was adopted as the loss function. The model underwent training for 500 epochs, using default batch size settings provided by Keras. The training process began with data loading and initial examination. Data was imported from a CSV file, with any extraneous whitespace removed from column names. The dataset was split into input features (X) and target values (y), and then divided into training (80%) and testing (20%) subsets. The Standard Scaler was applied to normalize both features and target values.

The ANN was developed using the Keras Sequential API, configured with the Adam optimizer and MSE loss function, and trained on the normalized training data. Post-training, the model's effectiveness was assessed on the test set using MSE and R^2 metrics. Furthermore, the predicted S11 values were plotted against the frequency, as depicted in Figure 8.

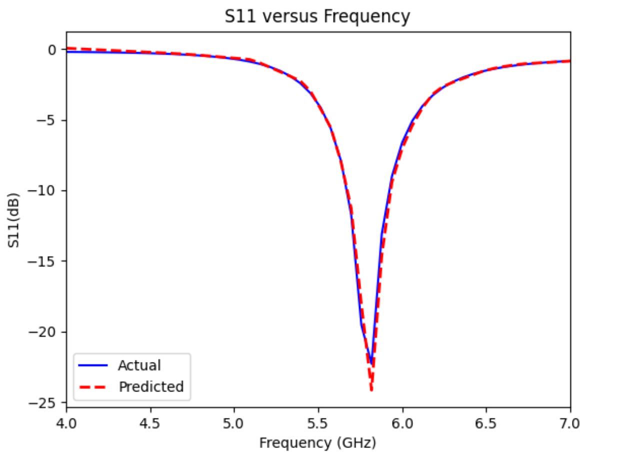


Fig. 8 S11 versus frequency (actual and predicted) using ANN model

(b) SVM architecture

Support Vector Machine (SVM) is basically deployed for classification issues, whereas the Support Vector Regression (SVR) is a type of SVM and it adapts the SVM concept to predict continuous values rather than discrete class labels. The SVM model's architecture as shown in figure 9 featured a SVR including a Radial Basis Function (RBF) kernel. The desired modeling accuracy was evaluated using Mean Squared Error (MSE) and R-squared score (R^2) with aim on minimizing MSE while maximizing R^2. GridSearch CV was employed for hyperparameter tuning, searching across a specified range for parameters C, gamma, and epsilon. An 11-fold cross-validation ensured robust model evaluation and avoided overfitting. Data preprocessing involved loading data from a CSV file, extracting features, and the S11 values as the target variable. The data was normalized using StandardScaler. The model's finest configuration was chosen based on the lowest MSE obtained during cross-validation. Post-training, the model's functioning was evaluated using MSE and R^2 metrics. These metrics were saved to a CSV file, and a plot comparing actual and predicted S11 values against frequency was generated as depicted in figure 10. The entire process leveraged Python libraries such as pandas, numpy, matplotlib, and scikit-learn, with careful attention to reproducibility by setting a random seed. This comprehensive approach ensured a well-tuned and accurately evaluated SVR model.

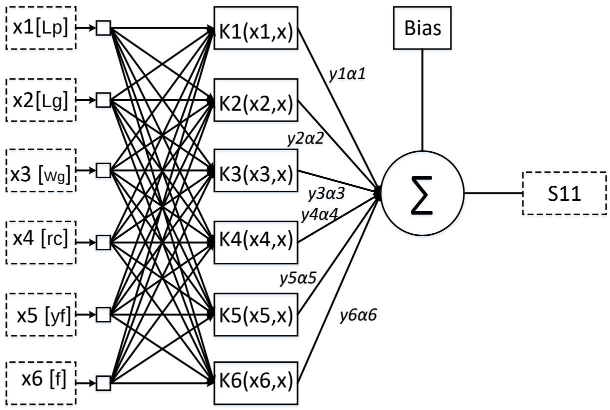


Fig. 9 SVM architecture

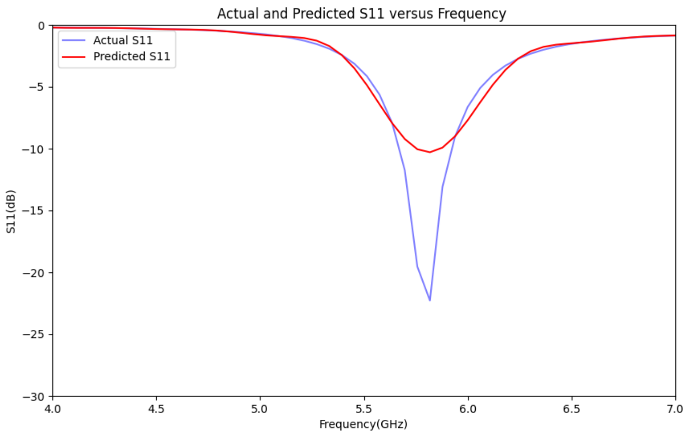


Fig.10 S11 versus frequency (actual and predicted) using SVM model

(c) GPR architecture

Gaussian Process Regression (GPR) model as illustrated in figure 11is employed to predict S11, which is a measure of reflection coefficient in antenna design, based on model input features such as frequency, lp, ls, lw, yf, and r1. After training, the model predicts

S11 values for given frequencies, allowing for accurate characterization and optimization of antenna performance.

