Design and Development of Compact CPW Fed Band-notched Antenna for UWB Application using Machine learning

A project report submitted in partial fulfillment of the requirements for B.Tech. Project

by

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CANDIDATES DECLARATION

We hereby certify that the work, which is being presented in the report, entitled **Design and Development of Compact CPW Fed Band-notched Antenna for UWB Application using Machine learning**, in partial fulfillment of the requirement for the award of the Degree of **Integrated Post Graduate (B.Tech + M.Tech)** and submitted to the institution is an authentic record of our own work carried out during the period *June 2021* to *october 2021* under the supervision of **Dr. Pinku Ranjan**. We also cited the reference about the text(s)/figure(s)/table(s) from where they have been taken.

Ankit Maurya

Date: 24-10-2021 Signatures of the Candidate

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Ranjan 31/10/21

Date: 24-10-2021 Signatures of the Research Supervisor

ABSTRACT

This paper provides an approach to design an antenna in the best way using machine learning techniques. Machine Learning can be used to speed up the antenna design process. The traditional antenna design process is time-consuming because the numerical methods used in the process are complex and require a lot of computation. The simulation software (HFSS) can only give the results of the parameters in the given dimension. So optimization is needed to meet the desired parameters. This research is focused on a Compact CPW Fed Band-Notched Antenna with a resonant frequency range between 2.9 - 21.6 GHz. There are five algorithms employed: Decision Tree, Random Forest, XGB Regression, K-Nearest Neighbor (KNN), and Artificial Neural Network (ANN). Among all algorithms, K-Nearest Neighbor gives the best result with accuracy up to 98%. From the obtained result, we can estimate the dimensions of the desired parameters, which previously could not be done by HFSS.

Index Terms: Miniaturized UWB antenna, WiMAX band-notched, CPW-Fed, bandwidth, arrival rate, Machine Learning, 5G communications, Decision Tree, Random Forest, XGB Regression, K-Nearest Neighbor (KNN), Artificial Neural Network (ANN)

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Finally, we are grateful to our Institution and colleagues whose constant encouragement served to renew our spirit, refocus our attention and energy and helped us in carrying out this work.

(Ankit Maurya)

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ABBREVIATIONS

UWB	Ultra Wide Band
FCC	Federal Communications Commission
HFSS	High Frequency Structure Simulator
CPW	Coplanar Waveguide

CHAPTER 1

INTRODUCTION

In the past ten years, as the cost of storing and processing data has dropped dramatically, machine learning has been increasingly used in various fields. It has become very easy to use machine learning to find optimized solutions in various fields. In recent years, the demand for high-speed and reliable communication networks has continued to increase. 4G LTE provides a faster and more reliable network, but it is not sufficient for future applications in the 5G era. Therefore, the need for a smart and efficient antenna design method becomes crucial.

Federal Communications Commission (FCC) has allocated the frequency band from 3.1 to 10.6 GHz for unlicensed UWB services by the [1]. Many opportunities for the designers have been developed with the allocation of UWB band. For the wireless application, plannar antennas are the most suitable candidate because of its large bandwidth, low cost and simple design. In previous years many UWB antennas for wireless application have been designed [2], [3], [4] . Due to the wide frequency range of UWB antennas the major disadvantage with the UWB systems is its interference with the other existing system. Therefore, to avoid the interference with the other wireless system it is necessary to notch out portions of the band. Various methods are used to develop the band notched characteristic in the UWB antennas [5], [6], [7]. In previous years many band notched antennas are designed using the various techniques. But all the previously available antennas are big in size with the small bandwidth. Therefore the need of antenna a large ultra wide bandwidth with band-notched characteristics increases. Table 1.1 shows the comparison of the previously available band notched antennas

In this paper, a Compact CPW-fed UWB antennas with a inverted U-shaped radiator and two rectangular ground plane is proposed. For the proposed antenna tapered shaped feed line is used to feed the antenna. The proposed UWB antenna works in the

Table 1.1: COMPARISON OF VARIOUS BAND-NOTCHED ANTENNAS WITH THE PROPOSED ANTENNA

Ref	Size (mm3)	Bands Covered (GHz)	Notched Band (GHz)
[8]	30× 28 × 0.8 3.0	3.0 - 11	5.0 - 5.8
[9]	34× 27 × 0.5	3.0 - 11	3.3 -3.8 and 5.1 - 5.8
[10]	22.5× 22.5 × 1	3.1-10.6	4.1 - 5.8
[11]	24× 34.6 × 0.8	3.1-10.6	3.4 - 3.8 and 5.4 - 5.8
[12]	30× 31 × 1.5	3.1-10.6	5.0 - 6.0
Proposed Antenna	23×10 × 0.8	2.9 -21.6	3.2 - 3.9

frequency range from 2.9 - 21.6 GHz with the operational bandwidth of 18.7 GHz. Further, to minimize the interference at WiMAX band having the frequency range from 3.3 to 3.8 GHz a inverted L-shape slot is etched out from the U-shaped radiator. There is no effect of this L-shape slot in the other operating UWB band. The proposed antenna has very compact size of 23× 10× 0.8mm^3 . The proposed antenna is validated using the commercially available High Frequency Structure Simulator (HFSS).

HFSS (High Frequency Simulation Software) can be used to design a basic prototype of the antenna. It can also perform simulations to obtain the optimal geometry of the antenna over a particular frequency range. Parameter S11, also known as reflectance coefficient or return attenuation, represents the amount of power that the antenna reflects. The graph between frequency and S11 depicts the antenna's radiated frequency and optimal performance.

When designing an antenna, the desired parameters are already known to the designer.. For example, the resonant frequency must be between 2.9-21.6 GHz, and the reflectance coefficient (S11) must be less than -10 dB, and the bandwidth must be greater than 100 MHz. If these parameters can not be achieved. It requires optimization. The optimization will be carried out by changing the size of the different parameters of the antenna to meet the desired parameters. Traditionally, the optimization process is carried out by means of the test and error method. This is because the optimization process takes time.

Machine learning approaches can be used to create multiple antenna models in order to provide accurate and quick design parameter predictions. They'll find hidden mathematical relationships in the data, allowing us to link input and output behaviour and create predictions. In this paper, we recommend using ML technology for antenna design optimization. Using machine learning algorithms, it is hoped that the reflectance coefficient (S11) can be predicted based on antenna parameters such as resonant frequency. Thus, it can help us avoid the endless loop of optimization through trial and error. There are five algorithms used in this research: Decision Tree, Random Forest, XGB Regression, K-Nearest Neighbor (KNN), and Artificial Neural Network (ANN). These algorithms were chosen because they can compute regression for nonlinear data, since the dataset generated after simulation is nonlinear. In conducting this research, a dataset consisting of resonance frequency, length of the L-shaped, width of the L-shaped and thickness of the L-shaped slot is obtained after antenna simulation using HFSS. The simulation is performed by trying out different antenna dimensions with resonant frequencies ranging from 2.9 to 21.6 GHz. Then, use the algorithm to make predictions. The R2 score value, and Mean Squared Error (MSE) value for the simulated and predicted reflectance coefficient (S11) is analyzed to measure the prediction accuracy.

