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Monopole Antenna Parameters Prediction using Machine Learning for IoT Systems

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Abstract Antenna design necessitates heavy simulation processes that require effort and time. However, the significant advancements in Artificial Intelligence (AI) approaches and the availability of relevant computational facilities have encouraged researchers to overcome the design constraints. Thus, this paper presents an approach for designing an antenna with an elliptical radiator for Internet of Things (IoT) applications using a Machine Learning (ML) algorithm. ML algorithms are utilized to optimize antenna designs, thereby minimizing simulation time and accelerating the overall design process. The geometric parameters of the antenna serve as inputs to the ML model, using a dataset comprising 200,200 samples. The model focuses on two output parameters: bandwidth and the reflection coefficient (S11).
Initially, efforts were directed toward predicting the decibel magnitude of the reflection coefficient using various ML algorithms, and the outputs were compared with each other to justify their performance. Additionally, predicted outcomes obtained from ML algorithms are compared with those from simulation results to validate the accuracy of these approaches. The antenna design is suitable for the frequency spectrum from 3.55 GHz to 6.9 GHz. The Random Forest Regressor algorithm yielded the most accurate results for predicting the reflection coefficient parameters, achieving an R-squared value of 99.927%, a MSE of 3.41%, an MAE of 4.43%, and an RMSE of 18.4%.

Keywords: Antenna Design; Artificial Intelligence; Internet of Things (IoT); Machine Learning.

1 Introduction

IoT refers to a network of interconnected things, utilizing physical devices embedded with software tools that facilitate effective and efficient data exchange with various systems. Additionally, challenges associated with IoT applications and adoption are site-specific. Application systems operating in rural or desert settings typically contain sensor units that must often be deployed across a wide surface area. These nodes are typically small, battery- or solar-powered units that require minimal power consumption to minimize maintenance efforts and associated costs. Similarly, a central node is interfaced with a cellular network, which may be located tens of kilometers away, for sending the collected data to the internet, accessible by monitoring and control centers [1].

Modern wireless communication can be complicated, making traditional antenna design methods challenging [2]. Antennas play a crucial role in modern communication networks, serving as the vital link between electronic devices and the electromagnetic spectrum. In the context of increasingly complex communication systems, antenna design optimization has become a crucial necessity to achieve optimal system performance. Moreover, conventional design methodologies often exhibit a very limited ability to handle the subtleties of modern requirements; thus, machine learning techniques have emerged recently as a strong paradigm. These indeed offer a wide range of new solutions that facilitate the design phase and enhance antenna performance, thereby overcoming the limitations inherent in conventional approaches.

Because Electromagnetic (EM) simulation tools are computationally expensive and exhibit a nonlinear relationship between design parameters and performance, antenna design is a challenging task. These problems are addressed by machine learning, which trains on simulated data to predict antenna performance quickly and accurately, eliminating the need for repeated simulations. Because of this, design time is decreased, and effective optimization across wide parameter spaces is made possible.

The authors in [3] proposed a 2×1 "Mickey-shaped" microstrip patch array that operates at 2.45 GHz (ISM band) and is fabricated on Rogers RT/Duroid substrates. Covers 2.42-2.465 GHz with HFSS simulation and VNA

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validation. The measured gain is approximately 9.2 dBi, with high agreement between the modeling and testing results.

This section presents the impedance response predictions for a two-layer, single-material structure. Moreover, a new prediction model was further developed based on an equivalent electric circuit. Quite often, using 3D EM simulation software to achieve optimum antenna performance is challenging and time-consuming. Challenges in all these areas are being addressed through the application of ML and DL to optimize antenna design, thereby enabling the prediction of resonance frequency, gain, reflection coefficient, and bandwidth, among others. Furthermore, these techniques facilitate the selection of the appropriate antennas for wireless applications [4–10]. For example, the authors in [11] proposed a microstrip patch antenna model using an ANN to predict antenna dimensions and resonance frequencies. However, the study did not evaluate the prediction accuracy of the ANN model using error metrics such as MSE, MAE, or RMSE, nor did it compare the ANN model predictions with those of other existing ML models. Another similar study focused on predicting the resonance frequency of patch antennas using an ANN [12].

