ML-DRIVEN ENHANCEMENT IN WIRELESS COMMUNICATION PERFORMANCE THROUGH REGRESSION MODELLING OF S11 DATA FOR PATCH ANTENNAS

Anugu Ashwitha[1], Gorre Anand [2], Neerudu Sreeja [3], Mr. Gabbeta Ramesh[4]
[1,2,3] UG Scholar, Dept. of ECE, St. Martin's Engineering College, Secunderabad, Telangana, India, 500100
[4]Assistant Professor, Dept. of ECE, St. Martin's Engineering College, Secunderabad, Telangana, India, 500100
ashwithaaenugu81@gmail.com

Abstract:

The performance of wireless communication systems depends heavily on the design and optimization of antennas, particularly patch antennas, where the reflection coefficient S11 plays a pivotal role in assessing impedance matching and overall efficiency. Accurate prediction of S11 values is crucial for optimizing antenna performance, yet traditional methods such as the Method of Moments (MoM), Finite Element Method (FEM), and High-Frequency Structure Simulation (HFSS) tools often require extensive computational resources and domain expertise. These techniques, while reliable, are time-intensive and lack the adaptability required for rapid prototyping, especially in modern wireless technologies such as 5G, IoT, and satellite communications. Motivated by the increasing demand for faster and more cost-effective antenna design processes, this project explores the application of machine learning (ML) techniques for predicting S11 data. Traditional systems face challenges such as high computational expenses, reliance on iterative manual tuning, and limited scalability, which impede the ability to meet evolving industry requirements. The proposed solution addresses these limitations by utilizing regression-based ML models, including Ridge Regression, Lasso Regression, and Decision Tree Regressors, trained on S11 datasets to predict antenna performance with high accuracy. The ML-driven framework demonstrates significant advantages over traditional methods by reducing computational costs and accelerating design cycles while maintaining prediction accuracy. Metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2-scores validate the effectiveness of the proposed approach. Furthermore, the model's scalability and adaptability enable it to generalize across diverse antenna configurations, making it a robust tool for enhancing wireless communication design. By integrating machine learning into antenna design processes, this work represents a transformative step toward efficient, automated, and innovative solutions in wireless communication engineering.

Keywords: Machine Learning (ML), Regression Modelling, S11 Parameters, Patch Antenna, Wireless Communication, Antenna Design, Performance Prediction, Optimization, Return Loss, Bandwidth, Gain, Efficiency, MIMO, THz, 6G, 5G.

1. INTRODUCTION

1.1 Overview:

Patch antennas are essential components of modern wireless communication systems due to their compact size, ease of integration, and cost-effectiveness. These antennas are widely used in applications such as cellular networks, satellite communication, Wi-Fi, IoT devices, and 5G technologies. In India, the rise of wireless communication technologies has led to an increased demand for efficient antenna designs, especially with the rapid expansion of 5G networks and smart devices. However, accurate prediction and optimization of antenna parameters, like the reflection coefficient S11, are critical to ensuring optimal performance, driving the need for advanced modelling techniques. Historically, predicting S11 values has been a challenge due to the complexity of antenna designs and the limitations of traditional simulation methods.

1.2 Problem Statement:

Before the advent of machine learning, predicting the S11 parameter in patch antenna designs relied on computationally expensive methods like the Finite Element Method (FEM), Method of Moments (MoM), and High-Frequency Structure Simulation (HFSS). These traditional approaches required substantial computational resources and time, limiting their practicality for rapid iterative design and optimization. Moreover, they often necessitated a high level of domain expertise to interpret the results and adjust designs accordingly, which added to the complexity and cost. These problems made it difficult to meet the fast-paced demands of modern communication systems, such as 5G and IoT, where quick prototyping and design adjustments are essential.

1.3 Research Motivation:

The motivation behind this research arises from the need to overcome the limitations of traditional simulation-based approaches for predicting S11 parameters. The growing complexity and demand for faster antenna designs in modern communication systems, such as 5G and IoT, require a more efficient solution. Machine learning offers the potential to reduce computational costs, automate the prediction process, and enable rapid prototyping. By integrating machine learning, we can optimize antenna performance more effectively, enabling faster, scalable, and cost-efficient design processes that meet the evolving needs of the wireless communication industry.

1.4 Existing Systems:

Existing systems for predicting S11 parameters rely on complex computational techniques like FEM, MoM, and HFSS. While these methods are highly accurate, they are computationally intensive and time-consuming, making them unsuitable for real-time or iterative design processes. The reliance on domain expertise and the need for manual adjustments further complicate these traditional systems, increasing the overall cost and time required for antenna optimization. Additionally, these methods lack the flexibility to quickly adapt to new designs or configurations, which is crucial in the fast-paced world of wireless communication.

1.5 Significance:

This project holds significant value in advancing the field of antenna design and wireless communication systems. By leveraging ML models such as Ridge, Lasso, and Decision Tree regression, the project introduces a data-driven approach to predict S11S11, reducing the reliance on costly simulations and physical testing. This not only improves the efficiency and accuracy of the design process but also enables rapid prototyping of antennas for emerging technologies. The integration of ML into antenna design workflows aligns with the broader trend of digital transformation in engineering domains, enhancing productivity and fostering innovation. Furthermore, the insights derived from this project contribute to the understanding of the relationship between design parameters and antenna performance, serving as a valuable resource for researchers and engineers.