The following is the structure of this paper: Section one, briefly, discusses the contents of the paper(such as introduction and antenna design). Section two describes the datasets. Section three explains the machine learning techniques. Section four explains the results. And section five concludes the paper.

1.1 MOTIVATION

Antennas are becoming more and more complex as modern radar and wireless communications evolve at a rapid pace, offering greater degrees of freedom in design, integration, and manufacturing constraints as well as design goal. Today, antenna design is mainly based on actual experiments and electromagnetic simulations of the designer. Traditional methods are inherently inefficient and computationally intensive, making them unsuitable when a large number of antenna design features need to be optimized, such as 3D printed antennas.

For solving complex 3D structural design problems, the (ML) approach can be extremely useful. There have been many uses of machine learning as an important tool for decision making and data analysis in many fields, from the recognition of handwritten digits to human genomics. Using ML approaches in the design and optimization process will not only speed up the antenna design process, but also reduce the human effort required in the process. Thus, the final cost of the process will be reduced. The main advantage of using the ML algorithm is that once we get the relational model we can predict the output for any data point which is very useful when we want to use the same sets data for different purposes.

1.2 OBJECTIVE

Optimisation of Compact CPW Fed Band-notched Antenna can be achieved by following the below steps:-

(a) Design a Compact CPW Fed Band-notched Antenna for UWB using ANSYS HFSS.

(b) Then perform simulation on the thousand antenna design and generate datasets.

(c) Perform optimisation on the dataset using machine learning techniques to identify the optimal design parameters for the Compact CPW Fed Band-notched Antenna.

(d) Compare the results obtained from the ANSYS HFSS(simualation result) with the result predicted by the machine learning algorithm to verify the accuracy of these techniques.

CHAPTER 2

LITERATURE REVIEW

In 2010, researchers Lin Guo, Fengyi Huang *, Yan Wang, Xusheng Tang studied dipole antennas and proposed a ultra-wideband (UWB) antenna fed by the line. The antenna is an 18 element logperiodic dipole antenna. The internal impedance is quite stable and satisfactory. A suppressed narrow band is further achieved in the th wide bandwidth by inserting an H-shaped slot in the center feed line of the antenna. The antenna measures 47.8mm by 42mm by 2mm. The simulation results show that the proposed antenna has stable directional radiation patterns, very low configuration and low fabrication cost , which is suitable for the UWB system.

Researcher GuoMin Yang demonstrated an ultra-compact logperiodic semicircular dipole antenna striped printed on a dielectric substrate. The antenna is made by cascading a straight LPDA line with 29 elements and serpentine LPDA lines with 11 elements. An ultra wide 20200 MHz band is achieved and the antenna gain is approximately 6 dBi in the 100 2200 MHz band. The simulation results show that the designed UWB LPDA has very stable radiation patterns throughout the frequency band, combined with a low profile and ease of manufacture, showing great potential for in-band(VHF and UHF bands) wireless communication.

Researchers A. Madannezhad, H. Ameri*, S. Sadeghi propose a miniature Vivaldi antenna for the proposed Ultra Wideband (UWB) applications. The antenna is designed to operate in the entire UWB spectrum from 3.1 to 10.6 GHz. The newly modified feed structure is used to miniaturize the Vivaldi antenna. The designed antenna is manufactured and tested. Experimental results show that the antenna's performance on the entire UWB frequency band is satisfactory.

CHAPTER 3

METHODOLOGY

3.1 ANTENNA DESIGN AND CONFIGURATION

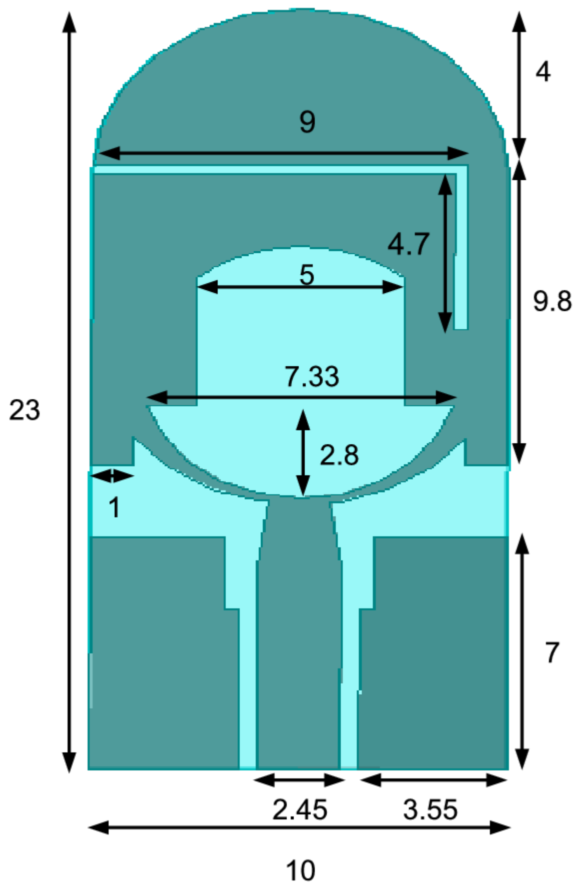

Figure 3.1: Geometry of the Proposed CPW-Fed Band-notched UWB Antenna.

The top view of the proposed UWB antenna with all the parametric values is shown in the Fig 3.1. The antenna is fabricated on the Fr4 substrate. The thickness of the substrate is 0.8 mm and has the dielectric constant ϵ_r = 4.4and loss tangent tan δ =

0.02. To design the antenna an inverted U-shaped patch is used as the radiator and two rectangular ground planes are designed on the both side of the feed line. The inverted U-shaped Radiator is connected to the ground plane using the arc shape structure. Also, for the good impedance matching the in the operational bandwidth two small slots are etched from the ground plane. The length and width of the slot is 2.2 mm and 0.35 mm respectively. The feed line used to connect the antenna to the CPW feed is a tapered shaped line with the thickness of 2 mm. Further, an inverted L-shaped slot is etched from the radiator to get the band-notched characteristic at the WiMAX (3.3-3.7 GHz) band. The length of the L-shaped slot is 5 mm and the width of the L-shape slot is 9 mm having the thickness of 0.3 mm. The overall length and width of the Fr4 substrate used for the antenna is 23 mm $\times$ 10 mm. The antenna has the circular shape from the top with the radius of 4 mm.

