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Comparative analysis of machine learning models to predict rectangular patch antenna dimensions

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Abstract: The nonlinear relationship between the antenna characteristics and their electromagnetic responses makes the design and optimization process difficult. In the face of these difficulties, antenna engineers use several techniques, including machine learning, because they have great capabilities that make them a very useful tool that can help researchers in this field. In this study, four machine Learning methods, artificial neural network (ANN), random forest, decision tree, and support vector regression (SVR), were used to predict the dimensions of a rectangular patch antenna by utilizing a dataset comprising 3111 simulated samples collected using high-frequency structure simulator (HFSS). The results showed that the random forest with 100 estimators exhibited outstanding performance in terms of prediction accuracy, with a mean square error (MSE) of 0.52.

Keywords: Artificial neural networks, decision tree, patch antenna, random forest, support vector regression

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1. Introduction

An antenna, which is an electrical system that radiates and receives electromagnetic energy, is a pivotal element in modern wireless communications. There are several types of antennas, such as horn antennas, dipole antennas, slot antennas, and patch antennas (Balanis, 2016; Kaur et al., 2021).

Since its discovery in 1953 by Deschamps (1953), patch antennas have been widely used due to their many advantages such as small size, lightweight, low cost, and ease of manufacturing (Dai et al., 2021). This type of antenna supports dual-polarization, and it is easy to mount on a rigid surface. All these features have made it common and widely used in many applications such as IoT (Elijah & Mokayef, 2020), military systems (Koçer & Aydemir, 2020), medical systems (Zaki et al., 2022), Radar systems (Palanivel Rajan & Vivek, 2019) and communication systems (Rana & Smieee, 2022).

Recently, with the development of wireless communication systems, the demand for antennas with higher specifications and capabilities has increased, which has motivated researchers and antenna designers to exploit the available technologies, tools, and resources that may help improve the efficiency and capabilities of antennas more accurately.

The non-linear relationship between various variables and dimensions of the antenna on the one hand, and between the electromagnetic results obtained by the several simulation software on the other hand (Chen et al., 2022), makes the design and optimization process difficult. In response to these challenges, antenna designers used several optimization techniques, including genetic algorithm (Boudjerda et al., 2022), particle swarm optimization (Girija et al., 2020), machine learning (Erricolo et al., 2019), and more. Specifically, Machine Learning (ML) has a great impact on this field.

The use of various machine learning algorithms and models to derive a relationship that can link the geometric dimensions of the antenna with its electromagnetic responses gave significant results, which made it a very powerful and useful tool in this field to deal with the non-linear relationship between the different variables in such problems, and this is done by extracting Non-linear characteristics from datasets that contain a large number of samples, which leads a prediction of new inputs from aspects of probabilities, which reduces considerable time and effort for designers compared to conventional methods. Figure 1 shows the traditional approach to antenna parameter optimizations.

Machine learning is a crucial branch of artificial intelligence that aims to develop models and systems that infer and learn from data, enabling them to perform tasks and make decisions on their own without explicit programming. It depends on analyzing patterns and taking advantage of them to achieve continuous improvement in performance, unlike traditional programming (Ghosh et al., 2023).

Figure 2 summarizes the differences between a traditional software system and one based on machine learning. In machine learning (Figure 2-b), we provide the system with input data and corresponding output data (results), and the system generates a model (program) capable of transforming input into output. In contrast, in traditional software systems (Figure 2-a), we manually identify patterns in the data and then write code (program) to process the data and produce the desired outcome (results).

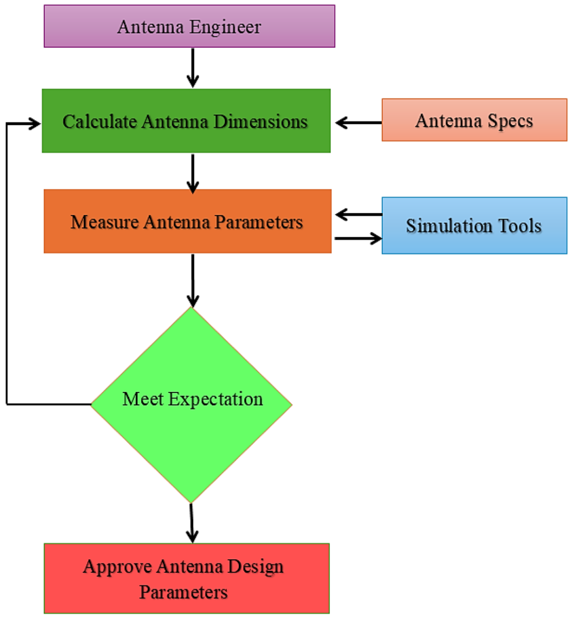

Figure 1. The traditional approach to antenna parameter optimizations.