Koziel proposed a machine learning-based framework incorporating an infill criterion for optimizing antenna designs. The approach significantly reduces computational costs while maintaining high accuracy in predictions. The method is beneficial for scenarios where optimization is resource-intensive [13]. Authors in [14] investigated the use of Deep Learning (DL) and Machine Learning (ML) algorithms to predict antenna design parameters, utilizing a dataset of 1,000 samples to enhance design efficiency.

The authors of [15] proposed AI approaches for optimizing IoT antenna designs. It demonstrates how AI can improve adaptability, efficiency, and performance, addressing the challenges of IoT systems that require versatile and efficient antennas.

This study employed supervised regression ML algorithms to predict antenna gain and resonance frequency accurately. The findings highlight the potential of machine learning to enhance the design and optimization process of antennas, providing reliable predictions [10]. This investigation utilized ML to optimize the characteristics of microstrip patch antennas.

Different ML classifiers are investigated in the paper [16] to detect the faults in solar panel systems. Decision Tree, KNN, Random Forest, and Extra Trees obtained a 1.000 F1 score, demonstrating very high efficiency. Only AdaBoost performed worse (0.591). These results highlight strong models for improved diagnostic precision, dependability, and cost-effectiveness in solar technology.

The results highlight the effectiveness of ML models in simplifying the design process and improving the efficiency of parameter optimization [17].

In [11], an Artificial Neural Network (ANN) a study proposed to be used in the design of a 'microstrip patch antenna,' to anticipate its dimensions and resonance frequencies. Error metrics such as MSE, MAE, or RMSE were not used to evaluate the accuracy of the predictions. Furthermore, the ANN model was not performed as well as other machine learning methods to ensure the validity of the predictive performance.

In general, ML models can be broadly categorized into three categories, namely, parametric, non-parametric, and semi-parametric, based on the nature of their parameterization methods [4]. In the case of a parametric model, the representation of the training data is done with the help of a fixed-size set of parameters, irrespective of the size of the training set. Examples include RSM, RBF models, ANN, DL, Elastic Net, and CatBoost.

Non-parametric models do not make strong assumptions about the mapping function and are flexible enough to adapt to the training data. Examples include RF, Extreme Learning Machines (ELM), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees (DT). Semi-parametric models incorporate the features of both parametric and non-parametric approaches. An example is the Kriging regression model [4].

From a deep learning perspective, advanced models such as Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GAN), and Convolutional Neural Networks (CNN) have been recently proposed for regression and classification tasks. The substantial contribution of recent breakthroughs in the research on ML has substantially improved the design parameters of electromagnetic devices, with recent results improving the accuracy, efficiency, and reliability of predictions.

The author in [18] compared MobileNetV1, V2, and V3 network architectures for classifying clean vs. dusty PV surfaces. Trained with 400 well-balanced images, MobileNetV1 obtained the best result (training accuracy 88.53%, validation accuracy 91.25%, F1-score 0.9114) and MobileNetV3 the worst. Results validate that MobileNetV1 is the most effective strategy for automating PV surface identification, enabling faster monitoring and higher power generation.

Table 1 summarizes the literature survey on antenna designs using ML and AI for IoT.

This work presents the prediction of the reflection coefficient (S11) of the proposed antenna design using six ML algorithms, namely Linear Regression (LR), Random Forest Regression (RFR), Artificial Neural Networks

(ANN), Decision Tree Regression (DTR), Lasso Regression, and Elastic Net Regression. To validate the accuracy and reliability of the predicted results, the performance metrics used were MSE, MAE, and RMSE [4].

