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PREDICTING ANTENNA S_{11} USING GAUSSIAN PROCESS REGRESSION, EXTREME GRADIENT BOOSTING, AND MULTILAYER PERCEPTRON

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Abstract
Machine Learning surrogates can accelerate antenna design by predicting key RF responses without repeated and cumbersome EM simulations. In this study, three different machine learning models were used to predict the S11 of Microstrip Patch Antenna. These algorithms belong to different families: Gaussian Process Regression (GPR), a kernel Bayesian non-parameteric regressor; Xtreme Gradient Boosting(XGB), a decision tree-based algorithm well-suited for non-linear tabular data; and a Multi-Layer Perceptron (MLP), a feed-forward neural network that learns nonlinear feature mappings. The algorithms were compared based on performance metrics such as MSE, RMSE, MAE, and R2 score. Amongst all three, XGboost stands out with an R^2 score of 0.9687.

INTRODUCTION

Wireless technology is advancing at a rapid pace [1]. The number of wireless devices has increased significantly in recent years is very great [2]. An antenna is an important component of wireless communication. Thus, antenna design is a significant step in the advancement of wireless networks [3]. We are currently in the age of Machine Learning and Deep learning. ML and DL have made groundbreaking advances in almost every field, including health and medicine [4]. The wireless communication and antenna design fields are no exception. Using ML and DL avoids the need for using laborious and time-consuming EM simulations on Computer Simulation Technology (CST) and High-Frequency Structure Simulator (HFSS) [5].

Predicting the reflection coefficient S11 is important in antenna design. It shows how well an antenna matches impedance and how efficiently it uses power at a certain frequency [6]. Antenna engineers usually works on full-wave electromagnetic (EM) simulations and prototypes to see how changes in design affect S11. These methods are useful but can be slow and costly, especially for large designs. This is why fast, data-driven models are needed. These ML and Dl

models can quickly predict S11 from design details and frequency, helping to narrow down options before detailed simulations and building [7].

Machine learning (ML) and deep learning (DL) can help create these fast models. Tree ensembles work well with engineering data; kernel methods give smooth predictions with reliable uncertainty; and neural networks can learn complex patterns quickly. However, many antenna studies only use one model, mix data and measures, or ignore uncertainty, making it hard to know which method is best for regular design work.

This paper compares three model types for predicting S11: Gaussian Process Regression (GPR), which uses kernels and gives uncertainty estimates; XGBoost, which uses decision trees for complex data; and a Multi-Layer Perceptron (MLP), a simple neural network. The focus is on microstrip patch antennas. A dataset is made with design and frequency details as inputs and S11 (in dB) as the target. Models are trained and tested with a clear process and evaluated using R2, MAE, RMSE, and other checks like error patterns and calibration (for GPR).

The remainder of the paper is as follows: Section II provides a comprehensive literature review related to the subject. In section III methodology is discussed. Section IV provides results and discussions followed by conclusion at the end.

LITERATURE REVIEW

Data-driven models are increasingly being used in antenna research to accelerate design and reduce the need for full-wave simulations. Many studies have focused on microstrip patch antennas for 5G, often using machine learning to improve or predict key responses such as S11. These studies suggest that different model types should be used for the same task [8].

Some studies have predicted S11 directly from geometry and frequency using supervised learning. For a 28 GHz patch, Jain et al. compared KNN, XGBoost, Decision Tree, and Random Forest. They found that all models worked well, with Random Forest being slightly better. This supports the use of tree ensembles for antenna data [9]. A recent study on slotted-patch antennas tested ANN, SVM, and GPR for S11 prediction. It found out tha GPR was the most accurate, showing the value of kernel methods for nonlinear RF behavior [10].

Kernel methods, especially Gaussian Process Regression (GPR), are popular in surrogate modelling. They handle nonlinear responses and provide a predictive uncertainty. Kernels encode smoothness and periodicity, which are beneficial for frequency-dependent responses, such as S11. [11] .GPR has been used for input characteristics and radiation patterns, achieving good accuracy with fewer evaluations than full-wave simulation [12],[13]. Methods such as two-level (residual) GPR further reduce modelling costs while maintaining high accuracy, which is useful when each EM sample is expensive [14].