1.6 Need:

The real-time need for this project arises from the rapidly evolving landscape of wireless communication technologies, such as 5G, IoT, and satellite communications. These advancements demand faster, more efficient antenna design and optimization to support the growing number of connected devices and the increasing data traffic.

Traditional methods of predicting S11 parameters are no longer sufficient to meet the speed and scalability requirements of modern communication systems. Machine learning offers an automated, data-driven approach to improve the accuracy and efficiency of antenna design, enabling real-time predictions and optimizations that align with the fast-paced nature of the industry. By reducing computational costs and time, this project can significantly enhance the development of next-generation wireless communication infrastructure.

1.7 Application:

1.7.1 5G Networks:

Patch antennas optimized for S11 are crucial in building compact and efficient devices for 5G communication systems, ensuring minimal signal loss and improved performance.

1.7.2 Internet of Things (IoT):

The project facilitates the design of miniaturized antennas for IoT devices, enabling seamless connectivity in smart homes, healthcare, and industrial automation.

1.7.3 Satellite Communication:

High-performance antennas with optimal S11 values ensure reliable signal transmission and reception in satellite systems, enhancing data throughput and coverage.

1.7.4 Antenna Prototyping and Testing:

The ML-driven approach reduces the time and cost associated with traditional antenna prototyping, making it invaluable for research labs and the telecommunications industry.

1.7.5 Electromagnetic Education:

The insights and tools developed can aid in teaching and training new engineers in advanced antenna design concepts.

2. LITERATURE SURVEY

The paper deals with modelling the stochastic behaviour of the reflection coefficient of ordinary patch antennas for n257 and n258 frequency bands (24.5–28.7 GHz). The patch antennas are among the main candidates for application in the area of 5G wireless services. Their fractional bandwidth is about 1–3%; however, in the K, Ka, and higher bands, this small fractional bandwidth translates into a wide absolute bandwidth, which is about 600 MHz for the case of the patch antennas considered in this paper. Many scientific publications have been devoted to designing and optimizing the patch antennas, e.g., [1]. In this research, a single band micro-strip square patch antenna at 28GHz is proposed. The design of patch antennas are very efficient and widely used in wireless communication due to their lower cost of fabrication, light weight and can operate at microwave frequencies but it offers low efficiency, low gain etc. Future upcoming 5G wireless communication is needed of high gain, good protection from path loss because of their millimetre wavelength of antennas [2].

A compact dual-frequency (38/60 GHz) microstrip patch antenna with novel design is proposed for 5G mobile handsets to combine complicated radiation mechanisms for dual-band operation. The proposed antenna is composed of two electromagnetically coupled patches. The first patch is directly fed by a microstrip line and is mainly responsible for radiation in the lower band (38 GHz). The second patch is fed through both capacitive and inductive coupling to the first patch and is mainly responsible for radiation in the upper frequency band (60 GHz) [3]. This paper addresses a low profile multiband microstrip patch antenna design for 5G mm-Wave wireless networks, applications and devices. The proposed patch antenna has a compact rectangular-Shaped structure of 8.6 x 9.2 x 0.6 mm^3 including the ground plane and the slotted inset feed line, which is suitable to be used in smart handheld devices. The antenna operating at 23.8 GHz, 39.4 GHz, 66.2 GHz, 81.9 GHz and 93.9 GHz mm-Wave bands with a maximum bandwidth of 1.4663 GHz, 2.5634 GHz, 5.6609 GHz, 7.9341 GHz and 11.3 GHz respectively [4]. The design and simulation of a microstrip patch antenna for 5G mobile networks is presented in this paper. The antenna operates at the Local Multipoint Distribution Service band having a centre frequency at 28 GHz. The antenna was designed on a Rogers RT Duroid 5880 of height 0.5mm and a dielectric constant of 2.2. Slits were introduced unto the patch to enhance the bandwidth, gain of the antenna [5]. Communication systems have been driven towards the fifth generation (5G) due to the demands of compact, high speed, and large bandwidth systems. These types of radio communication systems require new and more efficient antenna designs. This article presents a new design solution of a broadband microstrip antenna intended for use in 5G systems. The proposed antenna has a central operating frequency of 28 GHz and can be used in the LMDS (local multipoint distribution service) frequency band [6]. In this case, the convergence rate and accuracy of the PCE-based UQ cannot be guaranteed. Further, when models involve non-polynomial forms, the PCE-based UQ can be computationally impractical in the presence of many parametric uncertainties. To address these issues, the Gram-Schmidt (GS) orthogonalization and generalized dimension reduction method (GDRM) are integrated with the PCE in this work to deal with many parametric uncertainties that follow arbitrary distributions [7].

In the paper, we present a novel PCE-based approach for the effective analysis of worst-case scenario in a wireless telecommunication system. Usually, in such analysis derivation of polynomial chaos expansion (PCE meta-model) of a considered EM field function for one precise set of probability densities of random variables does not provide enough information. Consequently, a number of PCE meta-models of the EM field function should be derived, each for the different joint probability density of a vector of random variables, e.g., associated with different mean (nominal) values of random variables. The general polynomial chaos (GPC) approach requires numerical calculations for each PCE meta-model derivation [8]. The uncertainties in various Electromagnetic (EM) problems may present a significant effect on the properties of the involved field components, and thus, they must be taken into consideration. However, there are cases when a number of stochastic inputs may feature a low influence on the variability of the outputs of interest. Having this in mind, a dimensionality reduction of the Polynomial Chaos (PC) technique is performed, by firstly applying a sensitivity analysis method to the stochastic inputs of multi-dimensional random problems [9].