Table 1 Comparison of related work

Approach	Optimization method	Advantages	Disadvantages
Regression-based ML models [13]	Machine learning with an infill criterion Computational efficiency and accuracy.	Significant cost reduction with high prediction accuracy.	Limited to specific optimization scenarios Limited applicability to different antenna types
Neural networks and regression models.[14]	Deep learning and machine learning regression Prediction accuracy, RMSE, MAE	Improved prediction for complex dual-band antennas.	Computationally intensive. Incomplete training and dataset details. Focused only on dual-band antennas. Risk of overfitting
Ensemble and hybrid AI techniques. [15]	AI-driven optimization framework Performance improvement, adaptability.	Enhanced adaptability and efficiency for IoT antennas.	Limited generalizability without dataset scaling
Random Forest, Gradient Boosting, SVM.[10]	Supervised regression & MSE, RMSE, Accuracy	Accurate predictions for gain and resonance frequency.	Sensitive to dataset quality and model tuning
Regression models [17]	ML-based optimization model & Optimize efficiency and accuracy.	Simplifies the design process with effective predictions.	Focused on microstrip patch antennas only Lacks depth in design analysis. Broad coverage with limited technical detail. ML role not deeply explored.

The following are the key contributions of this research work:

- Simulation and Analysis: The proposed antenna design is simulated and analyzed with electromagnetic simulation tools.
- S11 Prediction: In this regard, the reflection coefficient, S11, is predicted by using different machine learning algorithms.
- Demonstration of reduced simulation time while maintaining prediction accuracy.
- Development of a machine learning-based surrogate model for efficient antenna design
- Comparative Analysis: A comparison study of different models is presented based on predicted results.

The rest of the paper is organized into the following sections: Section 2, entitled "Proposed Antenna Design"; Section 3, "Machine Learning Model to Optimize the Design Radiation using Machine Learning Models"; and Section 4 presents the work conclusion and future work.

2 The Proposed Design of the Antenna

Various antenna designs have been proposed for IoT applications [19–20]. The structure of the proposed antenna is illustrated in **Fig. 1**. In the proposed antenna design, three elliptical radiators are etched onto one side of the FR4 substrate, which has a dielectric constant of 4.3 and a thickness of 1.6 mm. The other side features a partial ground plane. The proposed design enables the adjustment of various geometric parameters, thereby increasing the range of input variables for machine learning algorithms. Changing the dimensions of the patch and the ground plane can fine-tune the operating frequency and bandwidth of the antenna to meet certain performance requirements. The optimal geometrical parameters, as shown in **Table 2**, were obtained through EM simulation.

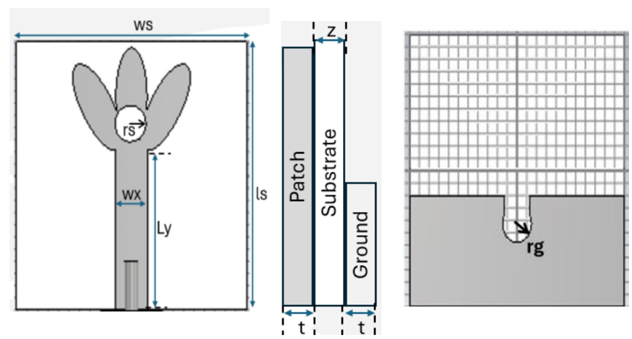

Fig. 1 Schematic of the proposed antenna design

Table 2 Parameters and dimensions of the proposed antenna

Parameters	value(mm)
W_S	22
L_S	22
r_s	1
Z	1.6
t	0.035
r_g	1
w_x	3
L_y	8

2.1 Simulation Results of Proposed Antenna

Figure 2 shows the design procedure for the antenna evaluations. It includes three steps for designing the antenna (antenna 1, antenna 2, and the proposed antenna 3) to satisfy the required specifications. Antenna-1, as shown in **Fig. 2a**, is considered the first step of the antenna, which consists of one elliptical shape. The simulated S11 result in **Fig. 3** reveals that antenna-1 has two resonance modes at 5.5 and 12 GHz, with a reflection coefficient of approximately -20 dB (matching is not excellent).