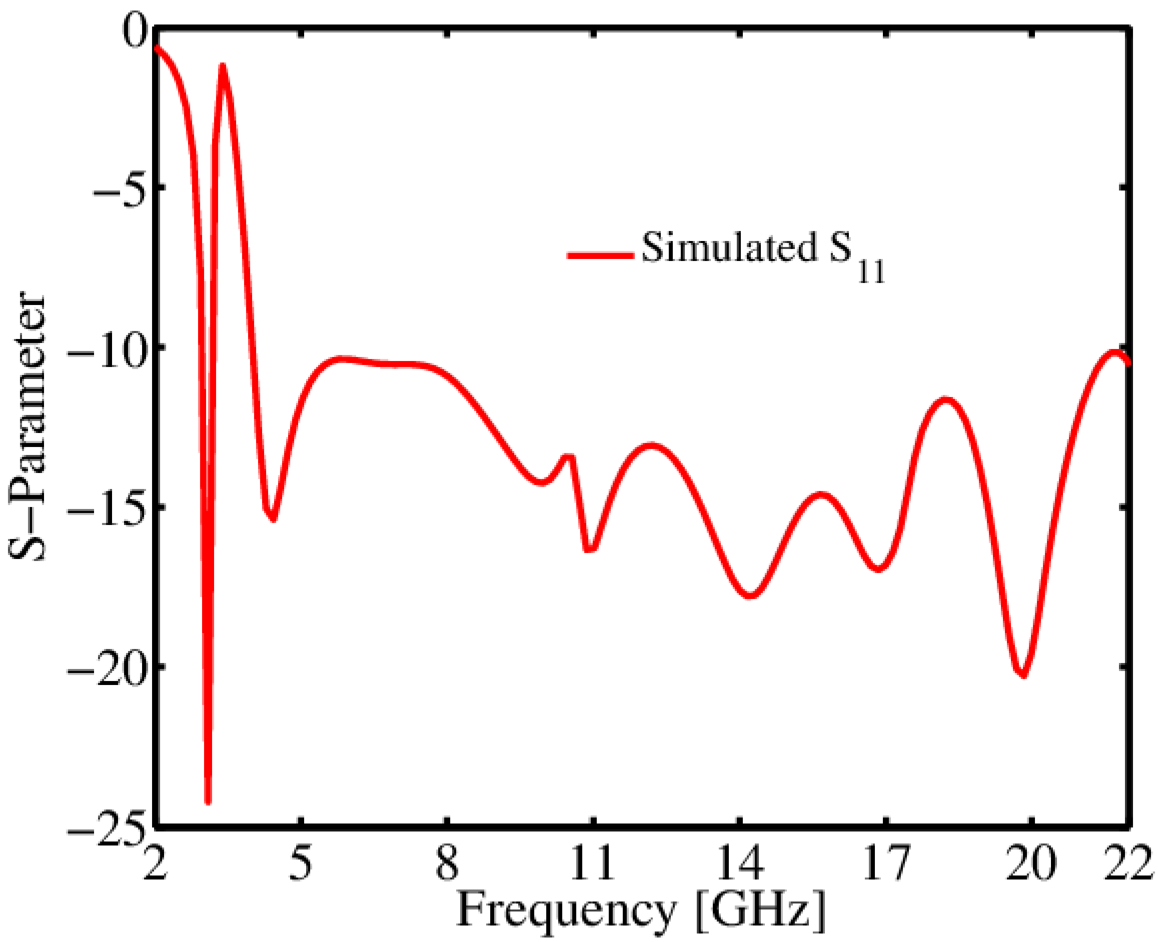

Figure 3.2: Simulated S-Parameter of the Proposed Antenna.

The simulated S-parameter curves for the presented antenna structure are shown in Fig 3.2. From the Fig it is clear that the antenna possesses the bandwidth of 18.7 GHz (from 2.9-21.6 GHz) together with the band-notch characteristic at WiMAX band ranges from 3.2-3.9 GHz. To study the effect of length and width of L-shaped slots on the frequency range of the notched antenna, the band length(h), width(l), and thickness(d) are varied. First, the length is varied from 3 mm to 7 mm. Simulated S-parameter curves of the proposed antenna for different lengths of L-shaped slots with frequency are depicted in Fig 3.3. From Fig it can be seen that as we increase the value of length, the notched band is shifted towards the lower frequency range.

The length of current path at the resonant frequency would be half of the guided wavelength. Therefore,

$$L1 = length(h) + width(l) - Thicknessofslot(d)$$

The L-shaped slot acts as a quarter-guided wavelength resonator, and thus a center rejected frequency f_n may be empirically approximated.

$$f_n = \frac{C}{4L_1\sqrt{\frac{\epsilon_r+1}{2}}}$$

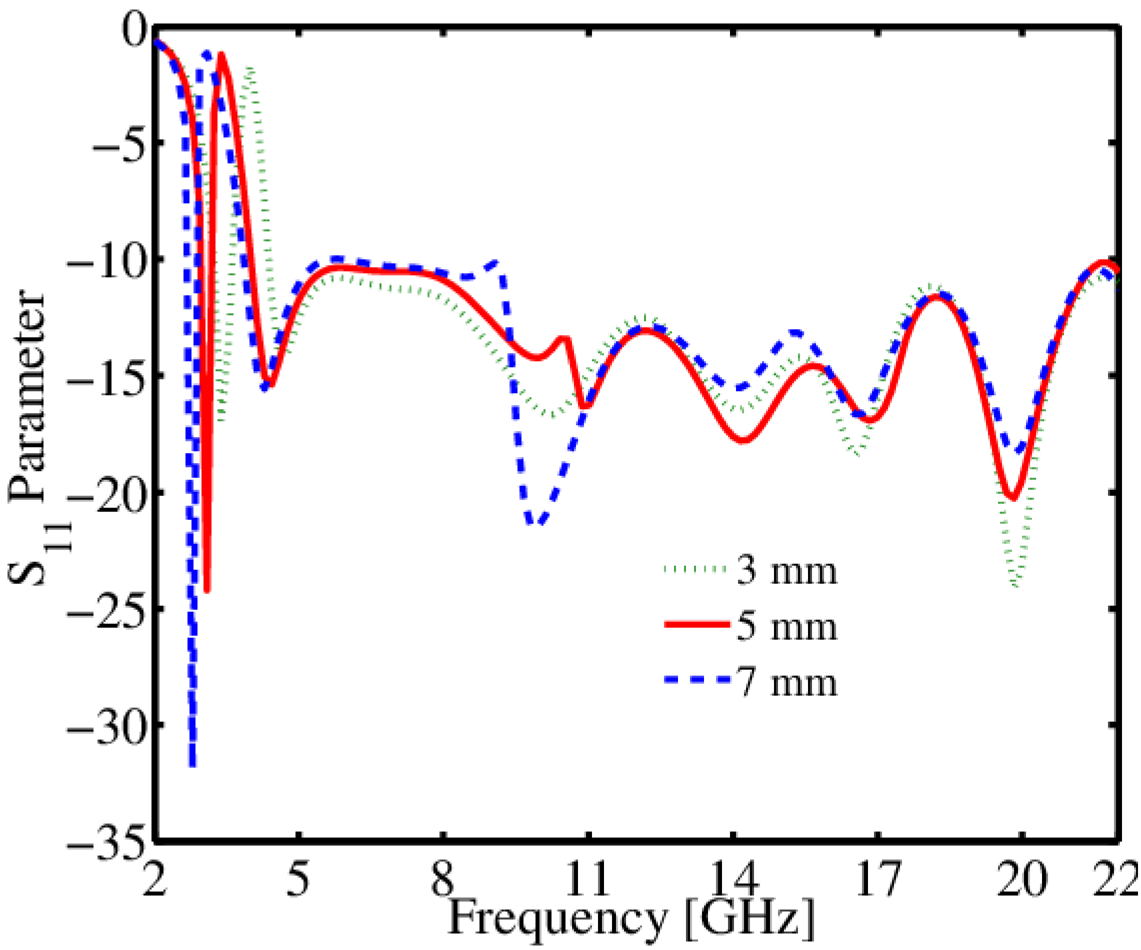

Figure 3.3: Variation for the Length of the Inverted L-shaped Slot.