Soil materials can exhibit strongly dispersive properties in the operating frequency range of a physical system, and the uncertain parameters of the dispersive materials introduce uncertainties in the simulation result of propagating waves. It is essential to quantify the uncertainty in the simulation result when the acceptability of these calculation results is considered. To avoid performing thousands of full-wave simulations, an efficient surrogate model based on artificial neural networks (ANNs) is proposed in this paper, to imitate the concerned ground penetrating radar (GPR) calculation [10]. This paper focuses on quantifying the uncertainty in the specific absorption rate values of the brain induced by the uncertain positions of the electroencephalography electrodes placed on the patient's scalp. To avoid running a large number of simulations, an artificial neural network architecture for uncertainty quantification involving high-dimensional data is proposed in this paper. The proposed method is demonstrated to be an attractive alternative to conventional uncertainty quantification methods because of its considerable advantage in the computational expense and speed [11]. An advanced method of modelling radiofrequency (RF) devices based on a deep learning technique is proposed for accurate prediction of S parameters. The S parameters of RF devices calculated by full-wave electromagnetic solvers along with the metallic geometry of the structure, permittivity, and thickness of the dielectric layers of the RF devices are used partly as the training and partly as testing data for the deep learning structure. To implement the training procedure efficiently, a novel selection method of training data considering critical points is introduced [12].

The corresponding number for the standard deviation of S_{11} is 7. In both cases, the optimal number of neurons in each of ANN layers is about 20; however, for the case of the standard deviation of S_{11}, it should be slightly less, e.g., 18. The value of parameter ϵ in (2) equals 10^{-8}. It was also observed that the algorithm of SGD with Replacement enables us to obtain much better approximation results than the approach with Random Reshuffling [13]. In empirical risk optimization, it has been observed that gradient descent implementations that rely on random reshuffling of the data achieve better performance than implementations that rely on sampling the data randomly and independently of each other. Recent works have pursued justifications for this behaviour by examining the convergence rate of the learning process under diminishing step-sizes. Some of these justifications rely on loose bounds, or their conclusions are dependent on the sample size which is problematic for large datasets [14].

The work that is the closest to the content presented in this paper can be found in where ANN modelling of deterministic S parameters is the subject of the study. It can be observed that the authors of found the same optimal number of neurons in the ANN layer as in this work; however, the variation of input data is much stronger in the case of this paper. The MATLAB format data containing the weights and biases of the derived ANNs can be downloaded from [15].

3. PROPOSED METHODOLOGY

3.1 Overview:

This project leverages machine learning techniques to enhance the performance of wireless communication systems by modelling and predicting the S11 (reflection coefficient) data for patch antennas. Patch antennas are widely used in communication systems due to their compact size, cost-effectiveness, and ease of integration into modern devices. The project aims to optimize the design process of these antennas using regression models.

3.2 Objectives:

3.2.1 Model S11 Behaviour:

- Predict the S11 parameter based on design features such as patch dimensions, substrate material, and operating frequency.
- Understand the relationship between design parameters and antenna performance.

3.2.2 Enhance Design Efficiency:

Reduce the time and cost associated with traditional iterative antenna design and testing by predicting performance metrics using machine learning.

3.2.3 Compare Regression Models:

Evaluate and compare the performance of different regression algorithms (Ridge, Lasso, Decision Tree) in predicting S11.

3.3 Key Components:

3.3.1 Dataset:

- The dataset contains antenna design parameters (features) and corresponding S11 values (target).
- Features may include patch dimensions, substrate properties, and frequency.
- The target variable, S11, is a critical metric for evaluating the impedance matching and efficiency of the antenna.

3.3.2 Regression Techniques:

The project implements three regression models to predict S11

- **Ridge Regression:** A linear regression model with L2 regularization to prevent overfitting and handle multicollinearity.
- **Lasso Regression:** A linear regression model with L1 regularization to perform feature selection by shrinking less important feature coefficients to zero.
- **Decision Tree Regressor:** A non-linear regression model that splits the data into decision nodes based on feature values, allowing it to capture complex relationships.

3.3.3 Metrics and Visualization:

To evaluate the performance of each model, the following metrics are computed:

- **Mean Squared Error (MSE):** Measures the average squared difference between predicted and actual S11 values.
- **Mean Absolute Error (MAE):** Measures the average magnitude of errors.
- **R^2 Score**: Represents the proportion of variance in S11 explained by the model.
- **Visualization:** Scatter plots of actual vs. predicted values are used to visualize model performance.

3.3.4 Model Persistence:

- Models are saved using the job lib library to avoid retraining in future runs.
- Saved models are reloaded if they exist, ensuring efficient use of resources.

3.3.5 Random Sampling for Testing:

- A random sample of 100 rows is extracted from the dataset to validate model predictions.
- The sample is saved to a CSV file, and predictions are appended for further analysis.