In the second step, a copy of the previous ellipse is rotated at an angle of θ = 30∘, θ = -30∘, and concatenated with the elliptical radiator from step 1 as shown in **Fig. 2 (b)**. Antenna-2 has two resonance points with a reflection coefficient of about -28 dB (matching is good). As a result, Step 3 has improved the bandwidth and reflection coefficient of -55 dB (matching is excellent). Furthermore, a circular slot is inscribed in step 3 to enhance the result. The variations of S11 vs Frequency with corresponding bandwidth for different steps are illustrated in **Fig. 3**.

The proposed antenna has a bandwidth of approximately 3.55 GHz to 6.9 GHz, suitable for IoT systems. The designed antenna has a single resonant frequency of 5.4 GHz. The reflection coefficient value of the proposed antenna is -55 dB at 5.4 GHz.

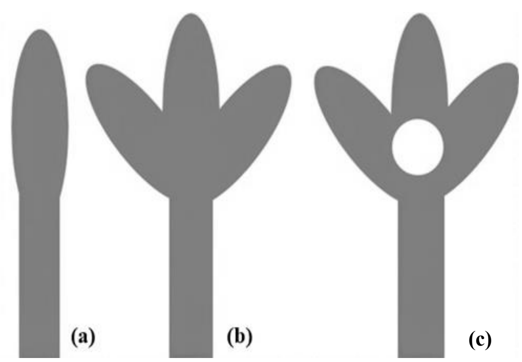

Fig. 2 The Evolution of the proposed antenna design (a) antenna-1 (b) antenna-2 (c) antenna-3

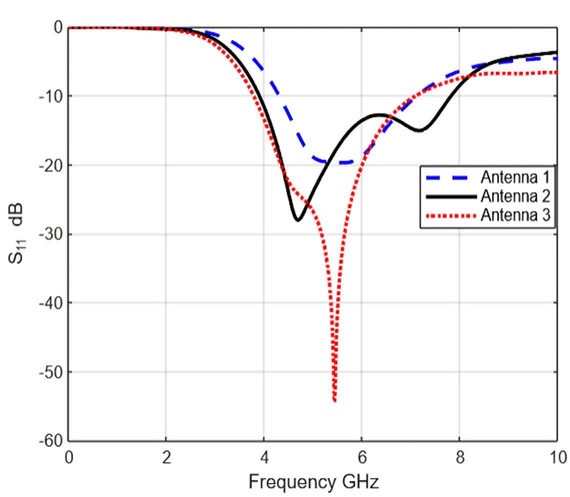

Fig. 3 Simulated S-parameter of the proposed antenna design

3 Optimization of the Designed Radiator using Machine Learning

This section utilizes six ML processes, including Linear Regression, Elastic Net, Lasso, Decision Tree Regressor, ANN, and Random Forest Regressor, to optimize S11.

3.1 Dataset

The EM program simulates the design of a structured antenna. Following the radiator design, datasets are produced by modifying various parameters. In the last couple of decades, ML has transformed many industries with its task automation, greatly influencing traditional engineering and scientific methodologies [21]. In antenna design, the approaches with ML techniques become more attractive owing to their excellent capability in learning from the data being simulated or measured during training, thus offering acceleration of the overall design procedure [22]. This would be more useful in applications that involve tuning multiple parameters or designing complex structures, where ML-based approaches can significantly save computational time. A dataset was created using the EM simulation tool to get around these restrictions. A unique automation script was developed to efficiently generate a substantial dataset. With the help of this script, a significant number of samples might be collected without the need for human interaction by automatically varying the antenna dimensions and initiating EM simulations programmatically. In addition to saving time, this method guaranteed consistent and organized data creation.

The dataset consists of 200,200 samples generated by varying several parameters of the proposed antenna design. This raises concerns about the generalizability of trained machine learning models, specifically, whether they can be effectively applied to different antenna geometries or significant modifications of the elliptical radiator design. It remains uncertain whether these models are suitable for broader antenna design challenges.