Where, L_1 is the overall slot length, L and W are the length and width of the L-shaped slot, ϵ_r is the relative dielectric constant, and c is the speed of the light. Total

Table 3.1: COMPARISON OF NOTCHED DESIGN EQUATION AND FULL-WAVE SIMULATED DATA

L(mm)	L_1(mm)	Resonant Frequency (GHz)	
		Full-wave simulation	Design equation
3	11.7	3.89	3.9
5	13.7	3.35	3.33
7	15.7	2.8	2.90

length calculated for the L-shaped slot is 13.7 mm for the center frequency of band-notched at 3.33 GHz. The design method is further validated by predicting the notch frequency for the data presented in Fig 3.3 and Table 3.1, the notched resonant frequency as a function of L is compared with the full-wave simulated data.

From Fig 3.3, it is clear that the resonant frequencies calculated from the design method are in agreement with the simulated data. Therefore, to get the band-notched characteristic at the WiMAX band 5 mm is selected as the final value for the length of the L-shaped slot.

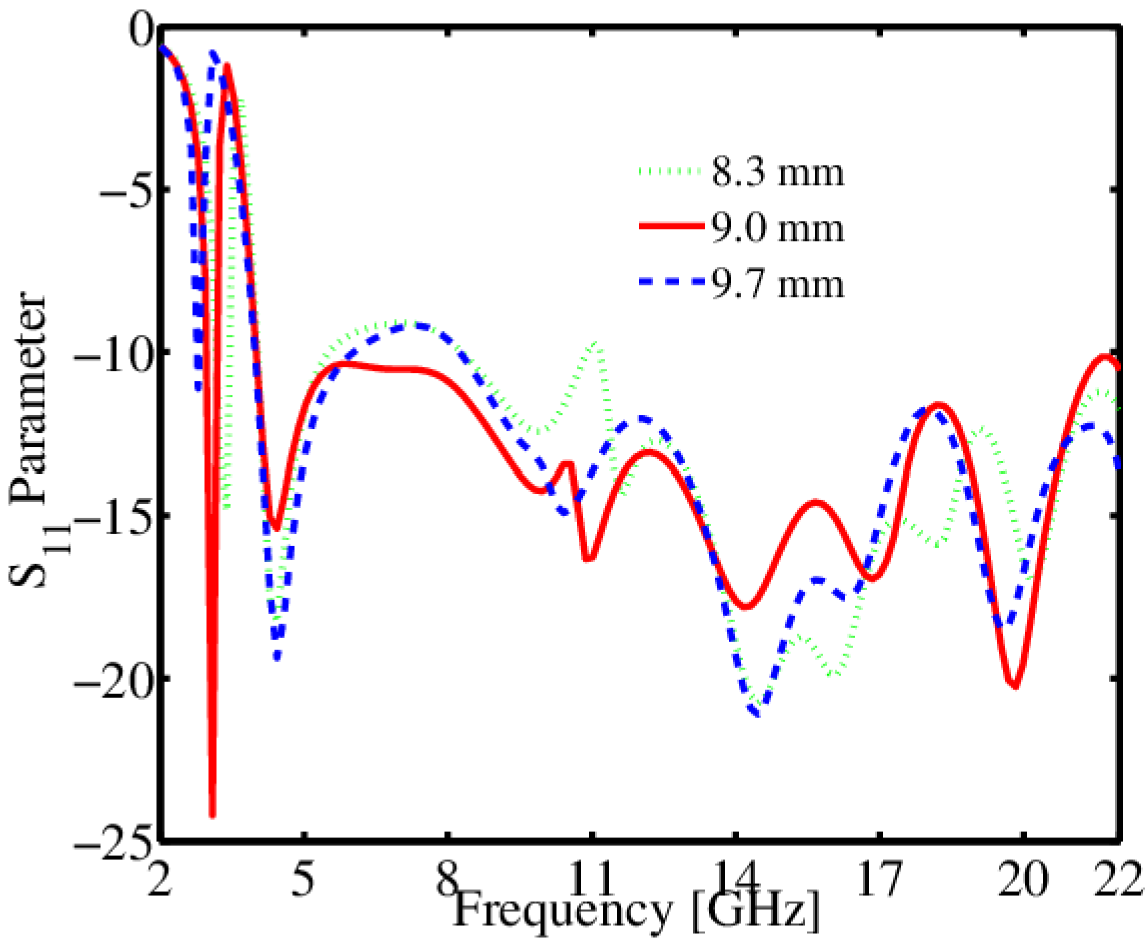

Figure 3.4: Variation for the Width of the Inverted L-shaped Slot.

After the variation of the length of the slot, the width is varied from 7 mm to 10 mm with a gap of 0.2 mm. The variation of the width of the L-shaped slot (for 3 values) is shown in the Fig 3.4. As seen from Fig on increasing the width of the slot, the band is shifted towards the lower frequency range and the bandwidth is also changed on varying the slot width. Therefore, to get the desired band-notched characteristic 9 mm is chosen as the final value.

After the variation of the length and width of the slot thickness(d) is varied from 0.2 mm to 0.4mm with a gap of 0.1 mm.

3.2 DATASET PREPARATION

In this research, to obtain a dataset we simulate our proposed antenna using electromagnetic wave simulation software called HFSS. This dataset will be used to make predictions.we observed two parameters in the simulation of the antenna. The 1st one is the resonant frequency(Freq) and 2nd one is the return loss or reflection coefficient(S11). The resonant frequency (frequency parameter present in the antenna) is the frequency at which the inductance value and the capacitance value cancel out. This frequency indicates that the return loss has reached its minimum value. Return loss is the loss of returned or reflected power due to impedance mismatch. The power is calculated by comparing the input power and the reflected power. Return loss is closely related to bandwidth. The bandwidth of an antenna is the frequency range in which it can work. In this document, the antenna bandwidth is calculated in the frequency range where the return loss value is less than -10 dB. After running simulations on HFSS, the simulation results are collected and stored in an Excel spreadsheet(xlsx). The data set(which we got after simulating the antenna) consists of 201 records and is divided into 1009 features. The 1st feature is the resonant frequency. We observed some common variables with different values in the features column except the resonant frequency column such as length(h) of L-shaped slots, width(l) of L-shaped slots, and thickness(d) of L-shaped slots. So we prepared a new dataset with these variables and frequency columns. and also we made a column with all values of these variables columns. These values are the return loss at the resonant frequency. After this, we got a new dataset. The new data set consists of 202608 records and is divided into 5 features: the resonant frequency(Freq), Horizontal Length of L-shaped slots(h), Vertical Length of L-shaped slots(d), Width of L-shaped slots(d), and return loss(dB) at the resonant frequency,. The first four features are used as independent variables, while the last one is used as dependent variables. We are depicting the relationship between dependent and independent variables using some plot.