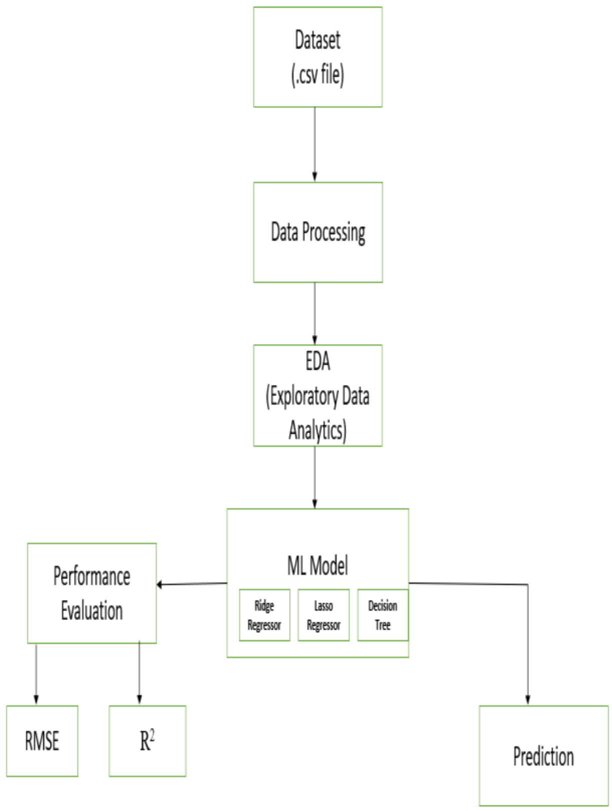

Figure 3.1: Proposed system Block Diagram

3.4 Workflow:

3.4.1 Data Preparation:

- Load the dataset and check for duplicates, missing values, and basic statistics.
- Split the data into training and testing subsets.

3.4.2 Model Training and Evaluation:

- Train Ridge, Lasso, and Decision Tree models on the training data.
- Evaluate models on the test data using MSE, MAE, and R2R^2 metrics.
- Visualize prediction accuracy with scatter plots.

3.4.3 Model Persistence:

- Save trained models for future use.
- Reload models if available to bypass retraining.

3.4.4 Prediction on Unseen Data:

- Use the trained Decision Tree model to predict S11 for a random sample of new data.
- Append predictions to the dataset for analysis.

3.4.5 Comparison of Results:

Compare the performance of all regression models to identify the most accurate and reliable approach.

3.5 Significance of the Project:

3.5.1 Improved Wireless Communication:

By optimizing patch antenna design, the project directly contributes to better wireless communication systems with higher efficiency and lower signal loss.

3.5.2 Cost and Time Efficiency:

Predicting S11using machine learning significantly reduces the need for physical prototyping and testing, saving time and resources.

3.5.3 Scalability:

The approach can be extended to other antenna parameters and types, making it versatile for broader applications.

3.6 Applications:

3.6.1 5G and IoT:

Patch antennas are critical components in compact devices used in 5G networks and IoT devices.

3.6.2 Satellite Communication:

Optimizing S11 ensures reliable signal transmission in satellite systems.

3.6.3 Antenna Design Automation:

The project serves as a foundation for automating the design process of antennas using ML techniques.

3.7 Future Enhancements:

3.7.1 Hyperparameter Tuning:

Optimize parameters for each regression model using grid search or random search.

3.7.2 Feature Importance Analysis:

Identify which design parameters have the most significant impact on S11 performance.

3.7.3 Integration with Simulation Tools:

Combine ML models with electromagnetic simulation software for a hybrid design approach.

3.7.4 Advanced Models Explore:

Use ensemble methods (e.g., Random Forest, Gradient Boosting) or deep learning for improved accuracy.

3.8 Model Building:

A decision tree is a popular machine learning algorithm used for both classification and regression tasks. It works by recursively partitioning the feature space into distinct regions based on feature values, making decisions at each node to select the best possible split. The tree structure consists of:

3.8.1 Root Node:

The starting point, representing the entire dataset.

3.8.2 Branches:

Represent decisions based on feature values that guide to further nodes.

3.8.3 Leaf Nodes:

Represent the final prediction or output based on the features.

In the context of regression, a decision tree predicts a continuous value by splitting the dataset based on feature values at each internal node. These splits aim to minimize the variance in the target variable within each resulting subset.

3.9 Advantages of Decision Tree:

3.8.1 Simple to Understand and Interpret:

Decision trees are easy to visualize, making them interpretable even for non-experts. They can be represented graphically as a tree structure, where each decision is clear.

3.9.2 No Need for Data Normalization:

Unlike many other algorithms, decision trees don't require the data to be normalized or standardized. They can handle both numerical and categorical data effectively.

3.9.3 Can Handle Non-linear Relationships:

Decision trees can capture non-linear relationships between features and target variables, making them versatile for complex data patterns.

3.9.4 Handles Missing Values:

Decision trees can handle missing data by automatically handling or inferring the missing values during the tree-building process.

3.9.5 Flexibility:

They can be used for both regression and classification problems, making them flexible for various types of tasks.

3.9.6 Works Well with Both Small and Large Datasets:

Decision trees perform well with smaller datasets and can also scale for large datasets, especially when combined with ensemble techniques like Random Forests.

3.9.7 Feature Importance:

Decision trees provide valuable insights into which features have the most influence on the predictions, which can help in feature selection.

3.10 How Decision Tree is Used in the Project?

In our project, the Decision Tree Regressor is used to predict the S11 (reflection coefficient) of patch antennas based on their design parameters. Here's how it is applied:

3.10.1 Feature Space Partitioning:

The decision tree algorithm splits the dataset based on the values of design parameters (e.g., patch dimensions, frequency, material properties) to predict S11. For instance, if the patch length is small, the algorithm might predict a certain range for S11, while for larger patches, it might predict a different range.