Machine Learning Algorithms for Prediction:

In this research, six machine learning algorithms — namely Linear Regression, Elastic Net, Lasso, ANN, DT Regressor, and RF Regressor — are used to predict the desired output. These algorithms are chosen because they can perform regressions on nonlinear data, which is very helpful and suitable for numerical predictions. Regression was selected as the primary method because the nature of the output of this problem is numerical. These models were implemented in Python 3, leveraging its simplicity and the ease of use of various libraries for data preprocessing, machine learning, and visualization.

3.2 Machine Learning Models:

Machine learning typically involves developing algorithms from data with the primary goal of generating predictions for new, unseen data. Some salient techniques involve regression, classification, and methods utilizing deep learning, particularly those employing neural networks. We undertake a research process for various forms of regression that can be generally applied in prediction and forecasting tasks [4].

Artificial Neural Networks (ANN):

ANNs are powerful tools for nonlinear regression, inspired by the behavior of biological neurons [23]. An ANN is composed of several interconnected layers: an input layer, hidden layers, and an output layer. The input layer receives the data features, and the hidden layers, which contain one or more layers, perform the computations using neurons linked through weighted connections. The output layer generates the final predicted values based on the processed information. Each neuron in the network applies weights to the input data, performs a computation, and then sends the results to the subsequent layers. Such an interconnected structure enables ANNs to capture and model complex relationships within the data, making them especially well-suited for addressing nonlinear challenges and issues.

ANNs, which are based on a model of biological neurons, are the most widely used technique for developing and calculating nonlinear regression [24]. An ANN is a multilayered structure. These layers are divided into three categories: hidden layer, output layer, and input layer. Neurons are present in each layer. Connectivity between neurons is mediated by matching linkages or weights. In essence, they carry out calculations and transfer information from the input to the output.

The ANN architecture consists of two hidden layers (64 and 32 neurons, with ReLU activation), an input layer with 15 neurons for the input features, and an optional third layer with 16 neurons. For regression problems, the output layer contains a single linearly activated neuron that estimates continuous values, such as S11 [dB].

Linear Regression:

Linear regression is one of the most widely used statistical and machine learning methods. It is a mathematical technique used to predict or forecast outcomes based on the relationship between a set of independent variables and a continuous dependent variable [12].

Random Forest Regression (RFR):

RFR follows the principles of classification and regression with the construction of multiple tree predictors. Each of the trees is developed based on a random vector that is independently chosen with respect to the input variables. In contrast to classification, which uses categories, random forest regression uses numerical values for the outputs. The decision trees are constructed using variables at every node to make a prediction [25].

Decision Tree Regression (DTR):

Decision tree regression generates a predictive model for an object based on its attributes. A tree-like format is the result of how this algorithm structures the data, making quantitative predictions of the dependent variable's outcome [26].

Lasso Regression (LR):

LR is a variant of linear regression that enhances the model by incorporating the shrinkage technique. It is mainly preferred when dealing with a high number of features, as it can efficiently perform feature selection by effectively reducing less relevant variables and enhancing the model's simplicity [27].

Elastic Net:

The Elastic Net is a modern machine learning model that seeks to find the optimal coefficients that minimize the sum of squared errors. Additionally, it penalizes the coefficients with the intention of an iterative process to converge on the best possible values for the coefficients. The Elastic Net was developed in response to some criticisms of the Lasso regression model, particularly its instability in variable selection, which is highly data-dependent. This improves the prediction curve much more smoothly and robustly, as Elastic Net leverages the strengths of both by integrating the penalty terms from both Lasso and Ridge regression models. Elastic Net is well-suited for handling high-dimensional data because it considers a larger set of variables during training. If some variables are highly correlated and form distinct groups, the model ensures the selection of a sufficient number of variables to represent these groups effectively [28].

3.3 Performance Measures

MAE, MSE (Montgomery Equivalency Scale), R-squared, and RMSE were used to evaluate prediction models and assess performance metrics. The measurement of errors and model accuracy was the reason behind selecting these metrics. Those metrics, including MAE, MSE, and RMSE, are scale-independent, considering absolute and squared values, while MAPE is scale-insensitive, focusing on error percentages. Mean Absolute Error, or MAE, tends to disregard outliers [25].