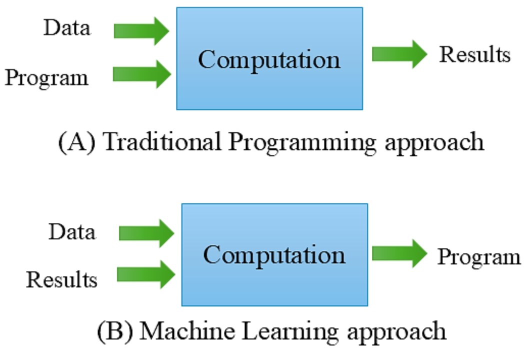

Figure 2. Difference between machine learning and conventional programming (Management Association, 2022).

Since the 1990s, a continuous development, the application of machine learning in the field of antennas has shown promising results, which brought it got the attention of many researchers (Choudhury et al., 2015).

Several machine learning algorithms have been applied by engineers in the field of antennas, in this work four algorithms have been used, which are artificial neural networks (Patil et al., 2023), support vector regression (Dai et al., 2022), random forest, and decision tree (Pavithran et al., 2021), concerning the results among all these algorithms, random forest showed an outstanding performance.

In this research work, we propose a novel approach of predicting patch antenna dimensions using several machine learning models such as ANN, SVR, random forest and decision tree using a dataset of 3111 simulated samples gathered through HFSS Simulation software.

This paper is organized as follows: the second section talks about the configuration of the antenna and the construction of the dataset, while in the third section, the machine learning algorithms were defined and implemented, in the fourth part, the evaluation criteria were discussed. In the fifth section, the performance of the models was tested and evaluated through the obtained results. Lastly, the conclusions were summarized.

2. Antenna structure and dataset

So far, and unlike some other fields, there is no unified dataset available for microstrip antennas that is considered a reference for researchers (El Misilmani et al., 2020). Because of this reason, everyone resorts to building a dataset from their own experience.

In this research, a rectangular patch antenna was designed using HFSS simulation software v 15.0, which is a powerful tool commonly employed in the field of electromagnetic analysis and antenna design. HFSS, which stands for High-Frequency Structure Simulator, enables engineers and researchers to simulate and analyze electromagnetic behavior accurately, it is an essential tool for predicting how antennas will behave in real-world conditions. To use HFSS, a Windows operating system with at least 16 GB of RAM, a multi-core processor, a compatible graphics card, and sufficient disk space for installation and data storage is required (Ansys HFSS, 2024). To obtain a dataset to be used in building machine learning models, the antenna illustrated in Figure 3 was created. The antenna was designed using an FR-4 substrate which was chosen for its widespread use and reliability in PCB manufacturing, with dimensions of 60 mm × 60 mm × 1.6 mm. The substrate thickness is 1.6 mm, the dielectric constant is $\varepsilon_r = 4.4$, and the loss tangent is $\tan\delta = 0.02$. The initials dimensions of the antenna can be obtained as follows:

2.1. Width of the patch

$$\mathrm{Wp} = \frac{\mathrm{c}}{2*\mathrm{Fr}}\sqrt{\left(\frac{\epsilon_\mathrm{r}}{2}\right)} \tag{1}$$

Where:
c: The speed of light,
Fr: The resonant frequency,
ϵ_r: The dielectric constant.

2.2. Length of the patch

$$\mathrm{L_{eff}} = \frac{\mathrm{c}}{2*\mathrm{Fr}*\sqrt{\epsilon_{\mathrm{eff}}}} \tag{2}$$

The effective dielectric constant ∈_eff is given by

$$\epsilon_{eff} = \left(\frac{\epsilon_r+1}{2}\right) + \left(\frac{\epsilon_r-1}{2}\right)\left(\sqrt{\left(1+\left(\frac{12h}{Wp}\right)\right)}\right) \tag{3}$$

Where h is substrate height and wp is the patch width.