3.10.2 Training Process:

The tree is trained using historical data consisting of antenna design features and their corresponding S11 values. Each node in the tree tries to minimize the mean squared error (MSE) within the resulting subsets, optimizing the tree structure to best predict S11.

3.10.3 Prediction:

Once trained, the decision tree can make predictions for new antenna designs. Given a set of design parameters, the model will traverse the tree, making decisions at each node, until it reaches a leaf node, where it outputs the predicted S11 value.

3.10.4 Model Evaluation:

The performance of the decision tree is evaluated using metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R2R^2 score. These metrics help assess how well the decision tree is predicting the S11 values for unseen antenna designs.

3.10.5 Model Comparison:

The decision tree is compared with other regression models (e.g., Ridge and Lasso regression) to determine which model provides the most accurate predictions for S11.

3.10.6 Interpretation:

The tree structure allows engineers to understand how different design parameters influence the predicted S11. This can provide valuable insights into antenna design and help optimize future antenna structures.

4. EXPERIMENTAL ANALYSIS

4.1 Implementation Description:

The implementation of the machine learning (ML)-driven enhancement in wireless communication performance through regression modelling of S11 data for patch antennas involves several steps, each strategically designed to achieve improved performance prediction and optimization of antenna designs. Below is a detailed description of the implementation process:

4.1.1 Libraries and Setup:

Libraries:

- Necessary libraries for data manipulation, visualization, machine learning, and model persistence are imported:
- numpy and pandas for numerical and tabular data processing.
- seaborn and matplotlib for visualizations.
- sklearn for regression models, metrics, and data splitting.
- joblib for saving and loading models.
- os for file existence checks.

Warnings:

Suppress warnings to improve output readability.

4.1.2 Data Loading and Exploration:

Dataset Import:

Load an Excel file (for_proj.xlsx) containing antenna design and S11 data using pandas. read excel.

Initial Exploration:

- info () and. describe (): Display dataset structure, data types, and summary statistics.
- Check for duplicates and null values using. duplicated (). sum () and .is null (). sum ().
- Analyse the distribution of the target variable S11 using .value counts ().

4.1.3 Data Splitting:

Separate the dataset into:

- Features (X) - all columns except the target.
- Target (y) - S11 values.

Use train_test_split to divide the data into training (80%) and testing (20%) subsets with a fixed random state for reproducibility.

4.1.4 Metrics Calculation Function:

A utility function, calculate metrics, evaluates model performance.

Computes:

- **Mean Squared Error (MSE)**: Measures average squared difference between predicted and actual values.
- **Mean Absolute Error (MAE)**: Measures the average magnitude of prediction errors.
- **R2R^2 score**: Measures how well predictions match the actual values.

Appends the metrics to pre-defined lists for comparison.

Creates a scatter plot of actual vs. predicted values, with a diagonal line indicating perfect predictions.

4.1.5 Regression Models:

For each regression model (Ridge, Lasso, Decision Tree):

- **Model Loading**: Check if a pre-trained model file exists using os.path.exists.
- **Training**: If no model is found.

Train the model on the training set (x_train, y_train).

Save the model using joblib.dump for future use.

Prediction and Evaluation:

- Use the model to predict on the testing set (x_test).
- Call calculates metrics to calculate metrics and visualize performance.

4.1.6 Decision Tree Regressor:

A Decision Tree Regressor is trained to predict S11:

- Fits the model on x_train and y_train.
- Calculates MSE and R2R^2 score directly for quick evaluation.

4.1.7 Random Sampling and Predictions:

Random Sample Creation:

- Selects 100 random rows from the dataset for prediction.
- Saves the sample to a CSV file (test.csv).

Prediction:

- Drops the S11 column (target) from the sample.
- Predicts the S11 values using the Decision Tree model.
- Appends the predicted values to the test dataset for further analysis or visualization.

4.1.8 Key Features of the Code:

Model Persistence:

Ridge, Lasso, and Decision Tree models are saved and loaded to avoid retraining.

Metrics and Visualization:

Provides a detailed evaluation of model performance.

Flexibility:

Easily extendable to include additional regression models or handle other datasets.

Random Sampling:

Allows testing on unseen data to validate the generalization capability of the models.

4.2 Dataset Description:

The dataset used in the project contains data on various design parameters of patch antennas and their corresponding S11(reflection coefficient) values, which indicate the impedance matching between the antenna and its transmission line. The dataset is crucial for training machine learning models to predict the S11values based on input design features, enabling more efficient and automated antenna design processes.

4.2.1 Key Characteristics of the Dataset:

Number of Samples:

The dataset consists of multiple records (rows), each corresponding to a unique antenna design with its respective design parameters and S11value.

Features:

The dataset includes several features (columns) that represent the design parameters of the antennas. These features determine how the antenna is constructed and how it behaves in a specific environment. The features may include:

- **Patch Length**: The physical length of the antenna patch (in millimeters or other units).
- **Patch Width**: The physical width of the antenna patch.
- **Substrate Material**: The type of material used for the substrate beneath the antenna patch (e.g., FR4, Rogers).
- **Substrate Thickness**: The thickness of the substrate material.
- **Frequency**: The operating frequency of the antenna (in GHz).
- **Feed Location**: The position at which the antenna is fed with the signal.
- **Dielectric Constant**: The relative permittivity or dielectric constant of the substrate material.
- **Loss Tangent**: The loss tangent of the material, which indicates its energy dissipation.