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |Pi - Oi| \qquad (1)$$

where n is the number of errors and $|Pi - Oi|$ denotes the absolute error.

The MSE is a commonly used estimating statistic. MSE is a popular metric for evaluating the efficacy of a regression model. MSE is a widely used metric because it is straightforward to understand and analyze. Its formulation is represented in Equation (2) [25].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Pi - Oi)^2 \quad (2)$$

RMSE is used instead of MSE to calculate the square root [28]. The root-mean-squared error (RMSE) measures how far estimates differ from reality. Equation (3) is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Pi - Oi)^2} \quad (3)$$

Figure 4 shows the flowchart of the ML algorithm implementation. It divides the dataset into two subsets: one with 70% for training, as recommended in [32], and another with 30% for testing. The training subset was used to train the ML model with various features and labels. The proposed model was trained and then applied to predict the reflection coefficient at the resonating frequency for given input parameters. In comparison to electromagnetic simulations, this machine learning approach significantly reduces prediction time with a small margin of error.

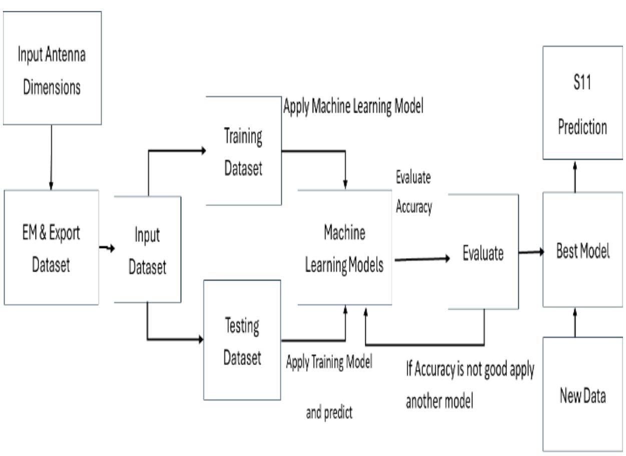

Fig. 4 Machine learning algorithm implementation flow

3.4 Result Analysis

This section outlines the results of the proposed antenna design and ML models. The antenna was developed and analyzed using an Electromagnetic (EM) simulation tool, and the ML algorithms were developed in Python. The performance comparisons are also presented. **Figure 5** shows the predicted versus actual values after applying the ML algorithm to the given data set for the S11 parameter.

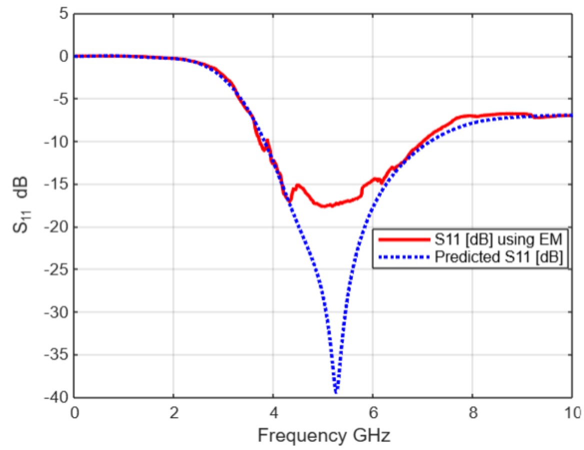

Fig. 5 S11 Prediction using ML vs S11 using EM Simulation

Table 3 presents a summary of the key performance metrics for various machine learning models, including linear regression, RF regression, DT regressor, Lasso regression, ANN, and elastic net algorithms. The error performance of each algorithm can be measured by MAE, MSE, RMSE, and R-squared. The random forest regression model is shown to have the lowest percentage error across MAE, MSE, RMSE (Root Mean Squared Error), and R-squared, with values of 4.43%, 3.41%, 18.4%, and 99.92%, respectively. The random forest regression model has performed better than the other regression models and yields the highest-quality results in all six scenarios.

