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Performance Analysis of Machine Learning Algorithms for Microwave Low-Pass Filter Design in Modern Communication Systems

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ABSTRACT

The increasing reliance on wireless networks for data transmission has increased the demand for microwave filters that are characterized by high efficiency, small size, and low cost. This study presents an improved design of a Butterworth low-pass filter that can be used in 5G networks at a cutoff frequency of 3.6 GHz. The design was developed using Advanced Design System (ADS) simulation software using an FR4 dielectric substrate. Modern communications require accurate designs to be provided in less time and effort, and achieve better performance. Therefore, several machine learning (ML) algorithms, such as artificial neural networks (ANNs), decision trees (DTs), linear regression (LRs), and support vector machines (SVMs), were used to optimize LPF designs. A dataset was created that included parameters of the length and width of filter transmission lines at different frequencies. The ML algorithms were then trained by generating their code in Python. The results demonstrate significant improvements in the various algorithms' prediction accuracy and computational efficiency. The ANN (Model 1) achieved the lowest average error of 0.17%, but with the longest training time, while the SVM provided a balance between accuracy and training time with an error of 0.21%. In contrast, DT achieved the fastest training times, but with a higher average error of 2.63%. This approach significantly reduced the need for manual tuning and simulation iterations. These results highlight the potential of machine learning techniques to optimize microwave filter designs, providing engineers with flexible and high-precision tools for modern communications applications.

Keywords:

Butterworth low pass filter; Machine learning (ML); Artificial Neural Network (ANN); Decision Tree (DT); Support Vector Machine (SVM); Linear Regression (LR).

1. INTRODUCTION

Communication networks extensively use electrical filters. These filters allow energy to pass through specified frequencies (called passbands) while restraining energy from passing through specified frequencies (called stopbands). This ability is important for making sure that high-frequency signals are transmitted clearly and reliably, such as in satellites, radar, and wireless networks. Also, filters make communication networks more effective and efficient by removing unwanted signals and background noise [1-3]. When creating electrical circuits with high frequencies, designers often use microstrip transmission lines. A conductive metal strip is attached to a metal layer called the ground plane on top of a dielectric substrate [4].

Microstrip technology and its components offer a plethora of advantages. Its zero-cutoff frequency enables a very wide usage of the frequency range. Also employs light-weight dielectric materials for its microstrip manufacture. This makes it an ideal choice for portable applications like mobile phones. This is how microwave components are designed using microstrip technology, such as filters, antennas, etc [5-7]. Achieving the necessary level of design precision is typically challenging because the equations that will be mentioned in (2.1) only give approximations for the needed characteristics. Not only make the computations complex and time-consuming, but they also may contain a margin of error, which can lead to inaccuracies in the design process. Because of this, designers may have to put in a lot of time doing and double-checking calculations, which adds time and money to the component development process [8,9].

So, there is a requirement to look through some other options that will enhance the accuracy of the design process, in other words, using ML algorithms to boost performance and reduce errors. ML is an Artificial Intelligence (AI) technique subfield whose ML is to teach computers new tricks and modify behavior based on previous errors and other data. [10]. They learn to examine data for patterns and make judgments based on that analysis, rather than being programmed to carry out a certain task. When it comes to the aforementioned problems, ML techniques are especially useful when it comes to producing more precise outcomes with less human intervention [11-13].

ML techniques allow designers to handle the optimization of microstrip line features, which means they don't have to perform complex calculations. The accuracy of designs can be improved by ML algorithms that learn from past data, find trends, and make very accurate estimated values [14,15]. The problem of determining the width and length values of the filter circuit elements using conventional equations was addressed in this study by combining a microstrip low-pass filter (LPF) with ML techniques, including DT, LR, SVM, and ANN. This procedure uses ML techniques to forecast these values based on the dataset to streamline and increase the accuracy of microstrip filter construction.