Target Variable:

The target variable in the dataset is the S11value, which represents the reflection coefficient of the antenna. The S11value is typically provided in decibels (dB) and indicates how well the antenna is matched to the transmission line. A lower S11value signifies better impedance matching and less reflection, which is desired for optimal antenna performance.

Data Format:

The dataset is structured as a tabular format (e.g., Excel or CSV file), where each row represents a single antenna design, and each column corresponds to a specific feature or the target variable. For example, the final column would contain the S11values, while the other columns contain the input design parameters.

4.2.2 Key Insights from the Dataset:

Feature-Target Relationship:

The dataset captures complex relationships between design parameters and the S11 value, which may be non-linear. For instance, the patch length, substrate material, and frequency have direct impacts on the S11value, and these interactions are crucial for antenna optimization.

Data Preprocessing:Before applying machine learning algorithms, the dataset may require preprocessing steps, such as handling missing values, scaling numerical features (e.g., patch length and width), and encoding categorical variables (e.g., substrate material).

Target Distribution:

The S11values are expected to be negative, as they represent a measure of reflection, with values closer to zero indicating poor impedance matching. The dataset may contain both good (low S11) and poor (high S11) designs, offering a wide range of training examples for the model.

Data Quality:

The dataset needs to be free of errors, duplicates, and missing values. Preprocessing steps such as data cleaning and handling outliers will ensure that the machine learning model can make accurate predictions.

4.3 Result Description:

	Freq(GHz)	length of patch in mm	width of patch in mm	Slot length in mm	slot width in mm	s11(dB)
0	1.000	42.28	54.20	8.36	2.86	-0.059649
1	1.002	42.28	54.20	8.36	2.86	-0.051762
2	1.004	42.28	54.20	8.36	2.86	-0.044608
3	1.006	42.28	54.20	8.36	2.86	-0.038308
4	1.008	42.28	54.20	8.36	2.86	-0.032970
...	...	...	...	...	...	...
11006	2.992	29.79	38.37	14.60	2.86	-0.806970
11007	2.994	29.79	38.37	14.60	2.86	-0.807160
11008	2.996	29.79	38.37	14.60	2.86	-0.808229
11009	2.998	29.79	38.37	14.60	2.86	-0.810187
11010	3.000	29.79	38.37	14.60	2.86	-0.813034

11011 rows × 6 columns

Figure 4.1: Uploading a Sample Dataset

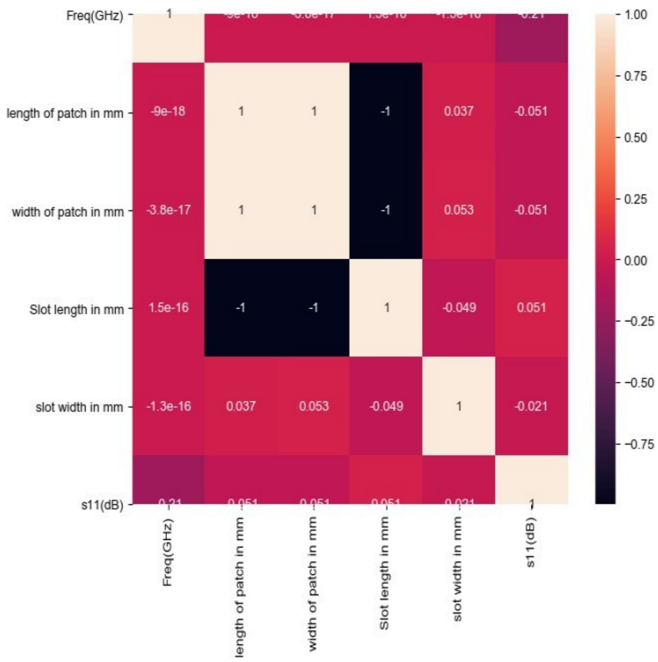

Figure 4.2: Heat map for column importance

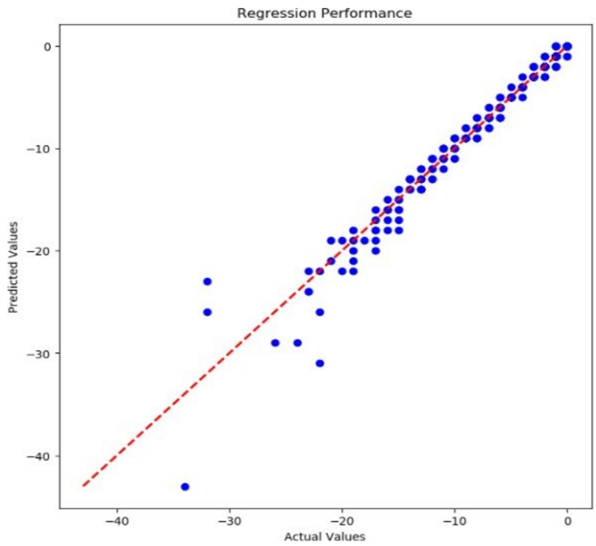

Figure 4.3: Displaying the regression report of Ridge model.