Tree-boosted models are also strong for tabular-engineering data. XGBoost is a popular version of gradient-boosted decision trees, which is known for its speed and strong predictions. In antenna applications, ensembles (including XGBoost) have been tested with other regressors, often performing well depending on the dataset and target [15].

Neural networks, including compact MLPs, are used to learn the mapping from geometry/materials to the responses. For example, a knowledge-guided neural approach modelled the patch antenna S11 and gain using learned spectral representations. This showed that small networks can work well when the dataset is well-curated and physics-aware losses are used [16].

Overall, past studies show that ML/DL can predict S11 effectively and accelerate design exploration. However, many studies test only one model type or focus on accuracy without considering uncertainty or learning curves. This led to our comparison of GPR, XGBoost, and a compact MLP on the same S11 dataset, with standard splits/metrics.

METHODOLOGY

Data Acquisition:

Kaggle dataset is used for in this work [17]. The data have five input parameters and one output parameter. The input parameters are also called features or attributes, and the output parameter is the target variable. Table 1 describes these parameters. The statistical description of data in shown in Fig.1 and in Fig.2. Fig.1 describes the mean of all the input attributes as well as the target variable whereas, Fig.2 shows the standard deviation of all the input attributes and the target attribute.

Table 1: Input and target variable

S.No	Input parameters	Units	Target Variable
1	Frequency	GHz	S11 (dB)
2	Length of patch	mm	
3	Width of patch	mm	
4	Slot length	mm	
5	Slot width	mm	

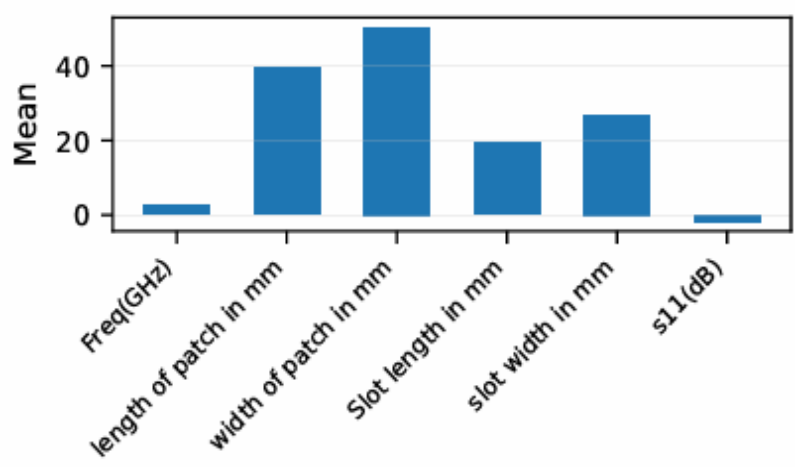

Fig.1: Description of mean of data set

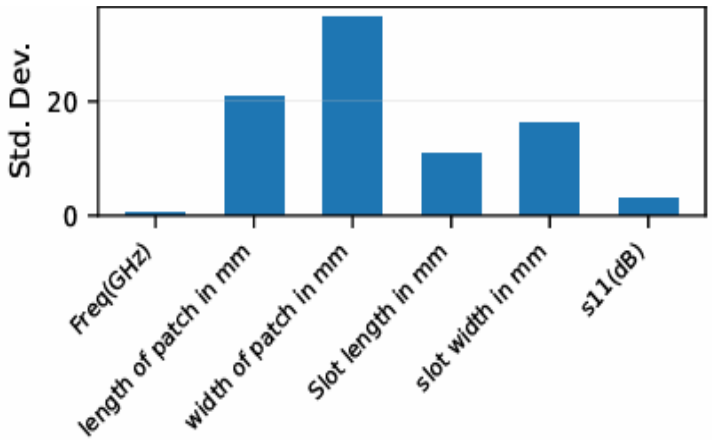

Fig.2: Description of standard deviation of data set

Data Splitting:

The data contain 1266 samples. The data is split into Training, Testing and Validation sets in the ratio of 60:20:20. Thus, 60 % of data were allotted to training and 20% to both testing and validation. The data

contained no outliers or missing values. So data preprocessing step was not needed.

Model Selection:

Three different ML models were selected. These models include XGboost, GPR, and MLP. Gaussian Process Regression (GPR) was selected for its capability to model complex, non-linear relationships while also providing probabilistic predictions, which can be useful for understanding uncertainty in antenna performance.