2. RELATED WORKS

Researchers used a different ML algorithm with filters like Butterworth and Chebyshev to work better and take up less size. Microwave and wireless applications are worked better with this way because it adds simulation tools like HFSS, MATLAB, and ADS to makes filter settings better.

In 2021, A. HATHAT[16] focused on using (ANN) to design microstrip LPF and BPF. The main goal is to provide a filter design that is faster and more efficient than conventional design methods. A Chebyshev LPF with a maximum attenuation of 0.1 dB and a cutoff frequency of 1 GHz was designed using the stepped impedance technique, while a Chebyshev BPF with a maximum attenuation of 0.5 dB with a cutoff frequency of 2.45 GHz was designed using the coupled line technique. After completing the designs and obtaining the physical dimensions for each design, a dataset was created whose features (inputs) were the physical dimensions, frequency, and substrate properties, while the labels (outputs) were (S21) and (S11). Using the ANN algorithm, the training model was created and evaluated, and the expected results of this model were accurate and close to the results of the traditional simulation, but more efficient in terms of speed.

In 2021, M. Sedaghat, et al. [17] presented an inverse modelling approach to solve the microwave filter design problem. This approach achieves the intended results using the result specifications instead of the design geometric dimensions. This work presents a single method to characterize the design behavior at any frequency using S-parameters, which are the dispersion parameters. A BPF with a cut-off frequency of 2.4 GHz was designed using the ADS simulation program. The output values of the S-parameters were obtained, and then a database containing these values was created. Using the least squares support vector regression LS-SVM algorithm, a training model was developed and implemented to predict mathematical equations to link the S-parameters and the physical dimensions, and obtain the expected values that were accurate and close to the values obtained from the simulation program. This research presented a topic that helps reduce the effort and time required to design filters, making it useful for applications in modern communications such as 5G and radar.

In 2022, Y. Zhou, and others [18] presented a new method for Multiphysics modeling using a Deep Hybrid Neural Network (DHNN). Multiphysics modeling means simulating several systems and designs using simulation programs, but this modeling is complex and requires high effort, time, and computational efficiency in addition to side effects such as electromagnetism and heat. This paper presented an example of its application on an LPF, where a multi-physics model was created based on DHNN algorithms and sigmoid and ReLU activation functions to simulate several values of design parameters (geometric dimensions). Based on this data, the model was trained, and the expected results were obtained, which were close to the real results, with the least time and effort.

In 2022, J. Vesely, and others [19] presented a method for classifying and designing microwave filters based on deep learning techniques. The main idea of the research was to build a model through which the structure of any filter can be recognized and determined by image processing. A BPF was designed using the coupled line technique, and an LPF was designed using the stepped impedance technique. Then, a dataset was created using the MATLAB program that contains different images for filter designs, and each image represented the real structure of the filter. Using the Convolutional Neural Networks (CNN) algorithm, a training model was created to recognize and extract the features of each image, such as edges, inductive and capacitive elements that make up the filter circuit and their number of repetitions, which helps to understand the algorithm in classifying the filter type and determining its order.

In 2023, J. Araujo, and others [20] studied how ML algorithms were used to make microwave filters design better. A material RO 3010, with a thickness of 1.27 mm, a dielectric constant of 10.2, and a feed resistance of 50 ohms, was used to make an LPF with a cutoff frequency of 1.7 GHz. Then, a 3D program that simulates was used to test this design and find the S-parameter coefficients. (S21) was important because it showed how the filter works at letting frequencies pass through or stopping them, and studied how the geometric factors (the filter's dimensions) affected (S21). An (ANN) algorithm was used to turn the modeling program data into a neural network to find out how the filter's dimensions affect its frequency response. This method helped to find the right dimensions of the microwave filter faster with less work.