2.3. Dimensions of the ground plane

$$\mathrm{W_{g_{=\,Wp+6h}}} \tag{4}$$

$$\mathrm{L_{g_{=Lp+6h}}} \tag{5}$$

The proposed antenna structure is depicted in Figure 3.

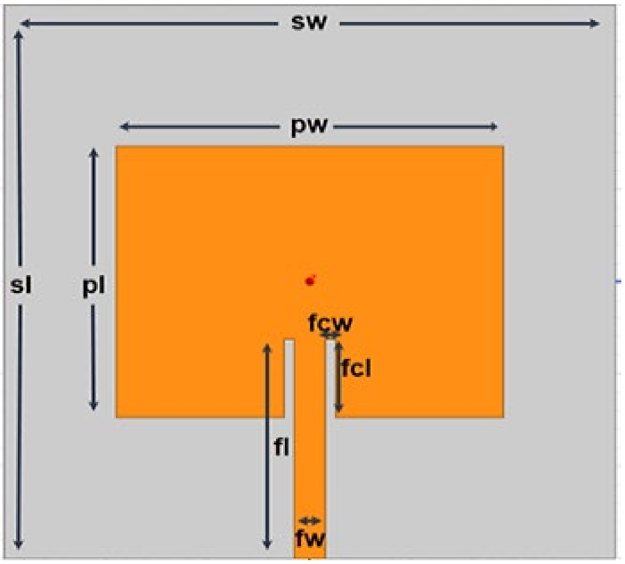

Figure 3. The proposed antena.

Figures 4 to 7 illustrate various performance metrics of the proposed microstrip patch antenna obtained using HFSS software.

2.4. Return loss

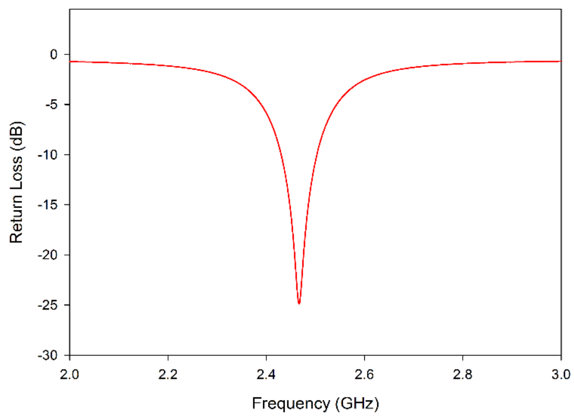

Figure 4. Return loss.

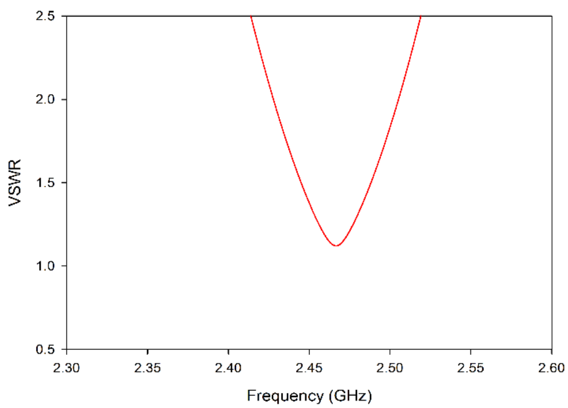

Figure 5. VSWR.

Return loss parameter of an antenna is a measure of its ability to transmit and receive signals efficiently which can be obtained by Equations (6) and (7) (Balanis, 2016). Figure 4 displays Simulated return loss Vs. frequency plot of proposed antenna obtained by HFSS. We could observe that the designed antenna is providing -24.88 dB return loss value at frequency of 2.46 GHz. This significant return loss at the specified frequency indicates excellent impedance matching and efficient radiation, making the antenna highly suitable for applications operating at this frequency.

$$\Gamma = \frac{z_L - z_0}{z_L + z_0} \tag{6}$$

$$Return\ Loss = -20 \log_{10} |\Gamma| \tag{7}$$

Where:
Γ: the reflection coefficient.

