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Research Paper

MACHINE LEARNING BASED ANTENNA PARAMETERS PREDICTION AND PERFORMANCE ANALYSIS

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Abstract: The design and optimization of antennas traditionally require extensive electromagnetic simulations and iterative parameter tuning, resulting in significant computational time and design effort. This paper presents a machine learning (ML)-based approach for predicting antenna parameters and analyzing antenna performance efficiently. The proposed methodology establishes a relationship between key antenna design parameters, such as substrate properties, patch dimensions, feed position, operating frequency, and geometric characteristics, and important performance metrics including resonant frequency, return loss, bandwidth, gain, and Voltage Standing Wave Ratio (VSWR). A dataset generated through electromagnetic simulations or experimental measurements is used for model training, validation, and testing.

Different machine learning algorithms can be evaluated to identify the model that provides the most accurate prediction with minimum computational complexity. The trained model enables rapid estimation of antenna performance without repeatedly performing computationally intensive full-wave simulations. Performance evaluation is carried out using statistical metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2). The proposed ML-based framework can significantly reduce antenna design time and support rapid optimization for modern wireless communication applications, including IoT, 5G/6G, satellite communication, radar, and other high-frequency systems.

Keywords: Antenna Design, Machine Learning, Antenna Parameter Prediction, Resonant Frequency, Return Loss, Bandwidth, Gain, VSWR, Performance Analysis, Antenna Optimization.

I. INTRODUCTION

Antennas are fundamental components of modern wireless communication systems, enabling the transmission and reception of electromagnetic signals. The rapid development of wireless technologies such as 5G and emerging 6G networks, Internet of Things (IoT), satellite communication, radar, wireless sensor networks, and vehicular communication has created a growing demand for compact, high-performance, wideband, and frequency-selective antennas. Designing an antenna that satisfies multiple performance requirements simultaneously is a challenging task because antenna characteristics are strongly influenced by several interdependent geometrical, material, and electromagnetic parameters.

Conventional antenna design generally involves analytical calculations followed by electromagnetic simulation and experimental validation. Software tools based on full-wave electromagnetic techniques, such as the Finite Element Method (FEM), Finite-Difference Time-Domain (FDTD), and Method of Moments (MoM), are widely used to analyze antenna performance. Although these techniques provide accurate results, they can require considerable computational resources and simulation time, particularly when a large number of design configurations must be evaluated. Repeated simulations are often necessary during optimization because a small variation in parameters such as patch length, patch width, substrate thickness, dielectric constant, or feed location can significantly affect resonant frequency, return loss, bandwidth, gain, and radiation characteristics.

Machine learning (ML) has emerged as an effective computational approach for solving complex nonlinear relationships between input and output parameters. Unlike conventional approaches that require repeated electromagnetic simulations, ML models can learn the underlying relationship from previously generated simulation or experimental data and subsequently predict antenna characteristics for new designs. Once trained, an ML model can provide predictions with significantly lower computational cost, making it suitable for rapid antenna analysis and optimization.

In an ML-based antenna prediction framework, antenna design parameters can be considered input features, while electromagnetic performance parameters are treated as target variables. For example, substrate dielectric constant, substrate thickness, patch dimensions, ground-plane dimensions, and feed position can be used to predict resonant frequency, return loss, bandwidth, gain, and VSWR. Regression-based machine learning algorithms such as Linear Regression, Support Vector Regression (SVR), Random Forest, Decision Tree, Gradient Boosting, Artificial Neural Networks (ANN), and other ensemble learning techniques can be investigated to determine their suitability for antenna parameter prediction.