In 2024, J. Davalos-Guzman, etal [21] presented a study to integrate ML techniques with physical simulation to improve accuracy and reduce computational costs while including thermal effects within the simulation to achieve a more comprehensive understanding of the actual performance of the filter and achieve a balance between simulation and computational accuracy. An LPF was designed with a cutoff frequency of 5 GHz and a frequency range of 0-10 GHz. Using the multi-physics simulation program COMSOL, thermal and mechanical effects were added to study the effect of changing the geometric parameters of the filter (width, length, and distance between lines) on the (S21). Then, a database was created containing these parameters. Using the Bayesian Neural Network (BNN) algorithm, a training model was created to analyze the extent of the impact of these changes on (S21), as it was found that any small change leads to an impact on the response of (S21).

In 2025, S. Javadi, and others [22] presented an innovative method for designing microwave filters based on ML techniques with a focus on improving the model through advanced tuning techniques to ensure achieving the required performance. The BPF was designed with three orders, third, fourth, and fifth, and their frequency range was, respectively, 2.8 - 3.2 GHz with a cut-off frequency of 2.9 GHz, 2.6 - 3.0 GHz with a cut-off frequency of 2.7 GHz, and 10.0 - 12.0 GHz with a cut-off frequency of 10.7 GHz. Using the coupling matrix method, these designs were created and tested to convert the theoretical specifications of the filter into physical dimensions that can be dealt with simulation programs. Then, the Extreme Gradient Boosting (XGBoost) algorithm was employed to develop a training model that predicts the filter's dimension values. To improve these values, the Simulated Annealing (SA) algorithm was used to enhance and modify the expected dimension values. This method provided improved designs and reduced the time and number of iterations required to reach the final design.

Table 1 shows a comparison between the proposed design and previous research. Note that in all research, only one type of dataset is used: raw (true) data with multiple features and a single label, without making any optimization to obtain the optimal response to the S-parameters (S21, S11). Also, the testing process is carried out using only one training algorithm. This research focused on using two types of datasets: true and optimized data in different frequency ranges. The features in this dataset were only frequency, while the labels were multiple: the physical values of the filter and the values of the S-parameters (S21, S11). This dataset was tested using four machine learning algorithms: DT, LR, SVM, and three different ANN models, to make this research more comprehensive in understanding the efficiency of each algorithm under different data conditions.

Table 1: Comparison with related works

Reference number	Filter type	Data type	Data description	Type of ML algorithm	Design environment	Accuracy or Error
[16]	LPF & BPF	1	**Features:** width, length **Labels:** S11 & S21	ANN	N/A	Error =0.95%
[17]	BPF	1	**Features:** S21 and S11 **Labels:** filter dimension	LS-SVM	ADS	N/A
[18]	LPF	1	**Features:** filter dimension **labels:** S11	DHNN	N/A	Error =0.223%
[19]	LPF & BPF	1	Images for filter design	CNN	MATLAB	Accuracy =90%
[20]	LPF	1	**Features:** Filter dimensions **labels:** S21	ANN	3D program	N/A
[21]	LPF	1	**Features:** width, length **labels:** S21	BNN	COMSOL	Error =1.3%
[22]	BPF	1	**Features:** width, length **labels:** S11& S21	XGBoost	CST	Error =2.3%
Proposed system	LPF	2	**Features:** Frequency **Labels:** width, length, S21, & S11	ANN, SVM, DT, and LR	ADS	Least error : DT=2.04% LR=2.02% SVM=0.21% ANN=0.17%

The primary objective of the study was not to develop a new machine learning (ML) algorithm but to apply and compare existing ML algorithms for the purpose of optimizing microwave low-pass filter (LPF) design. The originality of this work lies in the integration of simulation data and ML-based predictive modeling for filter parameter optimization in a practical design environment (ADS using FR4 substrate). While the algorithms themselves are not new, the application of multiple ML models to extract meaningful design insights in the context of 5G-relevant filter design represents a practical and original contribution.