2.5. Voltage standing wave ratio

The standing wave ratio (VSWR) is a crucial parameter that is inherently linked to the operating frequency and the return loss (Equation 8). It quantifies the efficiency of power transfer from the transmission line to the antenna. A lower VSWR value, closer to 1, signifies better impedance matching and minimal signal reflections (Balanis, 2016). In the provided VSWR plot (Figure 5), we observe that the VSWR values are consistently between 1 and 2 across the entire frequency range of our proposed antenna. This indicates a good impedance match between the antenna and the transmission line, ensuring efficient power transfer with minimal reflections. The VSWR value reaches its minimum at approximately 1.1208 at the frequency of 2.467 GHz, indicating the best match at this frequency.

$$\mathrm{VSWR} = \frac{1+|\Gamma|}{1-|\Gamma|} \tag{8}$$

Where:
Γ: Return loss value.

Table 1 provides a comparison between Voltage Standing Wave Ratio (VSWR) and Return Loss (in dB)

Table 1. Comparison between VSWR and return loss.

VSWR	Return Loss (dB)	Description
~1.1:1	~24.88 dB	Excellent matching, very minimal reflection.
~1.2:1	~20 dB	Very good matching, small reflection.
~1.5:1	~15 dB	Good matching, noticeable reflection.
~2.0:1	~10 dB	Acceptable matching, some reflection.
~2.5:1	~6 dB	Poor matching, significant reflection.
~∞:1	0 dB	Total reflection. Open circuit, cut, or no load.

2.6. Gain

Figure 6 presents the three-dimensional radiation pattern of the antenna, illustrating its gain across different directions in space. The gain, which measures the ability of the antenna to direct radiated power in a specific direction compared to an isotropic radiator, is depicted on a scale where the antenna attains a maximum value of 2.59 dBi. This value indicates that the antenna has a directional preference, focusing more energy on certain directions, which is crucial for applications requiring targeted communication. The three-dimensional plot provides a comprehensive view of how the antenna performs in all spatial directions, allowing for a better understanding of its overall efficiency and directivity.

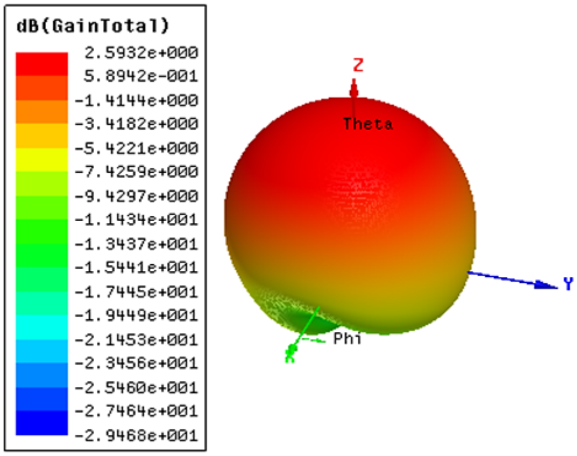

Figure 6. Gain.

2.7. Radiation pattern

Figure 7 shows the two-dimensional polar plot of the antenna radiation pattern, offering a cross-sectional view of the gain at specific planes. The radiation pattern is crucial for understanding how the antenna radiates energy in specific directions relative to its structure. In this plot, the red line represents the radiation pattern at a plane where the azimuth angle phi is 0 degrees, while the violet line corresponds to the radiation pattern at phi = 90 degrees This polar plot helps in visualizing the directional characteristics of the antenna in these specific planes, showing how the gain varies with the angle in each case. The differences between the red and violet lines highlight the anisotropic nature of the radiation, where the antenna's performance varies depending on the orientation.

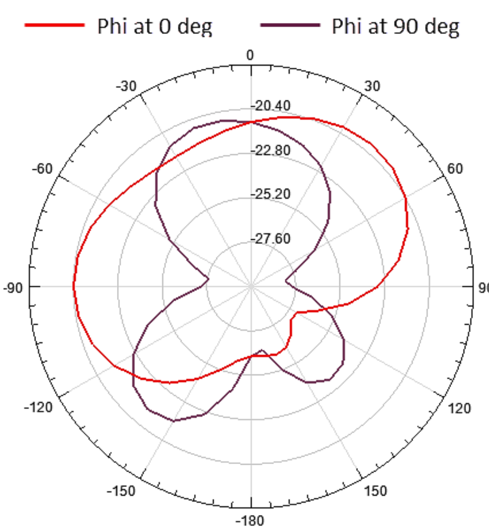

Figure 7. 2D radiation pattern (at phi=0 deg, phi=90 deg).