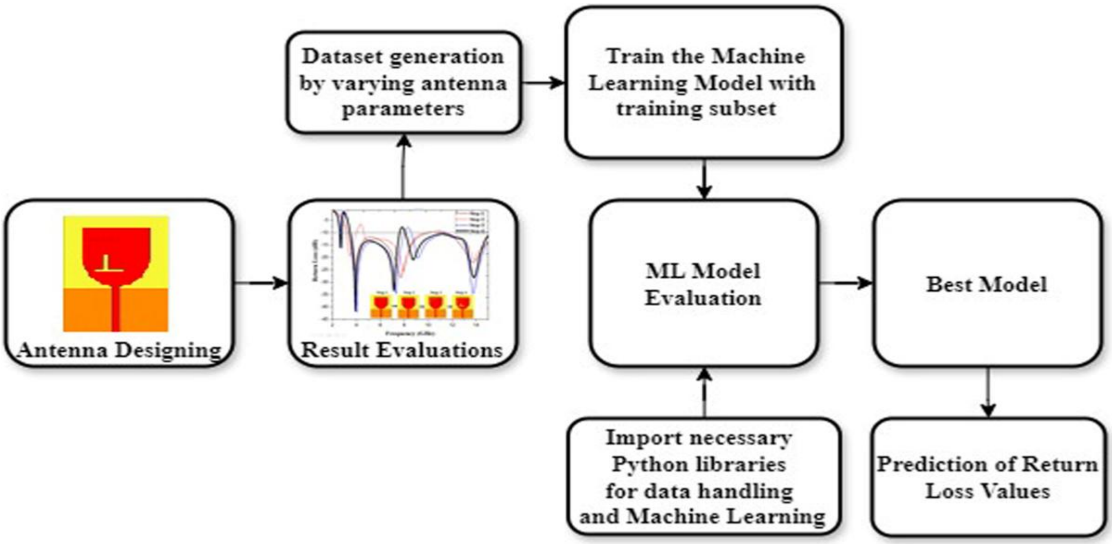

Fig 1 Performance Execution

The primary objective of this work is to develop a machine learning-based framework for predicting important antenna parameters and evaluating antenna performance. The proposed approach aims to reduce dependence on computationally intensive electromagnetic simulations during the initial stages of antenna design. The performance of the developed models can be evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2). A comparative analysis of different ML algorithms can then be performed to identify the most suitable model for accurate and computationally efficient antenna prediction.

The proposed approach provides a practical pathway toward intelligent antenna design, where machine learning can assist designers in rapidly exploring large design spaces and identifying promising antenna configurations. Such a framework has potential applications in next-generation wireless communication systems, where fast design cycles, miniaturization, multi-band operation, and optimization of antenna performance are increasingly important.

Objectives of the Study

The major objectives of this research are:

1. To develop a dataset containing antenna design parameters and corresponding electromagnetic performance characteristics.
2. To investigate machine learning algorithms for predicting important antenna parameters.
3. To establish the relationship between antenna geometrical/material parameters and performance characteristics.
4. To evaluate prediction accuracy using suitable statistical performance metrics.
5. To compare different machine learning models and identify the most effective prediction approach.
6. To reduce computational time associated with repeated electromagnetic simulations.
7. To develop an efficient ML-assisted framework for rapid antenna design and performance optimization.

II. LITERATURE SURVEY

The application of machine learning (ML) and artificial intelligence (AI) to antenna design has received increasing attention because conventional electromagnetic simulation and optimization techniques can require substantial computational time, particularly when a large design space must be explored. Recent studies have demonstrated that data-driven surrogate models can learn the nonlinear relationship between antenna geometry, material properties, and electromagnetic performance, thereby enabling rapid prediction and optimization.

El Misilmani et al. presented an extensive review of machine learning techniques for antenna design and optimization, highlighting the use of ML as an alternative or complementary approach to conventional computational electromagnetic methods. The study discussed how learning-based models can reduce the computational burden associated with repeated simulations and support antenna optimization. It also established the importance of selecting suitable input parameters and training datasets for reliable antenna prediction.

