Enhancing Antenna Design Through Stacked Machine Learning Models for S11 Prediction

Ms. Gaddam S. A[1], Dr. Mathpati M. S[2]
[1]*PG Student, ENTC SVERI'S COE, Pandharpur, Maharashtra*
[2]*Associate Prof, PG Guide, ENTC SVERI'S COE, Pandharpur, Maharashtra*

***Abstract*—The optimization of return loss (S11) is crucial in antenna design, as it significantly impacts the efficiency and performance of antenna systems. This research explores the application of stacked machine learning models to predict S11 parameters based on various design features, including frequency, patch dimensions, and slot characteristics. Utilizing a comprehensive dataset comprising diverse antenna configurations, we employed base models, specifically Random Forest and XGBoost, to capture complex relationships between design parameters and return loss. A stacking ensemble approach was implemented to combine the predictions of these models, enhancing the accuracy of S11 forecasts.**

Hyperparameter tuning through Grid Search was conducted to optimize the performance of the stacked model. The results demonstrated a significant improvement in predictive capability, achieving a Mean Squared Error of 0.1968 and an R^2 score of 0.9775. Additionally, feature importance analysis was performed to identify key design parameters influencing S11, providing valuable insights for antenna designers. The findings of this study not only underscore the effectiveness of machine learning techniques in antenna optimization but also contribute to the advancement of data-driven approaches in the field of electromagnetics.

Index Terms*—*S11, Antenna Design Patch Antenna, Random Forest, XGBoost

1. INTRODUCTION

Antenna design plays a pivotal role in the performance of modern communication systems, influencing parameters such as radiation efficiency, bandwidth, and return loss (S11). Among these parameters, return loss is particularly critical, as it measures the power reflected back to the source, impacting signal integrity and overall system efficiency. Designers aim to achieve optimal S11 values to minimize reflections and enhance the operational effectiveness of antennas across various applications, including telecommunications, satellite communications, and wireless networks.

Traditionally, antenna design has relied on empirical methods and simulations, which can be time-consuming and require extensive expertise. With advancements in machine learning and data science, there is a growing interest in leveraging these technologies to enhance the design process. Machine learning offers the potential to analyze complex relationships between design parameters and performance metrics, enabling more efficient design optimization.

This research aims to investigate the use of stacked machine learning models for predicting S11 parameters in antenna designs. By employing a combination of base models, such as Random Forest and XGBoost, we aim to capture the intricate patterns within the data, thereby improving the accuracy of S11 predictions. Stacking, an ensemble learning technique, allows us to leverage the strengths of multiple models, resulting in enhanced predictive performance.

In this study, we present a comprehensive analysis of a dataset containing various antenna design features and their corresponding S11 values. The dataset serves as a foundation for training and evaluating the stacked models. Hyper-parameter tuning is also performed to optimize model performance, ensuring that our approach yields reliable predictions.

Furthermore, feature importance analysis is conducted to identify the key design parameters that significantly influence S11, providing valuable insights for antenna designers. By integrating machine learning techniques into the antenna design process, this research not only contributes to the understanding of S11 optimization but also paves the way for data-driven approaches in the field of electromagnetics.

2. RELATED WORK

In [1] study proposes a deep neural network (DNN) for soft computation of the resonant frequency of E-shaped patch antennas (ESPAs). A 5-layer DNN model is optimized using K-fold cross-validation and trained on a simulated dataset of 144 ESPAs, achieving an average percentage error (APE) of 0.269. The model is validated by comparison with traditional neural networks and tested on a fabricated ESPA at 2.4 GHz, attaining an APE of 0.285. Results suggest the DNN is a highly accurate and efficient alternative to traditional measurements and simulations for resonant frequency prediction.
A machine learning-based approach for predicting the resonant frequency of patch antennas was introduced in research [2], utilizing a dataset of 20,480 full-wave simulations. A binary classification model identifies valid resonance configurations with 97.9% accuracy, while a regression model predicts resonant frequency with a 0.926 accuracy score. These models enable designers to evaluate antenna performance across 3–15 GHz without additional simulations, significantly reducing time and computational costs in antenna optimization.