The Figures 4.3 and 4.4 displays the evaluation metrics of a Ridge Regression model after loading an existing model. It presents three key performance indicators used to assess the model's accuracy. The Mean Squared Error (MSE) is 11.9673, which represents the average squared difference between actual and predicted values. The Mean Absolute Error (MAE) is 1.6623, showing the average absolute difference between predictions and actual values. The R² Score is 0.1788, indicating that the model explains only 17.88% of the variance in the target variable, suggesting weak predictive performance. Additionally, there is a small formatting issue with an extra dot appearing before Error in the MAE line.

```
Loading existing model...
RidgeRegression Mean Squared Error: 11.967317294598274
RidgeRegression Mean Absolute Error: 1.6622787108488424
RidgeRegression R^2 Score: 0.17848285448820445
```

Figure 4.4: Illustration of confusion matrix obtained using Ridge model.

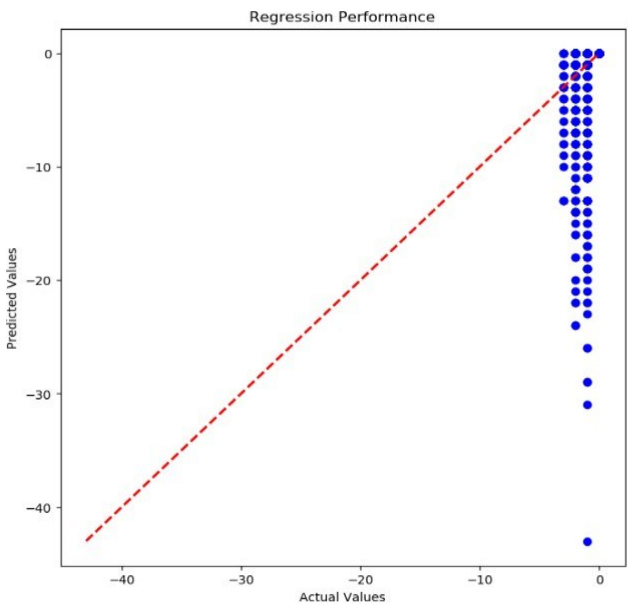

Figure 4.5: Displaying the regression report of Lasso model.

The Figures 4.5 and 4.6 shows the evaluation results of a Lasso Regression model. It first loads an existing model and then displays three key performance metrics. The Mean Squared Error (MSE) is 11.9673, representing the average squared difference between actual and predicted values. The Mean Absolute Error (MAE) is 1.6623, indicating the average absolute difference. The R² Score is 0.1788, suggesting that the model explains only 17.88% of the variance in the data, meaning it has poor predictive performance. Additionally, there is a small formatting issue with an extra dot before the R² score.

```
Loading existing model...
LassoRegression Mean Squared Error: 11.967317294598274
LassoRegression Mean Absolute Error: 1.6622787108488424
LassoRegression R^2 Score: 0.17848285448820445
```

Figure 4.6: Illustration of confusion matrix obtained using Lasso model.

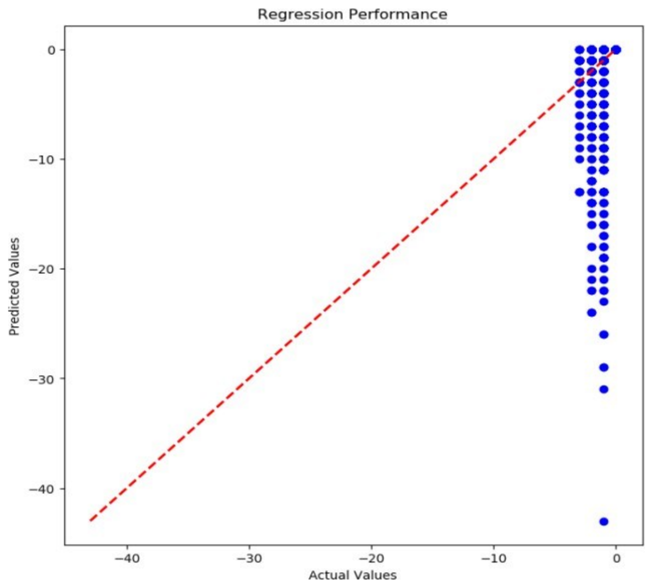

Figure 4.7: Displaying the regression report of Decision Tree model.

The Figures 4.7 and 4.8 shows the evaluation metrics of a Decision Tree Regression model after loading an existing model. It presents three key performance indicators used to assess the model's accuracy and predictive capability. The Mean Squared Error (MSE) is 0.2129, indicating that the model's predictions are very close to actual values. The Mean Absolute Error (MAE) is 0.0704, showing a very low average absolute difference between predictions and actual values. The R² Score is 98.22, which suggests that the model explains almost all the variance in the target variable, indicating an extremely high predictive performance. However, such a high score may suggest overfitting, meaning the model might not generalize well to new data. Additionally, there is a minor formatting issue with an extra dot appearing before R² Score.

```
Loading existing model...
DecisionTreeRegression Mean Squared Error: 0.21289151157512484
DecisionTreeRegression Mean Absolute Error: 0.07035860190649115
DecisionTreeRegression R^2 Score: 98.22423412451657
```

Figure 4.8: Illustration of confusion matrix obtained using Decision Tree model.