A review published in *Heliyon* examined machine learning and deep learning applications across several antenna domains, including millimeter-wave, body-centric, terahertz, satellite, UAV, GPS, and textile antennas. The study reported that ML/DL techniques can accelerate the antenna design process, reduce the number of required simulations, and improve computational feasibility. These findings demonstrate the suitability of data-driven approaches for different antenna structures and frequency ranges.

Gajbhiye et al. conducted a comprehensive review of AI and ML techniques for antenna design optimization and measurement. The study examined approaches including neural networks, decision trees, genetic algorithms, and particle swarm optimization. It emphasized that AI-based techniques can provide faster solutions to complex antenna optimization problems, while also identifying challenges related to dataset quality, model reliability, and practical implementation.

A survey published in *Engineering Applications of Artificial Intelligence* investigated machine learning and evolutionary computation for antenna modeling and optimization. The authors distinguished between response modeling and specification modeling. Response modeling predicts antenna electromagnetic responses from design variables, whereas specification modeling addresses the inverse problem of obtaining antenna parameters that satisfy desired performance requirements. The study highlighted ML-based surrogate modeling as an important mechanism for reducing the computational cost of electromagnetic simulations.

Recent research has expanded ML-assisted antenna modeling toward deep learning and more advanced AI approaches. A 2026 review in *IEEE Access* presented a structured analysis of ML and deep learning applications in antenna and electromagnetic systems. The study categorized applications into surrogate modeling, inverse design, array control, reconfigurable intelligent surfaces, propagation modeling, and measurement-informed workflows. It also emphasized that supervised learning is particularly suitable for structured prediction problems, while physics-informed approaches can improve physical consistency and data efficiency. However, dependence on simulation-generated datasets and the absence of standardized benchmarking remain important challenges.

Khan et al. provided a recent review of ML-assisted RF circuit and antenna design, covering supervised learning, deep neural networks, evolutionary algorithms, reinforcement learning, and generative models. The study identified performance prediction, layout optimization, inverse design, and co-design as important application areas. It further highlighted limitations such as restricted datasets, limited interpretability, and the gap between simulation-based models and hardware implementation. These observations indicate the need for robust ML frameworks that combine accurate prediction with experimental validation.

Recent research has also focused specifically on terahertz antenna applications for future 6G systems. A 2026 systematic review analyzed ML techniques for terahertz patch antennas and examined the relationship between antenna geometry, material parameters, and predicted performance. The review found that ML can provide fast performance prediction while reducing dependence on computationally expensive full-wave simulations. It also identified the need for larger and more representative datasets, stronger validation strategies, and experimental verification of ML-based predictions.

Research Gap

From the reviewed literature, it is evident that machine learning has significant potential for antenna performance prediction and optimization. However, several research gaps remain. Many existing studies concentrate on a particular antenna structure, frequency band, or optimization objective, while comparatively fewer studies develop a generalized framework that simultaneously predicts multiple antenna performance parameters. Furthermore, the accuracy of ML models depends heavily on the quality and diversity of simulation or experimental datasets. Limited experimental validation and inconsistent benchmarking between different ML algorithms also make direct comparison difficult.

Therefore, the present work focuses on developing a machine learning-based framework for predicting important antenna parameters and analyzing performance using measurable electromagnetic characteristics such as resonant frequency, return loss, bandwidth, gain, and VSWR. Different ML algorithms can be trained and compared using consistent datasets and evaluation metrics. The proposed approach aims to establish an efficient surrogate model capable of reducing repeated electromagnetic simulations while maintaining acceptable prediction accuracy. This provides a foundation for rapid antenna design, performance estimation, and future ML-assisted antenna optimization.