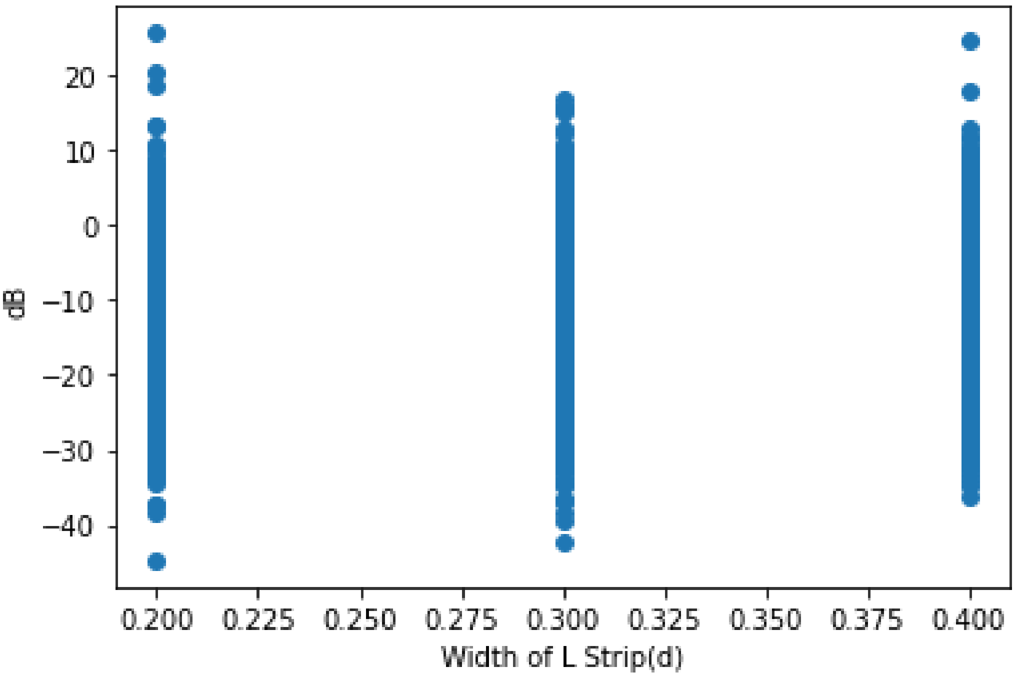

Figure 3.5: Depicting the relationship between Width of L strip and return loss

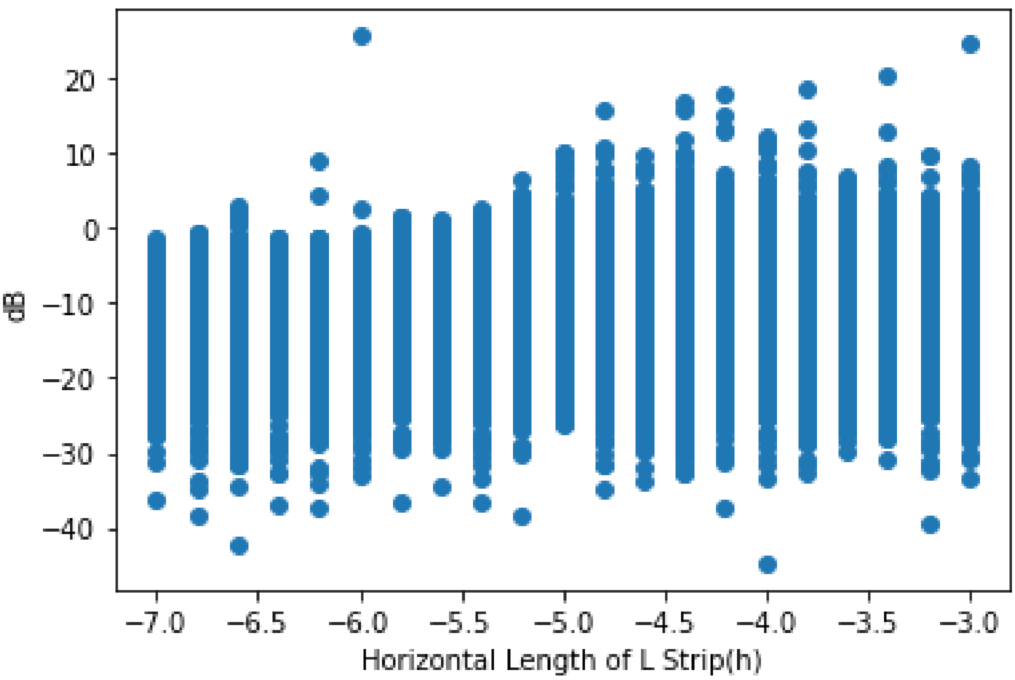

Figure 3.6: Depicting the relationship between Horizontal length of L strip and return loss

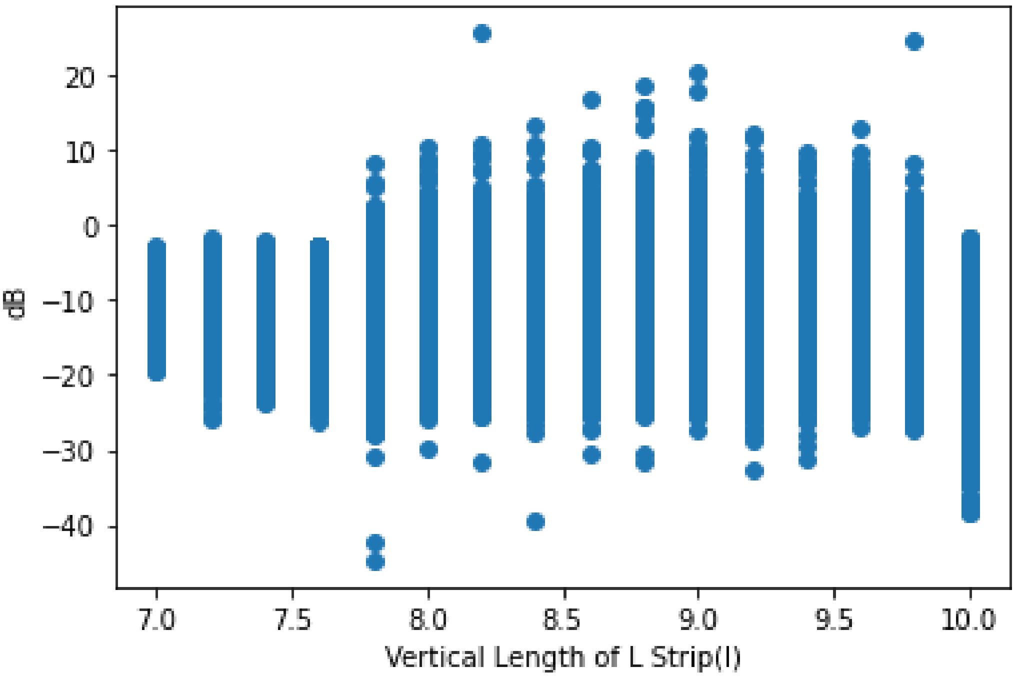

Figure 3.7: Depicting the relationship between Vertical length of L strip and return loss