2.8. Dataset collection

By changing the patch width from 26 to 31 mm with an increment of 0.1 mm and patch length from 35 to 41 mm with an increment of 1 mm to create different design configurations, a dataset of 3111 rows was collected. This dataset was stored in a table in a CSV (comma-separated values) file. The table contains five columns: patch length, patch width, frequency, bandwidth, and S11. The remaining variables were fixed to avoid the complexity of the work. The different design parameters are listed in Table 2.

Table 2. Parameters of antenna.

Parameter	Description	Value
Pl	Patch length	35mm to 41mm
Pw	Patch width	26mm to 31mm
Sw	Substrate Width	60mm
Sl	Substrate length	60mm
Fl	Feed length	23.8mm
Fw	Feed width	3.1mm
Fcw	Feed cut width	0.95mm
Fcl	Feed cut length	8.5mm
h	Substrate height	1.6mm

The dataset was divided into two parts: the first part contains 80% of the data and is used to train the models, while the second part contains 20% of the data and is used for testing. This division is in accordance with the recommendations in Grigorev (2021), ensuring that the models were trained on most of the data while being validated on unseen examples.

3. Machine Learning algorithm Implementation

With the dataset ready, we employed machine learning algorithms to predict the antenna dimensions based on desired performance metrics. In this research, SVR, random forest, ANN, and decision tree algorithms were chosen because they are capable of handling prediction tasks very well.

3.1. Decision tree

The decision tree stands as a prevalent machine learning algorithm applicable to classification and regression tasks, embodying a tree-like structure delineating decisions and their ensuing outcomes. Within the domain of machine learning, it serves to conceptualize decision-making predicated upon various features or attributes. Commencing with a singular node representing the entirety of the dataset, the algorithm iteratively partitions the dataset into smaller subsets contingent upon the values of specific features or attributes. This recursive partitioning continues until a predefined stopping criterion is met (Camacho, 2023).

3.2. Random forest

The random forest technique stands out as a highly potent tool utilized in predictive analytics. It yields results that are competitive with both boosting and adaptive bagging methodologies. By integrating random features alongside boosting, heightened accuracy in outcomes can be achieved, particularly when handling expansive datasets. However, it's worth noting that in certain instances, the application of random forest may predispose the model to overfitting, potentially resulting in noisy classifications or regressions (Chandra & Hareendran, 2021).

3.3. SVR

SVR, or support vector regression, is a machine learning technique derived from Support Vector Machine, tailored for regression tasks. It finds application in classification, regression, and signal processing. SVR effectively handles non-linear and high-dimensional challenges by employing the principle of local minimization (Rivera et al., 2023).

3.4. ANN

Artificial neural networks (ANN) are founded upon the structural and functional principles of biological neural networks in humans. Serving as a collection of algorithms, ANN possesses the capability to discern patterns inherent within datasets. These patterns are discerned from vectors, which serve as numerical representations encapsulating diverse forms of data. The primary objective of neural networks is to facilitate the clustering and classification of data points. Through the utilization of ANN, unlabeled data exhibiting similarities can be effectively grouped and classified, thereby enhancing the understanding and analysis of complex datasets (Gao et al., 2022).

Figure 8 shows the different steps involved in building artificial intelligence (AI) models to predict the antenna's length and width. The process begins with reading the dataset, followed by dividing it into two parts: 80% for training and 20% for testing. The different models mentioned above are then trained on the training data. Once the training is completed, the next step is to make predictions using the testing data. Finally, the results are evaluated by calculating the mean squared error between the actual data and the data predicted by the model.

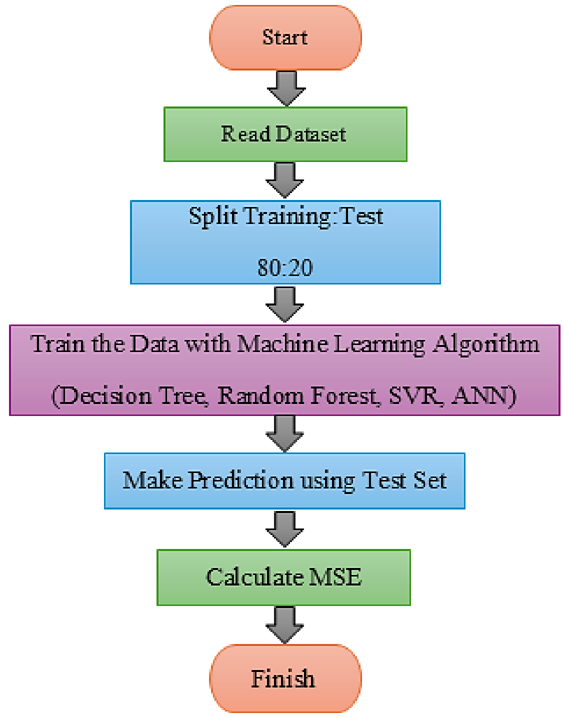

Figure 8. Different steps of building an artificial intelligence model.