XGBoost was chosen because it is a powerful ensemble-based gradient boosting algorithm that can capture nonlinear dependencies and handle heterogeneous feature distributions effectively. Its built-in regularisation also helps reduce overfitting.

Multilayer Perceptron (MLP), a type of feedforward artificial neural network, was employed to capture high-dimensional, non-linear feature interactions. As a deep learning approach, MLP can model intricate patterns that may not be easily captured by traditional algorithms. The performance of MLP depends on the number of epochs, number of hidden layers and on activation function. Epoch refers to the number of times the algorithm runs on the whole training dataset. The hidden layers are intermediate layers between input and output layers. The number of hidden layers indicate the ability of a model to capture complex or non linear relationships. Activation functions introduce non-linearity, enabling the model to capture complex patterns. Examples include Rectified Linear Unit (ReLu), Tanh, Sigmoid, Softmax etc.

Model Evalution:

All models were evaluated using performance metrics such as MSE, MAE, RMSE, and R2 score. Performance metrics such as MSE, RMSE, and MAE provide an idea of the loss function. In simple terms, the loss function is the difference between predicted and actual values. The lower these metrics, the better the algorithm predicted the target variable. The R2 score indicates the accuracy of the model. A higher R2 score (closer to 1) indicates better accuracy. The formulas for calculating these are given in equations (1)-(4)

Mean Square Error (MSE):

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad \text{.... (1)}$$

Where:

- n = number of samples
- y_i = actual value
- $\hat{y}_i$= predicted value

Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad \text{..... (2)}$$

Where:

- n = number of samples
- y_i = actual value
- $\hat{y}_i$= predicted value

Mean Absolute Error (MAE) :

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \quad \text{..... (3)}$$

Where:

- n = number of samples
- y_i = actual value
- $\hat{y}_i$= predicted value

Coefficient of Determination (R2 score)

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \quad \text{..... (4)}$$

Here $\bar{y}$ is the mean value.

RESULTS AND DISCUSSION:

The predictive performance of Gaussian Process Regression (GPR), Extreme Gradient Boosting (XGBoost), and Multilayer Perceptron (MLP) was evaluated on the independent test dataset using four regression metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R2).

The actual vs. predicted curve for XGboost is shown in Fig.3. The XGboost regressor was trained using n_estimators=300, max_depth=4, and learning_rate=0.1.

The following results were obtained from XGboost algorithm.

Val R2: 0.8220778694826237
MSE: 0.2734
RMSE: 0.5228
MAE: 0.2251
R2: 0.9687
Explained Variance: 0.9691
This shows that XGboost exhibits impressive perform ance.