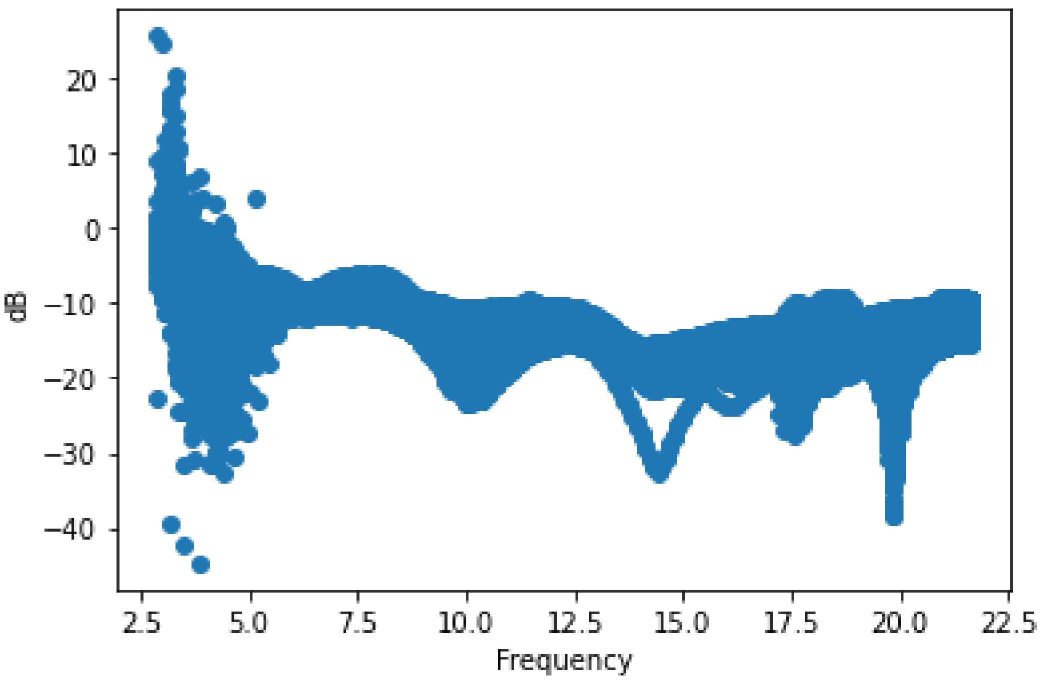

Figure 3.8: Depicting the relationship between the Resonant Frequency and return loss

3.3 MACHINE LEARNING ALGORITHM IMPLEMENTATION

Once a dataset is obtained, it can be split into two parts: training and cross-validation where the number of records in each depends on the total number of records present in the dataset. In our case, 80 percent records are used for the training set and the other 20 percent are used for cross-validation sets. Machine learning Algorithm is used to learn from the data and predict the best result for new desired input. It reduces the time to obtain results. Today, Machine Learning is actively used, perhaps in more places than people expect. In the current time there are many different algorithms present. The choice of algorithm depends on the amount of data, complexity of the problem and the mathematical formulation of the algorithm. In this paper, Five algorithms have been used to make predictions: Decision Tree(DT), Random Forest(RF), XGB Regression, KNN, and Artificial Neural Network(ANN). We have chosen these algorithms because they can compute regression on non-linear data. Since the desired output is in the form of numerical value, regression is the best possible method for making predictions. We implemented these algorithms using python3 language. Python3 is used because it is easy to implement and it has a large number of libraries available to support data preprocessing, machine learning algorithms, and visualization. After studying the dataset, we divided the dataset into two parts. The first part contains an 80 percent training set and the second part contains 20 percent cross-validation sets based on the recommendation in [13]. Then the training set is trained using a machine learning algorithm with various features and labels. After training and cross-validation the model, It can be used to predict the loss at the resonating frequency for the desired inputs. Using Machine Learning, predictions are done in very less time with very less error margin compared to HFSS simulation results. Following the completion of training, the prediction is made using the test set. Machine learning algorithm implementation flowchart shown in Fig 3.9.

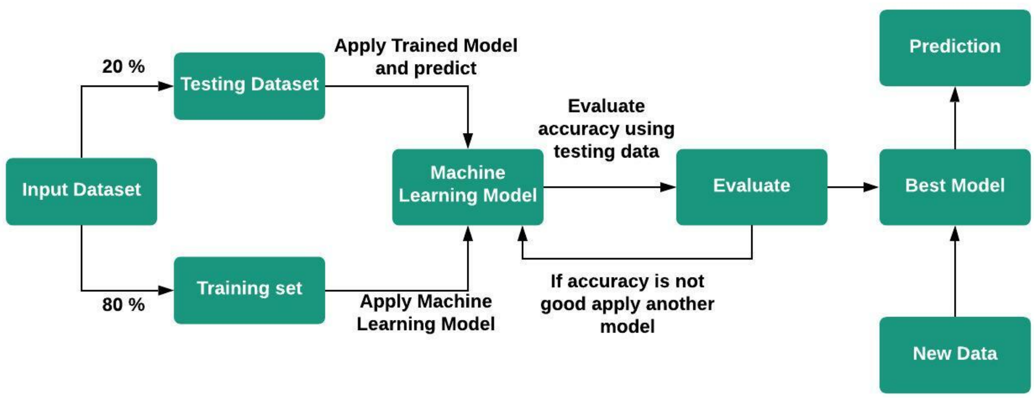

Figure 3.9: Machine learning algorithm implementation flowchart

3.3.1 DECISION TREE

Decision tree is a supervised machine learning algorithm and a predictive model to calculate the label value. Decision Tree is a graphical representation of all the possible solutions to a decision. Decisions are based on some conditions. Decision Tree is a very powerful model in more dimensions.This algorithm learns a simple decision rule that starts at the root node of the tree, follows the branch node associated with the value, and then goes to the next node until it reaches the leaf node to forecast the target value.[14] It can be explained very easily. For example, here is a task which says that should I take h to be greater than 10 or less than 10. you are confused about that so you will create a decision tree for it. Decision tree is shown in the below Fig 3.10