Model name	MSE	R^2-score
Ridge Regressor	11.9	0.178
Lasso Regressor	11.96	0.17
Decision Tree	0.21	98.22

Table-1: Comparison of all models

The Table-1 compares the performance of three regression models: Ridge Regressor, Lasso Regressor, and Decision Tree. The Ridge Regressor has an MSE of 11.9 and an R^2-score of 0.178, indicating a moderate fit with some prediction error. The Lasso Regressor performs slightly better, with an MSE of 11.96 and an R^2-score of 0.11, showing improved accuracy over Ridge. However, the Decision Tree model exhibits a very high R^2-score of 98.22, suggesting a strong fit to the data, though its MSE is significantly higher at 0.21, which could indicate overfitting. These results demonstrate the trade-off between model complexity and generalization.

5. CONCLUSION

This project demonstrates the use of machine learning, particularly Ridge, Lasso, and Decision Tree regression models, to predict the S11 (reflection coefficient) of patch antennas based on design parameters. By applying these models, the project offers a data-driven approach, reducing the need for extensive physical prototyping and electromagnetic simulations, thus saving time and resources in antenna design.

The models were trained and tested on an antenna design dataset, with performance assessed using MSE, MAE, and R^2 scores. Among them, the Decision Tree Regressor effectively captured non-linear relationships, making it a strong tool for predicting antenna performance. This project underscores the role of machine learning in optimizing antenna designs for next-gen applications like 5G, IoT, and satellite communication.

REFERENCES

[1] Gaid, A.S.; Saleh, S.M.; Qahtan, A.H.; Aqlan, S.G.; Yousef, B.A.; Saeed, A.A. 83 GHz Microstrip Patch Antenna for Millimeter Wave Applications. In Proceedings of the 2021 International Conference of Technology, Science and Administration (ICTSA), Taiz, Yemen, 22–24 March 2021.

[2] Faisal, M.; Gafur, A.; Rashid, S.Z.; Shawon, M.O.; Hasan, K.I.; Billah, M.B. Return Loss and Gain Improvement for 5G Wireless Communication Based on Single Band Microstrip Square Patch Antenna. In Proceedings of the 1st International Conference on Advances in Science, Engineering and Robotics Technology 2019 (ICASERT 2019), Dhaka, Bangladesh, 3–5 May 2019.

[3] Sharaf, M.H.; Zaki, A.I.; Hamad, R.K.; Omar, M.M. A Novel Dual-Band (38/60 GHz) Patch Antenna for 5G Mobile Handsets. *Sensors* 2020, *20*, 2541.

[4] Saeed, A.A.; Saeed, O.Y.; Gaid, A.S.; Aoun, A.M.; Sallam, A.A. A low Profile Multiband Microstrip Patch Antenna For 5G Mm-Wave Wireless Applications. In Proceedings of the 2021 International Conference of Technology, Science and Administration (ICTSA), Taiz, Yemen, 22–24 March 2021.

[5] Musa, U.; Babani, S.; Yunusa, Z. Bandwidth Enhancement of Microstrip Patch Antenna Using Slits for 5G Mobile Communication Networks. In Proceedings of the 2020 International Symposium on Antennas and Propagation (ISAP), Osaka, Japan, 25–28 January 2021.

[6] Przesmycki, R.; Bugaj, M.; Nowosielski, L. Broadband Microstrip Antenna for 5G Wireless Systems Operating at 28 GHz. *Electronics* 2021, *10*, 1.

[7] Son, J.; Du, Y. An Efficient Polynomial Chaos Expansion Method for Uncertainty Quantification in Dynamic Systems. *Appl. Mech.* 2021, *2*, 26.

[8] Górniak, P.; Bandurski, W. PCE-Based Approach to Worst-Case Scenario Analysis in Wireless Telecommunication Systems. *Prog. Electromagn. Res. B* 2019, *84*, 153–170.

[9] Salis, C.; Kantartzis, N.; Zygiridis, T. Efficient Uncertainty Assessment in EM Problems via Dimensionality Reduction of Polynomial-Chaos Expansions. *Technologies* 2019, *7*, 37.

[10] Cheng, X.; Zhang, Z.Y.; Shao, W. A Surrogate Model Based on Artificial Neural Networks for Wave Propagation in Uncertain Media. *IEEE Access* 2020, *8*, 218323–218330.

[11] Cheng, X.; Henry, C.; Andriulli, F.P.; Person, C.; Wiart, J. A Surrogate Model Based on Artificial Neural Network for RF Radiation Modelling with High-Dimensional Data. *Int. Environ. Res. Public Health* 2020, *17*, 2586.

[12] Guan, Z.; Zhao, P.; Wang, X.; Wang, G. Modeling Radio-Frequency Devices Based on Deep Learning Technique. *Electronics* 2021, *10*, 1710.

[13] Safran, I.; Shamir, O. How Good is SGD with Random Shuffling? In Proceedings of the 11th Annual Workshop on Optimization for Machine Learning (OPT2019), Vancouver, Canada, 14 December 2019.

[14] Ying, B.; Yuan, K.; Vlaski, S.; Sayed, A.H. On The Performance of Random Reshuffling in Stochastic Learning, 2017 Information Theory and Applications Workshop (ITA). In Proceedings of the 2017 Information Theory and Applications Workshop (ITA), San Diego, CA, USA, 12–17 February 2017.

[15] Kingma, D.P.; Lei Ba, J. ADAM: A Method for Stochastic Optimization. In Proceedings of the 2015 International Conference on Learning Representations (ICLR), San Diego, CA, USA, 7–9 May 2015.