4. Evaluation metrics

The various models that were implemented in this study can be evaluated through the following criteria:

Loss function

In regression analysis, the loss function is a mathematical function that measures the error between the predicted values and the actual values. The lower the loss function value, the better the prediction. There are several different loss functions that can be used in regression analysis, each with its strengths and weaknesses. Some of the most common loss functions include:

4.1. Mean squared error (MSE)

is a measure of the accuracy of a predictive model. It is calculated as the average of the squared errors between the predicted values and the actual values. The lower the MSE, the more accurate the model (Grigorev, 2021). It's computed using the following equation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \quad (9)$$

4.2. Mean absolute error (MAE)

is a measure of the average absolute difference between predicted and actual values. It is calculated by taking the absolute value of the difference between each predicted value and its corresponding actual value and then averaging the absolute differences. The lower the MAE, the better the fit of the model to the data (Hossain, 2023). MAE can be calculated using Equation (10):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| \quad (10)$$

4.3. Root mean square error (RMSE)

is a measure of the average magnitude of the difference between predicted and actual values. It is calculated by taking the square root of the mean of the squared differences between the predicted values and the actual values. The lower the RMSE, the better the fit of the model to the data. RMSE tells us how large are the errors that our model makes (Grigorev, 2021). It is calculated using the following formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \quad (11)$$

5. Results

In this section, all the MSE results obtained for each algorithm are presented.

5.1. Random forest MSE result

As shown in Figure 9, the MSE value gradually decreases with the increase of N-estimators from 0.61 to 0.53 and stabilizes almost after 60 to give its lowest value of 0.52 with N-estimator equal to 100.

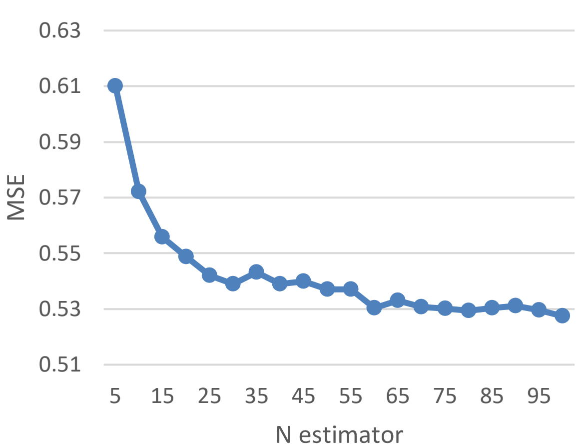

Figure 9. Random forest MSE result.

5.2. SVR MSE result

Figure 10 shows MSE for different values of epsilon and gamma. Where employed to refine the prediction outcome. Epsilon delineates the permissible error range, while gamma elucidates the influence of the trained data. When gamma is 0.1, the MSE value is around 0.65. When gamma is 0.01, the MSE value is around 16. When gamma is 0.001, the MSE value is around 0.87. When gamma is set to 0.01, the MSE value is approximately 1.05. Lastly, with gamma set to 0.0001, the MSE value is approximately 1.95. Thus, it can be concluded that gamma significantly impacts the prediction results. As the gamma parameter increases, the MSE value also increases. When altering the epsilon value, it doesn't yield as notable a difference as gamma. Therefore, it can be deduced that the epsilon parameter refines the prediction outcome. The lowest MSE is achieved when gamma is set to 0.1.and epsilon is 0.1.

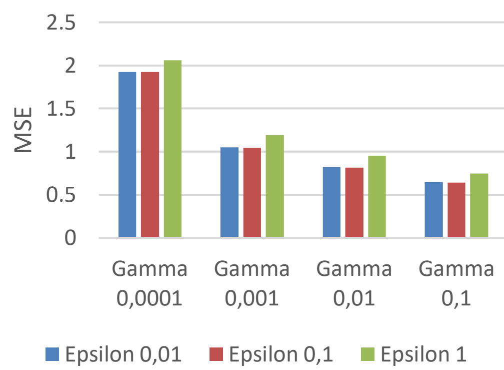

Figure 10. SVR MSE result.