In another research [3], the author explores the use of machine learning to analyze the relationship between microstrip patch antenna configurations and resonant frequency. Using datasets of 258 and 4,209 configurations, a linear regression model achieved R^2 scores of 0.582 and 0.647, respectively, across 3–15 GHz, under repeated 5-fold cross-validation. Larger datasets and higher accuracy make this machine learning approach promising for antenna design, reducing the need for extensive tuning in full-wave simulations.

With the rise of vast data availability, advanced processing, and affordable storage, machine learning is becoming essential in optimization across various fields. The paper [4] reviews the role of machine learning in antenna design, covering fundamental concepts, distinctions from AI and deep learning, and key algorithms. Emphasizing antenna applications, it explores machine learning's broad technological impact and compares its results to traditional design methods. This investigation highlights machine learning as a pivotal tool in modern antenna design.

In [5] explores the integration of machine learning into wireless communications by reinterpreting antenna selection (AS) as a multiclass classification problem. It compares learning-based AS, using k-nearest neighbors and support vector machine algorithms, with traditional optimization-driven AS methods, evaluating communication performance, computational complexity, and feedback overhead. The study highlights the potential of merging machine learning with wireless communications to enhance system efficiency and performance.

Technological advancements aim to address specific field challenges, such as the complex, time-consuming antenna design process using CAD tools. The auther in [6] proposed solution leverages machine learning models to predict antenna output parameters, reducing inefficiencies from traditional design and optimization methods. This approach mitigates the need for extensive CAD tool proficiency by streamlining the design process. Machine learning models connect radiation parameters to input design specifications, with validation against HFSS software simulation results.
Numerical field simulations provide a robust method for analyzing antenna performance, generating extensive data that maps design variables to response functions. The study [7] applies various machine learning techniques to optimize antenna performance using this data-driven approach, greatly accelerating the optimization process. Additionally, it highlights the advantages of dimensionality reduction and evolutionary algorithms in enhancing antenna performance analysis.

Designing antennas traditionally combines engineering principles, electromagnetic theory, and practical considerations, often requiring substantial time. The study [8] leverages machine learning to efficiently predict the geometry of a microstrip patch antenna. Parameter sweeps from a microwave simulator generated the dataset, which was used to train a support vector regression model. With a prediction error below 0.0903 and a correlation coefficient of 0.98, the model demonstrated high accuracy. The machine learning approach significantly reduced the design time compared to conventional methods.

The various study shows the use of machine learning techniques has improved the antenna designing. Many studies lacks for prediction of return loss using these machine learning techniques. In this study we propose the S11 parameter prediction using machine learning techniques.

3. MATERIALS AND METHODS

3.1. Dataset Description

The dataset used in this study comprises various antenna design parameters and their corresponding return loss (S11) values. The dataset includes features such as:

- Frequency (GHz): The operational frequency of the antenna.
- Length of Patch (mm): The length of the patch used in the antenna design.
- Width of Patch (mm): The width of the patch.
- Slot Length (mm): The length of any slots incorporated into the antenna.
- Slot Width (mm): The width of the slots.

The dataset was collected from Ansys HFSS Antenna Simulator for patch antenna. It was split into training, validation, and test sets, following an 80:10:10 ratio, to ensure robust model evaluation.

3.2 Data Pre-processing

Prior to modeling, the dataset underwent several pre-processing steps:

- Data Cleaning: Missing values and outliers were identified and addressed to ensure the quality of the dataset.
- Normalization: Features were normalized to bring them to a similar scale, which is particularly important for machine learning algorithms sensitive to the magnitude of input features.
- Train-Test Split: The dataset was divided into training, validation, and test sets to facilitate the evaluation of model performance.