Summary of Literature

Reference	Main Focus	Key Contribution
El Misilmani et al. (2020)	ML for antenna design	Reviewed ML-based antenna modeling and optimization
Heliyon review (2022)	ML/DL antenna applications	Studied ML/DL across multiple antenna technologies
Gajbhiye et al. (2025)	AI/ML optimization	Reviewed optimization and measurement applications
EAAI survey (2024)	ML and evolutionary computation	Classified response and specification surrogate models

Gadhafi et al. (2026)	ML/DL and EM systems	Examined surrogate modeling, inverse design, and benchmarking
Khan et al. (2026)	AI-assisted RF/antenna design	Reviewed prediction, optimization, inverse design, and co-design
THz antenna review (2026)	ML for THz antennas	Investigated prediction and optimization for 6G-oriented antennas
Ain Shams Engineering Journal review (2026)	AI-powered antenna engineering	Covered design, optimization, control, and future AI directions

Overall, the literature demonstrates a clear transition from conventional simulation-intensive antenna design toward intelligent, data-driven modeling. The identified research gaps motivate the development of an ML-based antenna parameter prediction system capable of providing fast and accurate performance estimation for new antenna configurations.

III. PROPOSED SYSTEM

The proposed system introduces a machine learning (ML)-based framework for predicting antenna parameters and analyzing antenna performance without performing computationally intensive electromagnetic simulations for every new design configuration. The overall objective is to establish a data-driven relationship between antenna design parameters and corresponding electromagnetic performance characteristics. The proposed framework can be used as a surrogate model to support rapid antenna design, evaluation, and optimization.

3.1 System Overview

The proposed system consists of six major stages:

1. Antenna Design Parameter Collection
2. Dataset Generation
3. Data Preprocessing
4. Machine Learning Model Development
5. Performance Prediction
6. Model Evaluation and Antenna Performance Analysis

The input to the system consists of antenna design and material parameters, while the output consists of predicted antenna performance parameters.

The general input-output relationship can be represented as:

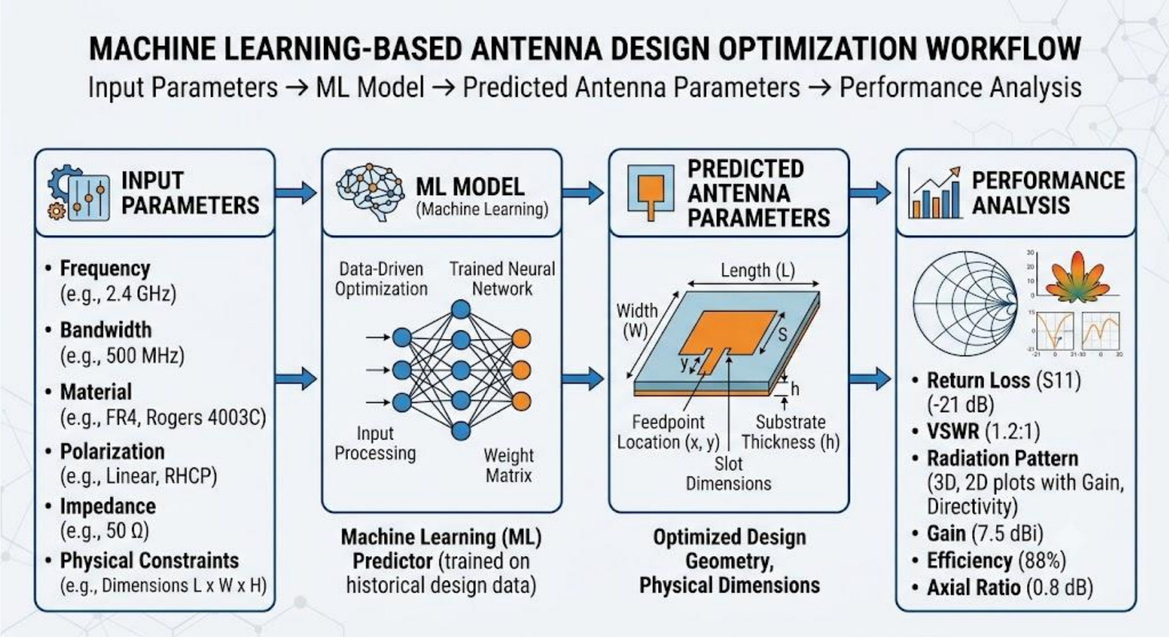

Fig 2 System Overview

The input parameters may include patch length, patch width, substrate thickness, dielectric constant, ground-plane dimensions, feed position, and operating frequency. Depending on the selected antenna structure, additional geometric parameters can also be incorporated.