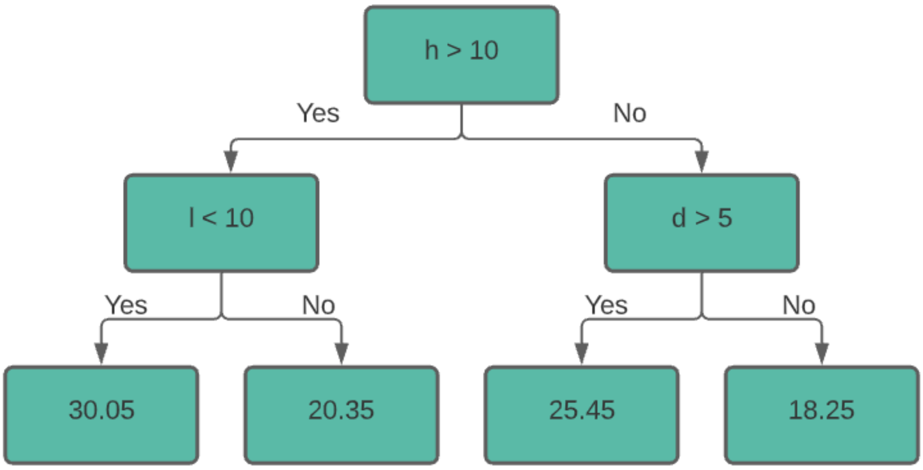

Figure 3.10: Basic Decision Tree

3.3.2 RANDOM FOREST

Random Forest Builds multiple decision trees and merges them together Or we can say Random Forest is a decision tree that combines many decision trees to produce a more accurate and consistent prediction. It also solves some overfitting problems which we got in some cases when we use Decision trees. Most of the time Random Forest is trained with a bagging method. The bagging method is based on the idea that it combines different learning models to improve the overall outcome.[15] If you're merging information from various models and then grouping it together. It will improve the overall outcomes. Random decision forests overcome the habit of overfitting decision trees to their learning set. It gives good results but not great so we use Hyper Parameter Tuning.

3.3.3 XGB REGRESSION

XGBoost stands for extreme gradient boosted trees. XGBoost is a decision-tree-based ensemble machine learning algorithm that uses a gradient boosting framework. XG-boost is an advancement of gradient boost. This is a very fast algorithm because of parallelization (it uses the maximum computation power of the machine). The idea is that we take a model and we have multiple versions of that chained together. So every tree within our boosting scheme here is going to boost the attributes that led to miss classification from the previous tree.[16]

3.3.4 K-NEAREST NEIGHBOR

K-Nearest Neighbor (KNN) is a supervised Machine Learning algorithm that can perform both classification and regression tasks using numbers(k) of neighbors(instances). In This Regression model First, we define the value of k means, which is the number of neighbors we want to use in this model. Then we take k nearest neighbors (KNN) of the new data point according to the Euclidean distance.[17]

$$\textbf{Euclidean distance (d)} = \sqrt{[(x2 - x1)2 + (y2 - y1)2]}$$

Where (x1, y1) new data point, (x2, y2) is one of its k nearest neighbors. After this, we calculate the Neighbors using the Euclidean distance formula. Then, we calculate the average of all Neighbors' distances. Now, this is the predicted value for the new data point.

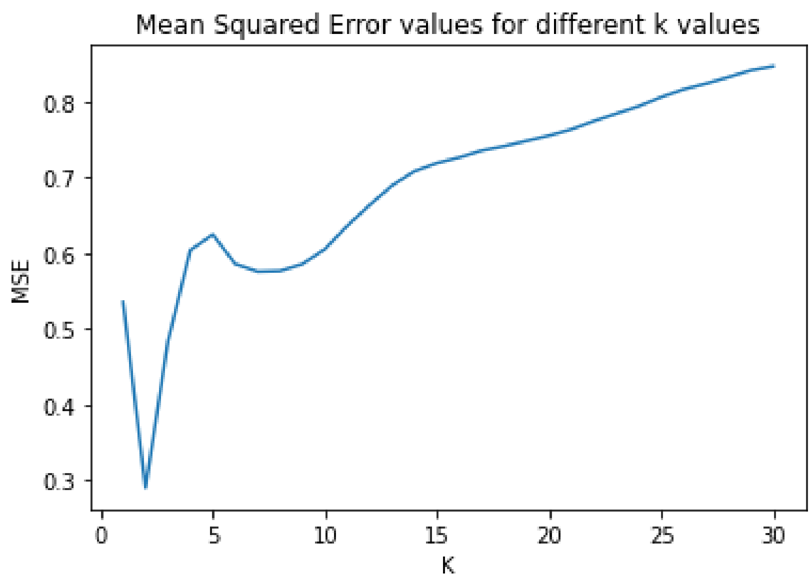

Figure 3.11: Mean Squared Error values for different k values Mean Squared Error values for different k values

We take 32 values of k from the range 1 to 31. We get the optimal value of k by comparing the error values on different values of k. The value of k with least error is taken as the optimal value. Here, k = 2 as the optimal value for training our best kNN regression model because we can clearly see that if we increase or decrease the value of k, Mean squared error increases and accuracy decreases. So for the best k-nearest neighbors model we take k =2. Fig 3.11 shows a variation of the Mean Squared Error value with varying k values.

3.3.5 Neural Network

A deep neural network (DNN) is a type of Neural Network (NN) in which multiple layers (Hidden layers) are present between the input and output layers. This algorithm is inspired by the structure of the human brain. Neural Networks (NN) take data and train themselves to recognize the pattern in this data and predict the outputs for a new set of similar data. A Neural Network is made up of neurons. These neurons are the core processing units of the network. First, we have input layers that receive the input and At last, The output layer predicts our final output. In between input and output layers, the hidden layers exist. Where they perform most of the computations required by our network.[18]-[19]

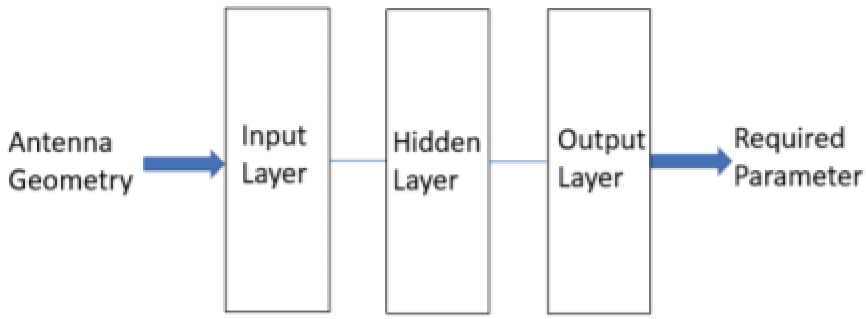

Figure 3.12: Neural Network Model Flow

A Deep Neural Network architecture that we used is shown in Above Fig 3.12. It has 3 hidden layers. These layers have 256, 128, 64 numbers of nodes respectively.We used Adam Optimizer. The batch size is 150 and the validation split of our data is 0.2.

3.3.6 HYPER PARAMETER TUNING

Parameter tuning was carried out using Grid Search which helps to find the optimal hyper parameters of a model. It gives the most accurate predictions. Grid Search is used to improve model performance. All Machine Learning Model is composed of two types of Parameter: -

1. That are learnt
2. That we choose

We can vary parameters which we can choose using grid search and calculate the best parameter for that model. Hyper parameter tuning in the Random Forests Method refers to fine-tuning parameters like maximum depth, maximum features, and the number of estimators that affect the model's learning process. We use Hyper Parameter Tuning in a random forest model. After varying the variables ('max_depth', 'max_features', 'n_estimators') we got the optimal solution at point (where max_depth=110, max_features=2, n_estimators=1000). Model accuracy at this point is equal to 0.974 and Mean squared error value is equal to 0.373.