Table 3 Comparison of six ML algorithms based on R-squared, MSE, MAE, and RMSE

ML Algorithm	R-squared	MSE	MAE	RMSE
Linear Regression	23.59 %	36.153	4.2817	6.0127
Elastic Net	19.69 %	37.999	4.4385	6.1643
Lasso	18.80 %	38.419	4.4722	6.1983
Decision Tree Regressor	99.8 %	0.0623	0.0652	0.2496
Random Forest Regressor	99.9 %	0.0341	0.0443	0.1846
ANN	98.27 %	0.8164	0.5671	0.9035

Figure 6 illustrates the variance in training and validation loss with increasing epochs for the reflection coefficient, where the number of epochs is set to 50.

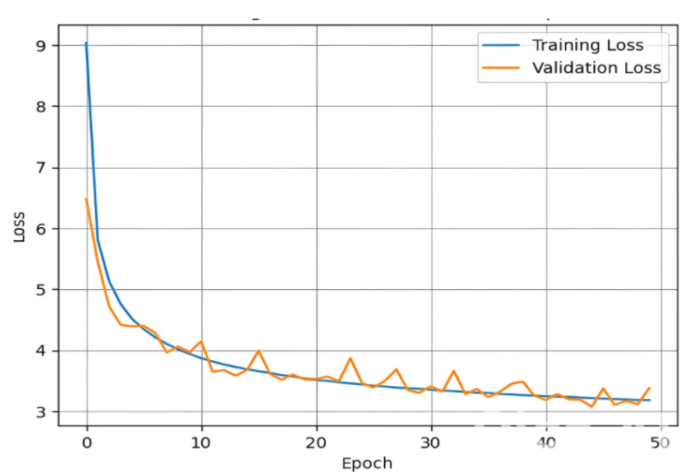

Fig. 6 Training and Validation loss in ANN model with epoch

learning algorithms for predicting antenna resonance and can be summarized as follows:

1. Predictive Accuracy: The models, particularly the Decision Tree and Random Forest regressors, achieve significantly higher R-squared values (99.8% and 99.93%, respectively) compared to the linear models used in the paper. This indicates a stronger ability to explain variance in the data.

2. Lower Prediction Errors: MSE, MAE, and RMSE metrics for proposed models are markedly lower, especially for the tree-based models, suggesting more precise predictions and reduced error rates.

3. Handling of Complexity: Advanced models like Random Forest and ANN in the results of the paper effectively capture complex, nonlinear relationships in the data, which simpler linear models may overlook.

4. Diverse Model Evaluation: The results encompass a wider variety of algorithms (including Elastic Net, Lasso, Decision Tree, and ANN), allowing for a comprehensive assessment and selection of the most effective model for specific applications.

5. Feature Importance Insights: The use of tree-based methods facilitates feature importance analysis, helping to identify which parameters significantly impact antenna performance, thereby guiding future design optimizations.

6. Modern Workflow Integration: Utilizing Python and libraries such as Sci-Kit Learn enables easier integration with contemporary data processing and machine learning workflows, making our approach more adaptable to real-time applications.

This paper demonstrates that employing advanced machine learning techniques yields superior predictive accuracy and reliability in antenna design tasks compared to traditional methods, as referenced in [2].

4 Conclusion

This paper presents the design of a compact triple-elliptical antenna used for IoT system applications via machine learning. Six different ML algorithms, including RF regression, linear regression, ANN, decision tree regression (DTR), Lasso regression, and Elastic Net regression, are used to predict the S parameter of the proposed antenna. Simulation results concerning S11 show very good accuracy with the predicted value obtained from different ML models. The proposed antenna operates between 3.55-6.9 GHz, which justifies its applicability to the IoT frequency band. In addition, the proposed antenna optimization is more effective with ML algorithms than traditional EM simulators. The current ML model isn't quite able to accurately predict the dimensions for every type of antenna design. Additionally, there are some other limitations, such as the small size of our dataset and the assumption of ideal conditions in our simulations.

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