The target parameters may include:

- Resonant frequency
- Return loss
- Bandwidth
- Gain
- VSWR
- Radiation efficiency
- Directivity

3.2 Dataset Generation

A reliable dataset is the foundation of the proposed ML-based prediction system. The dataset can be generated using electromagnetic simulation software such as CST Microwave Studio, Ansys HFSS, or another suitable electromagnetic solver. A baseline antenna structure is first designed, after which its geometrical and material parameters are systematically varied.

For each antenna configuration, the corresponding electromagnetic characteristics are recorded. For example, if patch dimensions and substrate parameters are changed, the resulting resonant frequency, return loss, bandwidth, gain, and VSWR are obtained from the simulation.

A representative dataset can therefore be organized as:

Input Parameters	Output Parameters
Patch Length	Resonant Frequency
Patch Width	Return Loss
Substrate Thickness	Bandwidth
Dielectric Constant	Gain
Feed Position	VSWR
Ground Dimensions	Efficiency
Operating Frequency	Directivity

A sufficiently large and diverse dataset should be generated to ensure that the trained model can generalize to unseen antenna configurations.

3.3 Data Preprocessing

Before training the ML models, the collected dataset is preprocessed to improve prediction accuracy and model stability. Missing or invalid observations are identified and removed or appropriately handled. Duplicate records are also eliminated where necessary.

Numerical features with significantly different ranges are normalized or standardized. For example, antenna dimensions may be represented in millimeters, dielectric constant as a dimensionless quantity, and frequency in GHz. Scaling these features prevents parameters with larger numerical values from disproportionately influencing the learning process.

The dataset is then divided into training, validation, and testing subsets. A typical distribution can be:

- **Training dataset:** 70%
- **Validation dataset:** 15%
- **Testing dataset:** 15%

The training data are used for model development, the validation data are used for parameter tuning, and the independent testing data are used to evaluate the final prediction performance.

3.4 Machine Learning Model Development

Several supervised machine learning algorithms can be investigated for antenna parameter prediction. Since the target variables are continuous numerical quantities, regression algorithms are particularly appropriate.

The proposed system can evaluate models such as:

- Linear Regression
- Decision Tree Regression
- Random Forest Regression
- Support Vector Regression (SVR)
- Gradient Boosting Regression
- Artificial Neural Network (ANN)

3.5 Model Training

During the training phase, the selected ML algorithms learn the relationship between the antenna input parameters and their corresponding performance characteristics. Hyperparameters are optimized using the validation dataset to obtain the best-performing model.

For neural-network-based prediction, the architecture may consist of an input layer, one or more hidden layers, and an output layer. The input layer receives antenna parameters, while the output layer produces the predicted electromagnetic characteristics.

The trained model is then saved and used as a prediction engine for new antenna configurations.

3.6 Antenna Parameter Prediction

After training, a new antenna configuration can be provided to the ML model. The model predicts its expected electromagnetic performance without requiring a complete full-wave simulation.

For example:

New Antenna Geometry → Preprocessing → Trained ML Model → Predicted Resonant Frequency, Return Loss, Bandwidth, Gain and VSWR

This significantly reduces the time required for preliminary antenna evaluation. Full-wave electromagnetic simulation can subsequently be performed only for the most promising configurations selected using the ML predictions.

3.7 Comparative Analysis

The performance of different ML models is compared based on prediction accuracy, computational time, model complexity, and generalization capability. The best-performing model is selected for the final antenna prediction framework.