3.3.7 LOSS FUNCTION

In regression computations, the loss function represents the accuracy of the prediction. The more accurate the prediction, the less the loss function's value. The error can be calculated using a variety of loss functions, including the sum of absolute error (SAE), the sum of squared error (SSE), mean absolute error (MAE), mean square error (MSE), and so on. Mean squared error (MSE) is measured as the average squared difference between predictions and actual observations. The advantage of MSE over other loss functions is that as the data amount grows, the overall error reduces. MSE combines all of the errors (using average) into a single value, making it simple to decide if the findings are excellent or bad. The equation for determining MSE is shown in the equation below.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y_i})^2.$$

3.4 PARAMETERS PREDICTION USING ML ALGORITHM

For predicting the best parameters using the ML algorithm, we have selected a range of values for our parameters. Width of the L Strip is varied between 0.2 to 0.5mm with a difference of 0.1mm, which gives us 3 different values for this parameter. Similarly, Horizontal Length of the L Strip is varied for -3 to -7.1 mm with the difference -0.1mm, which gives us 41 different values. Similarly, Vertical Length of L Strip is varied for 7 to 10.1 mm with the difference 0.1mm, which gives us 31 different values. Earlier we had the 201 values for frequency between 2.9 and 21.6GHz. So, combining all values of these 4 parameters gives us a dataset of 766,413 rows and 4 columns.

After training the ML models with the dataset obtained from HFSS, we will select the best model with the highest R2 score and lowest MSE value. Then we will run this dataset of 766,413 rows and 4 columns on that model and will predict the S11 value for it. Then we will select those parameters which gave us the lowest S11 value. Those will be our best parameters.

CHAPTER 4

RESULTS

R2 score is one of the popular matrices for regression model evaluation. R2 score tells us how accurate our regression model is. It is the amount of the variation in the output dependent attribute that can be predicted based on the input independent variable (s).

$$R2 = 1 - SSres / SStot$$

R2 score and MSE result for each algorithm is shown in this section. The MSE and R2 score is calculated by comparing the predicted outcomes with the actual data obtained from the simulation.

Table 4.1 summarizes the R2 Scores and MSE value anticipated by several ML approaches. Different Model approaches names are shown in the first column of the table such as Decision tree, Random forest, XGB regression, KNN, and ANN. The R2 score evaluated by each ML approach is listed in the next columns, and the MSE value evaluated by each ML approach is listed in the last column. Mean squared error (MSE) is measured as the average squared difference between predictions and actual observations. The R2 score and MSE value both are used to evaluate the performance of a regression-based machine learning model.

Table 4.1: DIFFERENT MODELS R2 SCORE AND MEAN SQUARED ERROR (MSE)

	Model	**R2 Score**	**MSE**
1	Decision Tree	0.919	0.933
2	Random Forest (No Tuning)	0.961	0.509
3	Random Forest (Hyper Parameter Tuning)	0.974	0.373
4	XGB Regression	0.939	0.794
5	K-Nearest Neighbor	0.978	0.290
6	Artificial Neural Network	0.924	0.983

As shown in Table 4.1, KNN with n_neighbors=2 gives us the best prediction accuracy. Then we created a new dataset. We created this new dataset by varying Width of L Strip(d), Horizontal Length of L Strip(h), Vertical Length of L Strip(l) and Freq parameters. It has large data approx 766413 rows and 4 columns. Now, We applied a previously trained model (which gives best training, testing accuracy with less MSE value) on this new dataset. KNN with parameter n_neighbors is equal to 2 is the best model as we can see from Table 4.1. Then we predicted the S11 values for our new dataset of 766413 rows and 4 columns on this KNN model. **It gave us the minimum value for S11 equals -35.77640827992235 Where Width of L Strip is 0.3mm, Horizontal Length of L Strip is -6.5mm and Vertical Length of L Strip is 10.0mm at the frequency of 19.8235 GHz.**

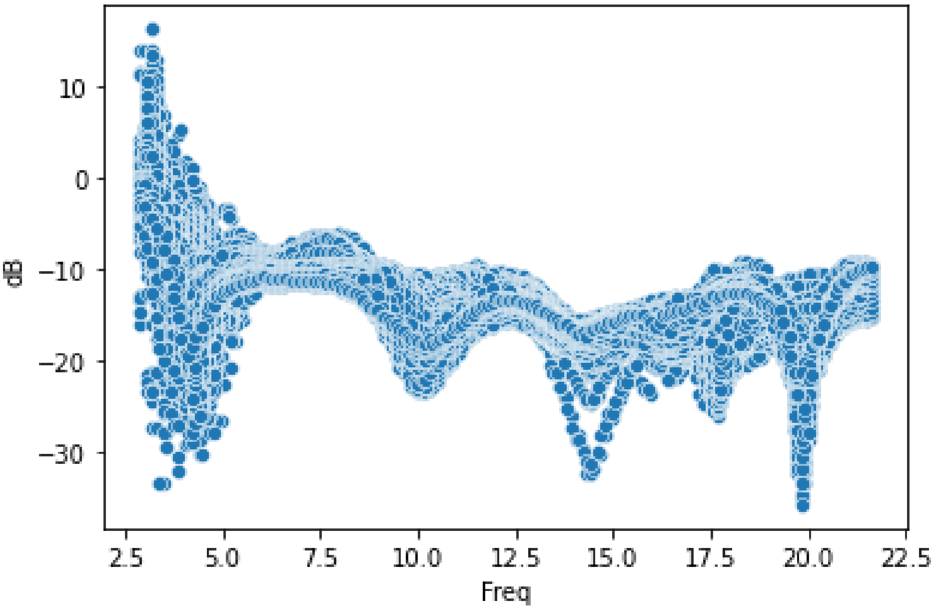

Figure 4.1: Depicting the relationship between the Resonant Frequency and return loss for new Dataset

CHAPTER 5

CONCLUSION

In this paper, Five distinct machine learning algorithms are utilized to predict the optimal values of design parameters for a Design and Development of Compact CPW Fed Band-Notched Antenna for UWB(ultra wide band) Application Using Machine Learning: Decision Tree, Random Forest, XGB Regression, K-Nearest Neighbor, and Artificial Neural Network. This communication begins with a brief description of these techniques, followed by an explanation of how these techniques are applied to a Compact CPW Fed Band-Notched Antenna. In our investigation, both Random Forest with Hyper Parameter Tuning and K-Nearest Neighbor(KNN) provided more accurate predictions than others. In conclusion, this new method is more effective in relation to the traditional method of optimizing the electromagnetic field simulation to achieve optimal antenna design. This discovery shows that machine learning technologies are likely to revolutionize electromagnetic simulation technology. It is difficult to optimize complex antenna designs using a large number of design parameters due to the calculated power limit of the electromagnetic field tool. This problem can be solved by introducing machine learning technology into simulation software. The ultimate goal of this communication is to expand the range of approaches to learning machines to complex design structures.

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