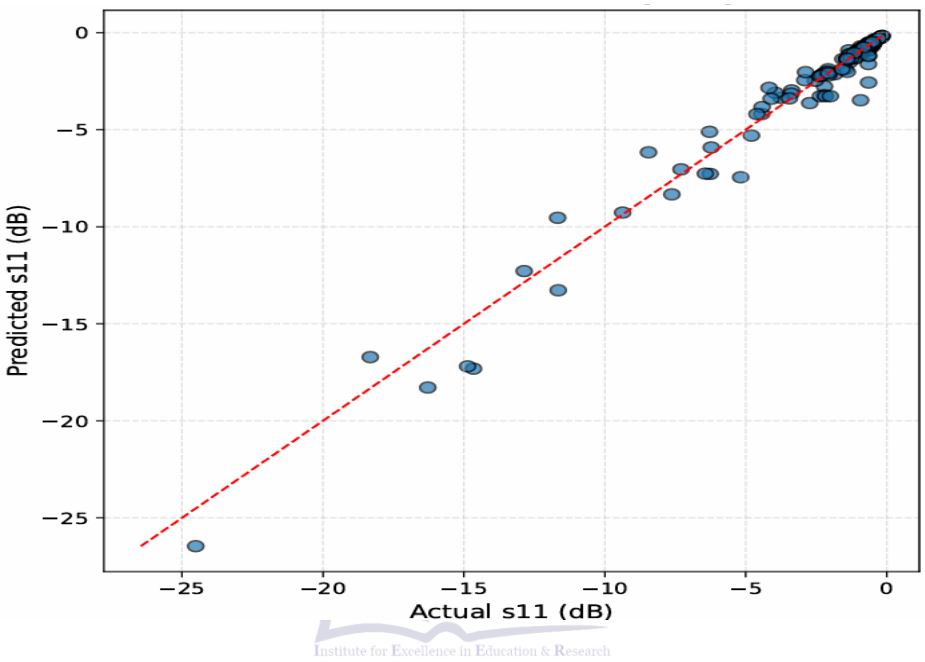

Fig.3: Actual vs Predicted curve (S11 dB) for XGBoost

Fig.4 shows actual vs predicted plot for GPR. GPR achieved validation accuracy of 0.756523. The following are results obtained from GPR model.
Val R2: 0.7565236492924434
MSE: 1.5852
RMSE: 1.259
MAE: 0.2161
R2: 0.8186
Explained Variance: 0.8204
From these results, it is evident that though GPR delivers results, it falls short compared to XGBoost. In otherwords, GPR's ability to capture complexity in data is relateively limited.

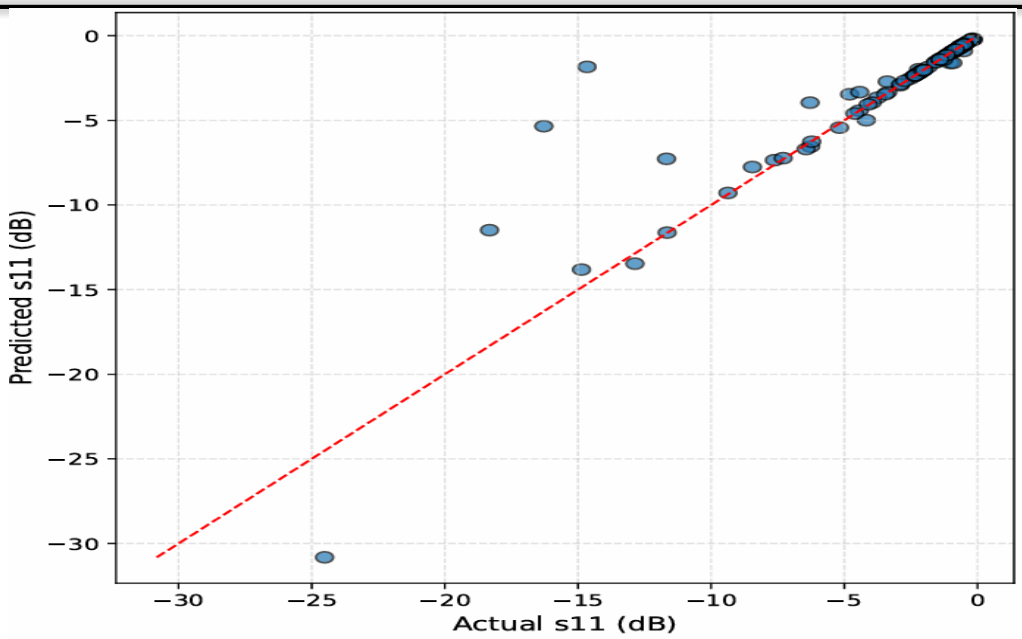

Fig.4: Actual vs Predicted plot for GPR.

Fig.5 Shows actual vs predicted plot for MLP. The Multilayer Perceptron (MLP) model was implemented using the TensorFlow Keras API in Python. It consists of an input layer which corresponds the number of features in the dataset, followed by two fully connected (Dense) hidden layers. Both hidden layers contain 64 neurons each utilizing the ReLU activation function to introduce non-linearity. The output layer comprised a single neuron with a linear activation function for regression output. The model was trained using the Adam optimizer, employing Mean Squared Error (MSE) as the loss function. Total 200 epochs were used.

Table-2: Training configuration of the MLP model

No. of Epochs	Hidden Layers	Neurons per Hidden Layer	Activation Function (hidden layers)	Loss function	Metrics
200	2	64	ReLu	MSE	MAE,R2

The performance metrics for MLP are the following:
MSE: 0.3374
RMSE: 0.5809
MAE: 0.3519
R^2: 0.9614
Val R2: 0.802

Based on the performance metrics, MLP outperforms GPR but still falls slightly short of XGBoost. While it delivers stronger results than GPR, its accuracy and predictive ability do not quite match the superior performance achieved by XGBoost.The comparison of regression performance for all 3 models based on MSE, RMSE, MAE, and R2 are depicted in Talbe 3 and also shown in graphs in Fig.6. The right axis shows R2 for testing data.