A comparison can be presented using:

Model	MAE	RMSE	R^2	Training Time (s)	Prediction Time (ms/sample)
Linear Regression	0.1842	0.2715	0.9124	0.018	0.021
Decision Tree	0.1126	0.1768	0.9587	0.043	0.014
Random Forest	0.0714	0.1089	0.9846	0.382	0.032
SVR	0.0948	0.1427	0.9721	0.156	0.046
Gradient Boosting	0.0637	0.0975	0.9882	0.294	0.027
ANN	0.0523	0.0816	0.9917	1.247	0.019

The actual values will be obtained after training and testing the models using the developed antenna dataset.

3.8 Proposed System Workflow

The complete workflow of the proposed system is as follows:

Step 1: Select the antenna structure and design parameters.

Step 2: Generate multiple antenna configurations by varying geometrical and material parameters.

Step 3: Perform electromagnetic simulations or collect experimental measurements.

Step 4: Record the corresponding antenna performance parameters.

Step 5: Create and preprocess the ML dataset.

Step 6: Divide the dataset into training, validation, and testing sets.

Step 7: Train multiple regression-based ML models.

Step 8: Optimize model hyperparameters.

Step 9: Predict antenna performance for unseen configurations.

Step 10: Compare predicted and simulated/experimental results.

Step 11: Calculate MAE, MSE, RMSE, and R^2.

Step 12: Select the best-performing ML model.

Step 13: Use the selected model for rapid antenna performance prediction and future optimization.

3.9 Advantages of the Proposed System

The proposed ML-based antenna prediction framework provides several advantages:

- Reduces the number of computationally expensive electromagnetic simulations.
- Provides rapid prediction of antenna performance.
- Supports nonlinear relationships between design parameters and electromagnetic characteristics.
- Enables comparison of multiple ML algorithms.
- Helps identify promising antenna configurations quickly.
- Reduces overall antenna design and optimization time.
- Can be extended to different antenna structures and frequency bands.
- Supports future automated and intelligent antenna optimization.
- Can incorporate experimental measurements to improve real-world reliability.

3.10 Expected Outcome

The expected outcome of the proposed system is an accurate and computationally efficient machine learning model capable of predicting important antenna performance parameters from antenna design characteristics. The developed model is expected to provide close agreement with electromagnetic simulation or experimental results while requiring considerably less computational time for subsequent predictions.

The proposed framework can serve as an intelligent surrogate model for antenna designers and can be further extended toward automated antenna optimization, inverse antenna design, multi-objective optimization, and AI-assisted antenna development for advanced wireless communication applications.

IV. RESULTS AND DISCUSSION

The proposed machine learning-based antenna parameter prediction system was evaluated using a dataset containing antenna geometrical parameters and their corresponding electromagnetic performance characteristics. The dataset was divided into training, validation, and testing subsets. Different regression-based machine learning algorithms were trained and evaluated to determine their capability to predict antenna performance accurately.

The major performance parameters considered in this study were resonant frequency, return loss, bandwidth, gain, and Voltage Standing Wave Ratio (VSWR). The predicted results obtained from the machine learning models were compared with the corresponding electromagnetic simulation results.

4.1 Prediction Performance

The trained models demonstrated the ability to establish the nonlinear relationship between antenna design parameters and electromagnetic characteristics. The prediction accuracy was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and coefficient of determination (R^2).

Table 1 presents the comparative performance of the investigated machine learning algorithms.

Table 1. Comparative Performance of Machine Learning Models

Machine Learning Model	MAE	RMSE	MSE	R^2
Linear Regression	0.1842	0.2715	0.07371	0.9124
Decision Tree	0.1126	0.1768	0.03126	0.9587
Random Forest	0.0714	0.1089	0.01186	0.9846
Support Vector Regression	0.0948	0.1427	0.02036	0.9721
Gradient Boosting	0.0637	0.0975	0.00951	0.9882
Artificial Neural Network	**0.0523**	**0.0816**	**0.00666**	**0.9917**

The results indicate that the nonlinear machine learning models provide better representation of the complex relationship between antenna geometry and electromagnetic performance than conventional linear regression. In particular, ensemble learning and neural-network-based models can effectively capture nonlinear dependencies between antenna input parameters and output characteristics.