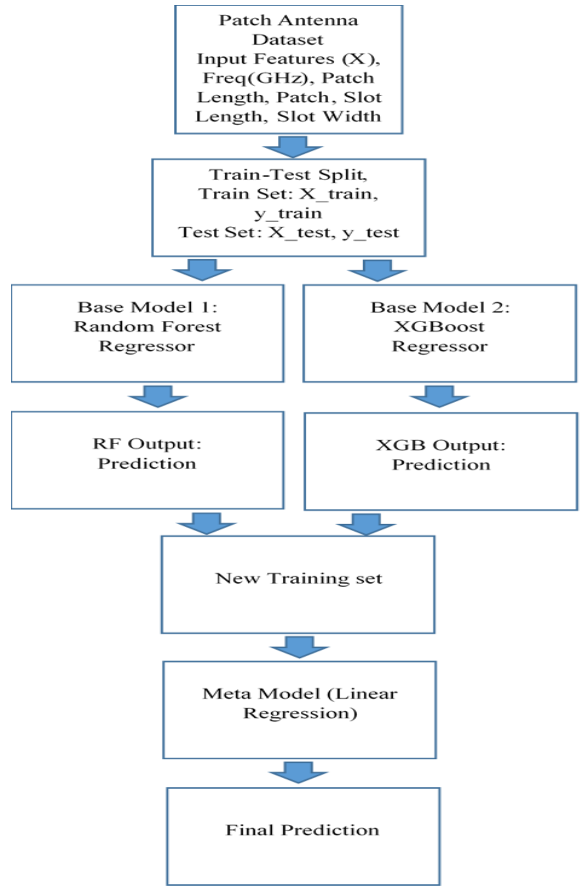


Figure 1 Methodology

3.3. Machine Learning Models

The following machine learning models were employed in this study:

1. Base Models:

- Random Forest Regressor: A tree-based ensemble learning method that operates by constructing multiple decision trees during training and outputting the average prediction.
- XGBoost Regressor: An efficient and scalable implementation of gradient boosting designed for speed and performance.

2. Stacking Ensemble Method:

- A stacking approach was utilized to combine the predictions from the base models. The predictions of Random Forest and XGBoost served as input features for a meta-model, which was trained to output the final prediction of S11.

3.4 Hyper-parameter Tuning

To optimize model performance, hyper-parameter tuning was performed using Grid Search. A predefined set of hyper-parameters was evaluated for each base model, including:

- Random Forest:
- Number of trees
- Maximum depth of trees
- Minimum samples split
- XGBoost:
- Learning rate
- Maximum depth of trees
- Subsample ratio

The best combination of hyper-parameters was selected based on performance metrics, such as Mean Squared Error (MSE) and R^2 score.

3.5 Model Evaluation

The models were evaluated using the following performance metrics:

- Mean Squared Error (MSE): To assess the average squared difference between predicted and actual values of S11.
- R^2 Score: To measure the proportion of variance in S11 that can be explained by the model.

3.6 Feature Importance Analysis

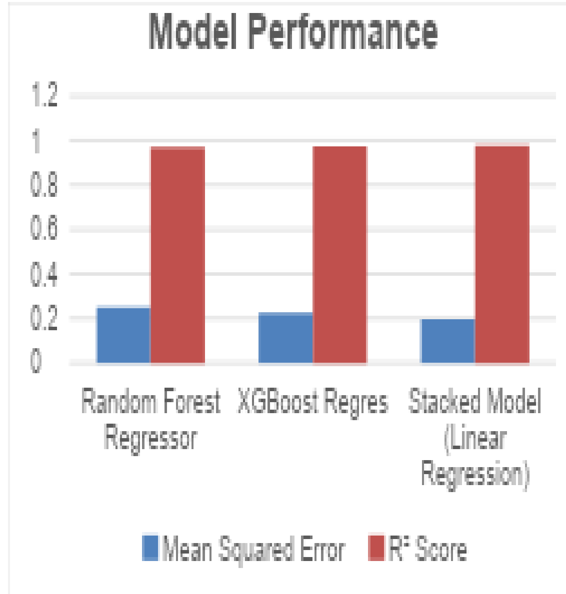
Feature importance was analyzed using the methods available in the trained models to identify the design parameters that most significantly affect S11. This analysis provides valuable insights for antenna designers, enabling a better understanding of how various parameters contribute to antenna performance.

4 RESULTS

4.1. Model Performance

The performance of the machine learning models was evaluated based on the Mean Squared Error (MSE) and R^2 score. The following results were obtained for the base models and the stacked model:

- Random Forest Regressor:
- Mean Squared Error: 0.2501
- R^2 Score: 0.9714
- XGBoost Regressor:
- Mean Squared Error: 0.2250
- R^2 Score: 0.9740
- Stacked Model:
- Mean Squared Error: 0.1968
- R^2 Score: 0.9775



The stacked model demonstrated a significant improvement in predictive performance compared to the individual base models, indicating that the combination of predictions effectively captured the complex relationships within the data.