3. THE PROPOSED METHODOLOGY

In the initial design phase, the fundamental dimensions of the microwave LPF, including the length and width of elements (L1, C2, L3), were calculated using analytical equations that will be clarified in section 3.1.1. These equations define the basic electrical properties based on the chosen substrate, cutoff frequency, and impedance levels. However, these traditional methods only provide approximate values, often requiring iterative tuning to achieve the desired frequency response. To enhance the accuracy, ML techniques were introduced to bridge the gap between analytical approximations and real-world performance. Specifically, the ML algorithms (DT, SVM, LR, ANN) were trained using a dataset generated from these equations, capturing a wide range of frequency-dependent behaviors. This dataset included calculated lengths and widths as outputs, where the input was a range of frequencies corresponding to S21 and S11 responses. By learning the nonlinear relationships between these parameters, the ML models were able to refine the initial estimates, significantly reducing the average error and improving the filter's overall response. This approach not only improved the accuracy of the predicted dimensions but also minimized the need for repeated physical simulations and manual adjustments, streamlining the overall design process. In this way, ML techniques provided a powerful optimization layer on top of the conventional analytical methods, effectively enhancing both the speed and precision of the design process.

3.1. Design a Microstrip Low-Pass Filter (LPF)

The following parameters are used to create the low-pass filter using the stepped impedance technique. The cut-off frequency was used at 3.6 GHz because it is widely used in 5G networks for modern communications:

Cutoff frequency (fc): 3.6 GHz
Number of elements (n): 3
Circuit components: $L1$, $C2$, $L3$
System impedance ($Z0$): 50 ohms
Low impedance (ZL): 20 ohms
High impedance (ZH): 120 ohms
Butterworth filter coefficients (g): $g0$=1, $g1$=1, $g2$=2, $g3$=1[23].
Substrate dielectric constant (ϵr): 4.4
Substrate height (h): 1.66 mm

3.1.1. Mathematical Equation Used

In building the filter, the equations from (1) to (11) were used to calculate the filter coefficients [24-27]:

$$L = g1 \cdot \frac{Zo}{2\pi\, fc} \quad (1)$$

Where L is the value of inductor $L1$ and $L3$

$$C = g2 \cdot \frac{1}{2\pi\, fc\, Zo} \quad (2)$$

Where C is the value of capacitor $C2$.

$$\lambda o = \frac{c}{fc} \quad (3)$$

Where λo is wavelength in air.

$$\lambda go = \frac{\lambda o}{\sqrt{\epsilon o}} \quad (4)$$

Where λgo is the guided wavelength of the source.

$$\lambda gl = \frac{\lambda o}{\sqrt{\epsilon l}} \quad (5)$$

Where λgl is the guided wavelength of inductance L.

$$\lambda gc = \frac{\lambda o}{\sqrt{\epsilon c}} \quad (6)$$

Where is the guided wavelength of capacitance C.

For $w/h < 1$:

$$\epsilon_{re} = \left[\frac{\epsilon r+1}{2}\right] + \left[\frac{\epsilon r-1}{2}\right] * \left[1 + \frac{12*h}{wo}\right]^{-0.5} \quad (7)$$

Where ϵ_{re} is the effective dielectric constant for the source and w is the width.

For $w/h > 1$:

$$\epsilon_{re} = \left[\frac{\epsilon r+1}{2}\right] + \left[\frac{\epsilon r-1}{2}\right] * \left[1 + \frac{12*h}{wo}\right]^{-0.5} 0.04 \left[1 - \frac{w}{h}\right]^2 \quad (8)$$

Where ϵ_{re} is the effective dielectric constant for the source and $\boldsymbol{w}$ is the width.

$$lL = \frac{\lambda gl}{2\pi} \sin^{-1}\left[\frac{wc*L}{zh}\right] \quad (9)$$

Where lL is the length of inductance, and wc is the angular frequency.
$wc = 2\pi fc$.