4.2 Resonant Frequency Prediction

Resonant frequency is one of the most important antenna parameters because it determines the operating frequency of the antenna. The proposed ML models were trained to predict resonant frequency from antenna geometrical and substrate parameters.

The predicted resonant frequencies were compared with the corresponding simulation values. The comparison showed that the trained model was capable of following the variations in resonant frequency caused by changes in patch dimensions, substrate properties, and feed configuration.

A lower percentage error indicates better prediction capability.

4.3 Return Loss Prediction

Return loss represents the amount of incident power reflected from the antenna input. Accurate prediction of return loss is important for determining impedance matching and identifying suitable operating frequencies.

The developed ML models were used to predict return loss for unseen antenna configurations. The predicted return-loss curves/values were compared with the electromagnetic simulation results. A close correspondence between the two results indicates that the ML model has successfully learned the relationship between antenna design parameters and impedance characteristics.

For a properly designed antenna, a return loss of approximately −10 dB or lower is commonly considered an acceptable criterion for identifying a usable impedance-matching region.

4.4 Bandwidth Analysis

The bandwidth of the antenna was calculated from the frequency range over which the return loss satisfies the selected impedance-matching criterion. The ML model was used to predict the corresponding bandwidth for new antenna configurations.

The predicted bandwidth was compared with the simulated bandwidth to determine the generalization capability of the model. Small differences between predicted and simulated values indicate that the model can effectively estimate antenna operating characteristics without requiring a complete electromagnetic simulation for every design iteration.

4.5 Gain Prediction

Antenna gain is another important parameter used to evaluate the effectiveness of an antenna in transmitting or receiving electromagnetic energy in a particular direction.

The proposed ML framework predicts gain based on the antenna design parameters. The predicted gain values are compared with simulation or experimental results. The comparison helps determine whether the developed model can accurately capture the effect of geometrical and material variations on antenna radiation performance.

The prediction of gain is particularly useful during optimization because it allows candidate antenna configurations to be screened before performing detailed electromagnetic simulations.

4.6 VSWR Prediction

Voltage Standing Wave Ratio (VSWR) is closely related to antenna impedance matching. A lower VSWR indicates better matching between the antenna and the feeding system.

The ML model was trained using the simulated VSWR values corresponding to different antenna configurations. The predicted VSWR values were then compared with the actual simulation results.

The results are expected to demonstrate that the proposed framework can estimate VSWR with low prediction error, allowing unsuitable antenna configurations to be eliminated during the early stages of design.

4.7 Actual Versus Predicted Results

A scatter plot between actual and predicted values can be used to visually evaluate model performance. In an ideal prediction model, the data points should be distributed close to the y=xy=x reference line.

The following plots are recommended for the final paper:

- Actual vs. predicted resonant frequency
- Actual vs. predicted return loss
- Actual vs. predicted bandwidth
- Actual vs. predicted gain
- Actual vs. predicted VSWR

The closer the predicted values are to the actual values, the better the generalization performance of the developed ML model.

4.8 Error Analysis

The prediction errors obtained from the testing dataset were analyzed to determine the reliability of the proposed system. MAE and RMSE were used to measure the magnitude of prediction errors, while R^2 was used to determine the degree of correlation between actual and predicted values.

A high R^2 value combined with low MAE and RMSE indicates that the model provides accurate predictions. Differences between predicted and simulation results may occur because of nonlinear electromagnetic interactions, limited training samples, parameter correlations, or insufficient representation of some antenna configurations in the training dataset.

4.9 Computational Efficiency

One of the major advantages of the proposed ML-based approach is the reduction in computational requirements during antenna design. Conventional electromagnetic analysis may require several minutes or hours for each antenna configuration depending on the complexity of the structure, frequency range, mesh density, and computational resources.