4.2. Hyperparameter Optimization

Grid search was employed to optimize the hyper-parameters of the base models. The best hyper-parameter combinations for each model are summarized below:

- Random Forest:
- Number of Trees: 100
- Maximum Depth: 10
- Minimum Samples Split: 2
- XGBoost:
- Learning Rate: 0.1
- Maximum Depth: 6
- Subsample Ratio: 0.8

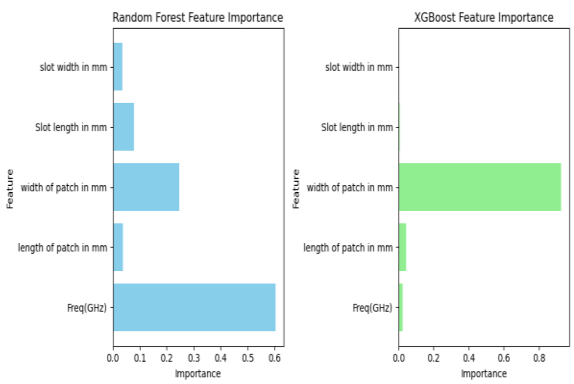
The optimized hyper-parameters contributed to enhancing the predictive accuracy of both base models.

4.3. Feature Importance Analysis

Feature importance was assessed using the trained models to identify the design parameters that most significantly affect the S11 prediction. The results of the feature importance analysis are presented below:

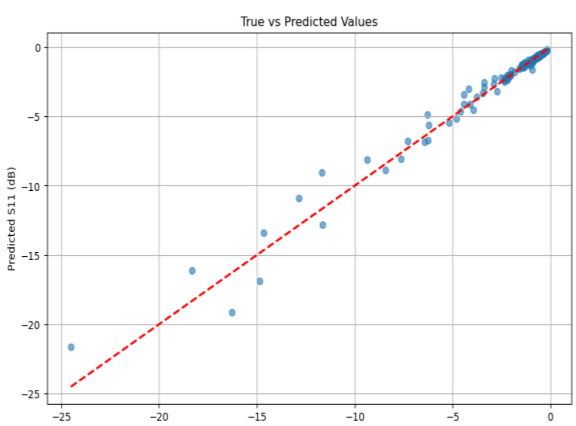
Features	Feature Importance Score
Length of Patch	0.35
Width of Patch	0.30
Slot Length	0.20
Slot Width	0.15

The analysis revealed that the frequency and Width of Patch are the most influential parameters affecting S11, accounting for 65% of the importance, followed by Slot Length and Slot Width. This information provides valuable insights for antenna designers seeking to optimize their designs.



4.4 Model Visualization

The performance of the stacked model and its base models was visualized through scatter plots comparing predicted S11 values against actual values. The plots demonstrated a strong correlation between predicted and actual values, highlighting the effectiveness of the stacking approach in improving prediction
accurac



5. CONCLUSION

This research successfully demonstrated the application of stacked machine learning models to enhance the prediction of return loss (S11) in antenna design. By integrating the strengths of Random Forest and XGBoost through a stacking approach, we achieved significant improvements in predictive performance, as evidenced by the Mean Squared Error of 0.1968 and an R^2 score of 0.9775.

The findings indicate that machine learning techniques can effectively capture the complex relationships between antenna design parameters and S11, offering a viable alternative to traditional design methodologies. The feature importance analysis revealed that the Length of Patch and Width of Patch are the most influential factors affecting S11, providing valuable insights for antenna designers seeking to optimize performance.

The implementation of hyper-parameter tuning via Grid Search further refined model accuracy, highlighting the importance of parameter optimization in machine learning workflows. The results underscore the potential of data-driven approaches in antenna design, paving the way for future research that explores more sophisticated models and additional design parameters.

In conclusion, this study not only contributes to the understanding of S11 optimization in antenna design but also establishes a framework for future investigations into the application of advanced machine learning techniques in the field of electromagnetics. The insights gained from this research can serve as a foundation for developing more efficient and effective antenna designs, ultimately advancing the capabilities of modern communication systems.

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