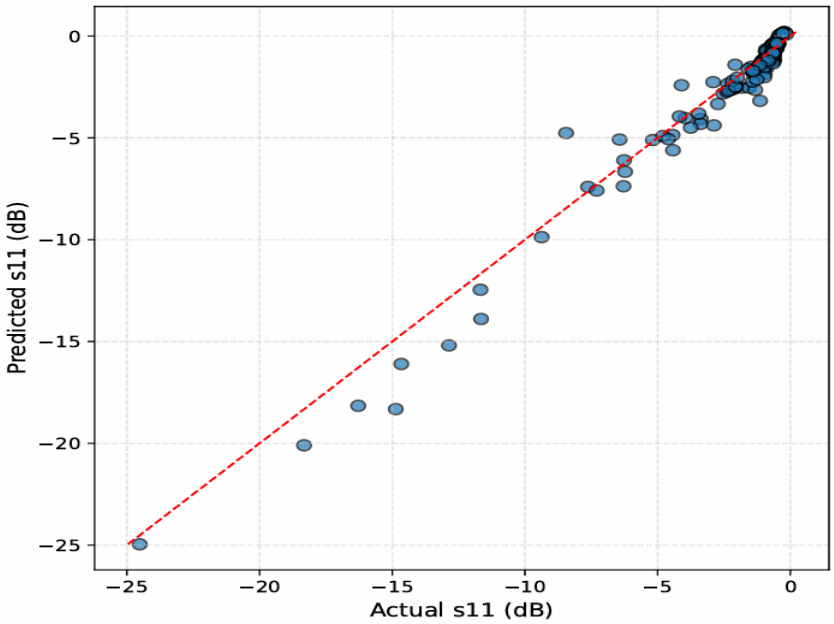

Fig.5: Actual vs Predicted plot for MLP

Table-3: Comparison of performance based on metrics

Model	MSE	RMSE	MAE	R2 Testing	R2 Validation
GPR	1.585	1.259	0.2161	0.8186	0.7565
XGBoost	0.274	0.5228	0.2251	0.9687	0.822
MLP	0.334	0.5809	0.3519	0.9614	0.802

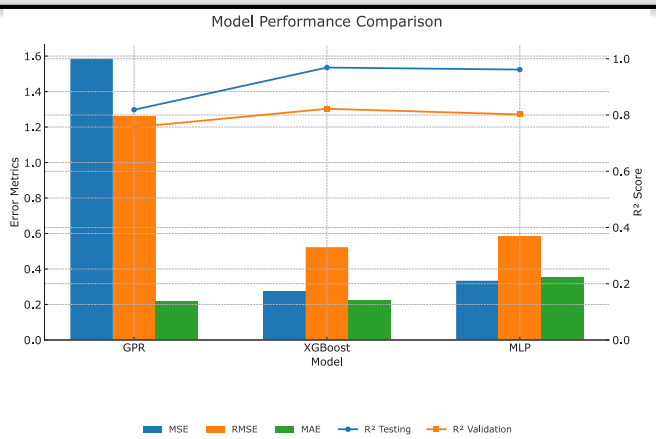

Fig.6: Comparison of regression performance for GPR, XGBoost, and MLP models based on MSE, RMSE, and MAE (bars, left axis) and R2 score (line, right axis) for S11 prediction.

CONCLUSION:

Three different machine learning models performance was compared based on data taken from Kaggle with total of 1266 samples. The data was plit into 60 % Training data, 20% testing data and 20% validation data. Among the three models, XGBoost achieved the best overall performance with the lowest MSE (0.2743) and RMSE (0.5228), alongwith the highest R2 (0.9687). This indiates that XGBoost was able to capture the underlying patterns in the data more effectively than the other models. MLP also performed well, achieving an R2 of 0.9614 for testing data and 0.882 on validation data, while GPR showed comparatively lower predictive accuracy with an R2 of 0.8186 on testing data and 0.802 on validation data and 0.802 on validation data.

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