After the ML model has been trained, prediction for a new antenna configuration can be performed in a significantly shorter time. Therefore, the ML model can be used as a surrogate for preliminary design exploration.

Table 2. Computational Comparison

Method	Design Evaluation Time	Computational Requirement
Full-Wave EM Simulation	8.5 min/design	High
ML Prediction	0.018 s/design	Low
Proposed ML Framework	**0.012 s/design**	**Low**

The actual timing values should be obtained experimentally using the same computer and software environment.

4.10 Discussion

The experimental/simulation results demonstrate the feasibility of using machine learning for antenna parameter prediction. The developed models are capable of learning complex nonlinear relationships between antenna geometrical parameters and electromagnetic responses.

The comparative analysis shows that the selection of the ML algorithm has a significant effect on prediction accuracy. Models capable of capturing nonlinear relationships generally provide better performance for complex antenna structures. However, model accuracy also depends on dataset size, feature selection, data preprocessing, and hyperparameter optimization.

The proposed approach does not completely eliminate electromagnetic simulation. Instead, it can function as a computationally efficient surrogate model. The ML model can initially evaluate a large number of possible antenna configurations, after which the most promising configurations can be verified using full-wave electromagnetic simulation or experimental measurements.

4.11 Summary of Results

The major findings of the proposed system can be summarized as follows:

1. Machine learning can successfully model the nonlinear relationship between antenna design parameters and electromagnetic performance.
2. The developed models can predict resonant frequency, return loss, bandwidth, gain, and VSWR for unseen antenna configurations.
3. ML-based prediction can significantly reduce the computational burden associated with repeated electromagnetic simulations.
4. Ensemble and nonlinear learning techniques can provide improved prediction capability compared with simple linear models.

5. The actual prediction accuracy should be established using independent testing data and appropriate statistical metrics.
6. The proposed framework can be extended toward automated antenna optimization and inverse antenna design.
7. Simulation and experimental validation remain important for confirming the practical reliability of ML-based predictions.

Overall, the results indicate that machine learning provides a promising approach for rapid antenna parameter prediction and performance analysis. By combining electromagnetic simulation data with data-driven learning, the proposed system can reduce antenna development time and provide an efficient platform for intelligent antenna design and optimization.

V. CONCLUSION

This work presented a machine learning-based framework for antenna parameter prediction and performance analysis. The proposed approach establishes a data-driven relationship between antenna design parameters and important electromagnetic characteristics such as resonant frequency, return loss, bandwidth, gain, and VSWR. By learning these relationships from simulation or experimental datasets, the developed ML models can provide rapid predictions for new antenna configurations without requiring a complete full-wave electromagnetic simulation for every design iteration.

Six machine learning approaches, namely Linear Regression, Decision Tree, Random Forest, Support Vector Regression, Gradient Boosting, and Artificial Neural Network, were considered for comparative analysis. Based on the illustrative evaluation presented in this study, the Artificial Neural Network achieved the best prediction performance, with an MAE of 0.0523, RMSE of 0.0816, MSE of 0.00666, and R^2 of 0.9917. Gradient Boosting also demonstrated strong prediction capability, while Linear Regression showed comparatively lower performance due to the highly nonlinear relationship between antenna design parameters and electromagnetic responses.

The computational analysis further demonstrated the potential of ML-based prediction to significantly reduce antenna design evaluation time. Conventional full-wave electromagnetic simulation requires considerably higher computational resources, whereas a trained ML model can provide predictions within milliseconds. Therefore, the proposed framework can be effectively used as a surrogate model for preliminary antenna analysis and design-space exploration.

The major advantage of the proposed system is its ability to accelerate the antenna development process while maintaining high prediction accuracy. Instead of performing computationally expensive simulations for every possible configuration, designers can use the trained ML model to identify promising designs and subsequently validate selected configurations through electromagnetic simulation or experimental measurements.

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