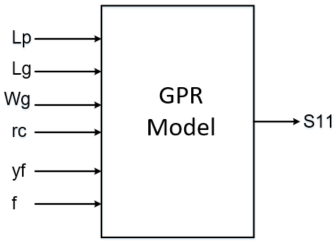


Fig. 11 GPR model

The desired modeling accuracy was evaluated using MSE and R^2, with the goal of achieving a low MSE and a high R^2, indicating better performance. The GPR model utilized a combination of a Rational Quadratic kernel and a White kernel, with hyperparameters such as length scale set to 1.0, alpha to 0.5, and noise level to 0.1. The data preprocessing involved standardizing both the features and the target variable using Standard Scaler to ensure they have a mean of 0 and a standard deviation of 1, which helps in improving the model performance. From the dataset features were extracted along with the target variable. The training process included sorting the data by frequency, scaling the features and target variable, and fitting the GPR model on the scaled data. After training, MSE and R^2 of the the model was evaluated, and the predictions were inverse-transformed to obtain the actual predicted values. The results were visualized by plotting the authentic and predicted S11 values against frequency as illustrated in figure 12.

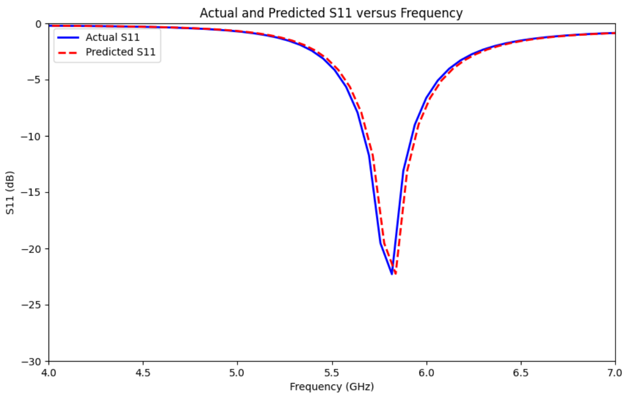


Fig. 12 S11 versus frequency (actual and predicted) using GPR model

(d) Predicted results from ML models

Table 3 displays the R-square score and the MSE value which are exploited to assess the performance of the machine learning model. R-square score gives the response of how good our model is in terms of accuracy. It is the amount of variation in the output dependent attribute that can be predicted based on the input independent variable as depicted in equation 9.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \tilde{y})^2} \quad (9)$$

$\hat{y}$ is the predicted output

$\tilde{y}$ is the mean value of output

Mean squared error is measured as the average squared variation among predictions and actual observations as shown in equation 10.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N} e_o^2 \quad (10)$$

Where e_o is output error given by difference in desired output and expected output

Table 3 Different models R-square score and mean squared error

S. No	Model	R-square score	MSE
1.	ANN	0.92	0.05
2.	SVM	0.78	0.005
3.	GPR	0.99	0.00003

Table 3 indicates that GPR has better performance metrics as its MSE is very low (0.00003) and the R square score being very high (0.99) in comparison to the other two model. This showcases that the prediction of GPR is the best. .Figure 13 shows the plot of S11 variation with frequency as predicted by the GPR model, alongside the simulated and measured results. It is observed that the prediction of S11 plot by GPR matches to the simulated results.

The machine learning models used in this study greatly decrease computation time compared to HFSS simulations, as detailed in Table 4. The table presents the time required to predict the S11 parameter over the frequency range of 4 GHz to 10 GHz for the optimized antenna parameters.

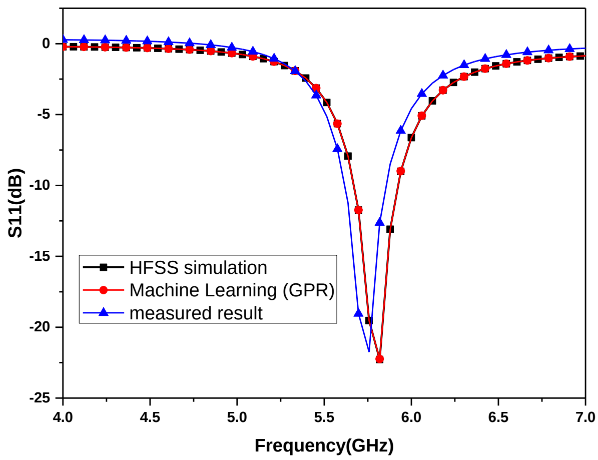


Fig. 13 S11 versus frequency (simulated, machine learning, measured) of Proposed Antenna

The ML models outperform HFSS in terms of speed, with GPR being the quickest, followed by ANN and SVM. The computation times reported in the manuscript were achieved on a system with the following hardware specifications: Intel(R) Core(TM) i5-8350U CPU, 4 cores, 7.8 GB RAM, running Windows version 11.

Table 4 Comparison of Computational Time between HFSS and ML Models (ANN, SVM, GPR)

S. No	Parameter	HFSS	ANN	SVM	GPR
1.	Time	15mins	10 ms	100 ms	5ms

5. Conclusion

This paper introduces square patch antenna with a circular slot being designed using HFSS. The optimized antenna design is not only theorized but also fabricated and rigorously tested, confirming its operational frequency range spanning from 5.6 to 5.85 GHz making it suitable for applicable for 5.8 GHz WLAN band. The study also employs Artificial Neural Network, Support vector machine, and Gaussian Process Regression to predict parameters, specifically focusing on the prediction of the S11 parameter. Notably, Gaussian process regression emerges as the algorithm providing the most accurate predictions.

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