$$lc = \frac{\lambda gc}{2\pi} \sin^{-1}[wc * c * zl] \quad (10)$$

Where lc is the length of capacitance and wc is the angular frequency.
$wc = 2\pi fc$.

$$lo = \frac{\lambda go}{8} \quad (11)$$

Where lo are the length of the source

3.2. Simulation Setup

The ADS software was employed to configure the simulation with the subsequent objectives:

- Finding dimensions: Calculate the length and width of each of $L1$, $C2$, and $L3$ using the previously given equations.
- Range of frequencies: To see how well the filter works at different frequencies, the program runs at 0.5 MHz steps from 0 GHz to 20 GHz.
- There wasn't enough -3 dB attenuation with the S21 and S11 settings at the cutoff frequency. This is because the previous equations only give an approximate value of the length and width.
- It was necessary to determine the optimal numbers for this width and length to achieve the required results.
- To do this, ADS's optimization properties were used to fine-tune the filter size by making many changes to the program.

Figures 1 and 2 show the proposed filter design using the ADS software interface without and with optimization.

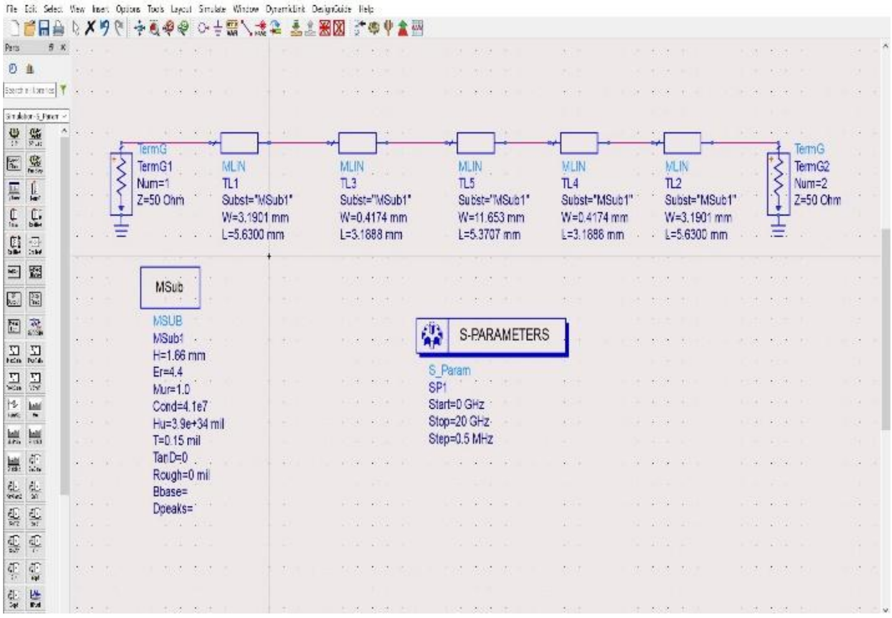

Fig. 1 Schematic design for LPF using ADS without optimization.