5.3. Decision tree MSE result

Figure 11 illustrates the MSE values across various random states. The MSE decreases as the random state is incremented from 0 to 5, ranging from 0.65 to 0.60. Regrettably, the MSE rises until it reaches until it the value of 0.73 when the random state is elevated to 25. Afterward, it varies until the random state reaches 35. The MSE reaches its minimum when the random state is set to 5. The fluctuating outcome occurs due to the inherent nature of the random state, which randomly selects the data.

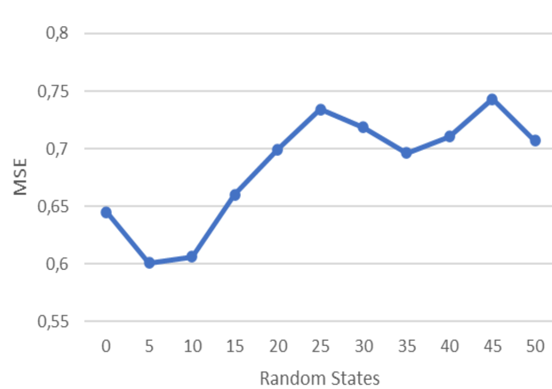

Figure 11. Decision tree MSE result.

5.4. ANN MSE result

The decrease of the MSE value with the increase in the number of hidden layers, recorded the lowest value at the number of layers 6, to return to fluctuation after that, as shown in Figure 12.

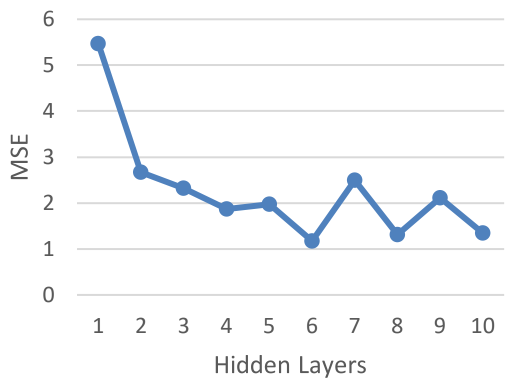

Figure 12. ANN MSE result.

6. Result comparison

The best prediction results obtained from the four algorithms are listed in Table 3 with their parameters.

Table 3. Best results obtained.

Algorithm	Parameter	MSE
ANN	Hidden layers 6	1.17
Decision tree	Random state 5	0.6
Random forest	N-estimator 100	0.52
SVR	Gamma 0.1, Epsilon 0.1	0.64

As shown by Table 3, the ANN algorithm reaches the lowest MSE of 1.17 when the network has six hidden layers, The decision tree algorithm achieves its lowest MSE of 0.6 at random state 5, whereas the random forest achieves 0.52 with 100 estimators. And the last for the SVR algorithm, the MSE value of 0.64 is reached when the gamma is 0.1 and the epsilon is 0.1. Among all these algorithms, the random forest algorithm exhibited the best performance in predicting the antenna dimensions.

In Table 4, we compared our results with those obtained in similar studies utilizing machine learning techniques for antenna design and optimization.

Table 4. Comparison with related research papers in literature.

Ref.	Methodology	Result
(Su et al., 2022)	ANN	MSE: 0.484%
(Sathuluri et al., 2022)	SVM	RMSE: 0.1163
(Aoad, 2021)	Decision tree	MSE: 0.038
(Kumawat & Agarwal, 2021)	ANN	MSE: 0.2249
This work	Random forest	MSE: 0.52

7. Conclusions

This paper presents research on the use of machine-learning algorithms to predict the size of rectangular microstrip patch antennas. Four algorithms were used for prediction: ANN, SVR, decision tree and random forest. The results showed that a random forest with 100 estimators provided the best prediction accuracy, with a mean square error (MSE) of 0.52. This means that it is now possible to estimate the dimensions of rectangular microstrip patch antennas according to the specified parameters, which was not possible before using antenna simulation software.
Future research can explore the inclusion of more design parameters such as substrate material properties, different patch shapes (circular, elliptical), and varying feed techniques. This can help in creating more generalized models that can predict the dimensions for a wider range of antenna types.

Conflict of interest

The authors have no conflict of interest to declare.

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