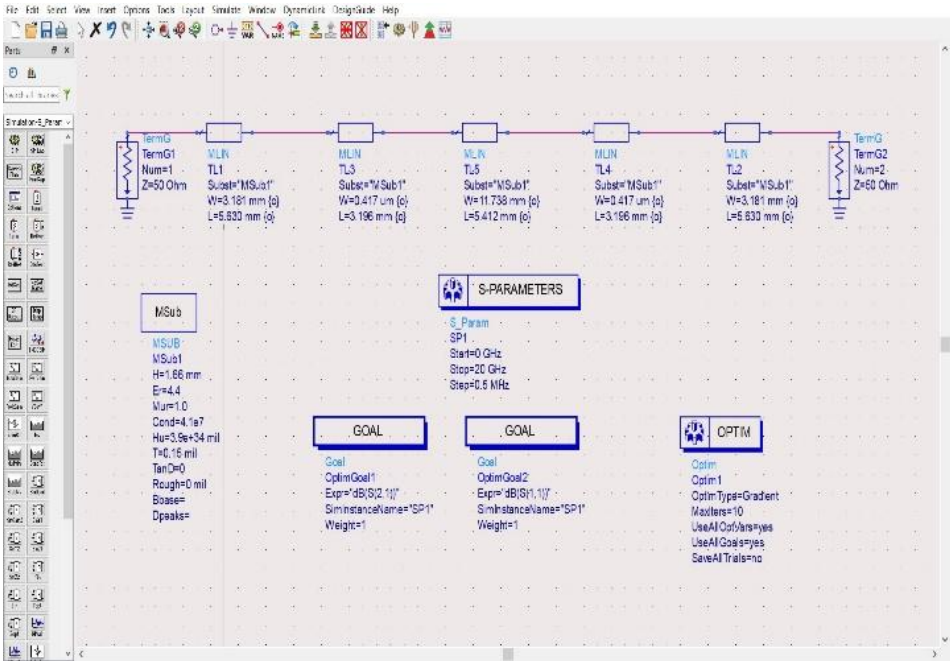

Fig. 2 Schematic design for LPF using ADS with optimization.

4. MACHINE LEARNING MODELS

Although there are other machine learning techniques, it was preferred to choose the most popular and extensively used algorithms in this study, including DT, LR, SVM, and ANN, due to their high prediction accuracy and quick training times.

4.1. building dataset

In this paper, the equations written in the methodology section are used to calculate the width and length values of each filter element (L1, C2, L3) in a microstrip LPF at each frequency within the range. The dataset's features (inputs) only include the cutoff frequency range (fc), while the labels (outputs) are the computed widths and lengths: $\boldsymbol{wo}$, $\boldsymbol{wl1}$, $\boldsymbol{wc2}$, $\boldsymbol{wl3}$, $\boldsymbol{lo}$, $\boldsymbol{lL1}$, $\boldsymbol{lc2}$, and $\boldsymbol{lL3}$. The dataset was created in frequency ranges from 1 GHz to 6 GHz with a 0.05 GHz increment step.

The previous equations give approximations and don't take the exact filter response at the -3dB point into account in terms of S21 and S11. To overcome this constraint and obtain more precise findings, optimized values are created using the (ADS) program that can improve the overall alignment with the filter's intended performance and fine-tune the output datasets by modifying the parameters using this strategy. Improving the initial settings to get closer to the target specs was a significant part of the optimization process. Created two of the final datasets: first, the approximate values originally derived using the equations for the same steps, and second, the optimized values produced using ADS for a step size of 0.05. Table 2 presents the results in detail.

Table 2: Characteristics of Building Data

No. of dataset	source	Step in GHz	Rang of freq. in GHz	No. 0f values
Dataset1	From equations	0.05	1 - 6	100
Dataset2	Optimization properties in ADS	0.05	1 - 6	100

4.2. The Used Algorithms

After the completion of the dataset, it was evaluated using the DT, LR, SVM, and ANN algorithms with Python code to determine the expected length and width values based on both the optimized and approximate datasets. The S21 and S11 response plots for each method were examined, and these anticipated values were noted in the next tables. The overall performance of low-pass microstrip filters can be improved by using these ML models to anticipate the geometric dimensions of the filter elements.

4.2.1. Decision Tree (DT)

One kind of non-linear prediction model is DT regression, which uses the feature values as inputs to create a model. It is a recursive method that starts with each node representing a decision based on an attribute value and continues until the best splits are discovered [28]. To manage the tree depth and assure the reproducibility of the results for this research, these parameters were set as max_depth=5 and random_state=1.

4.2.2. Support Vector Machine (SVM) Regression

SVM uses a tolerance margin to find the best line to fit. A flat function with a deviation from the actual goal values of no more than epsilon (ε) is the desired outcome. For this study, all available processors were used for parallel processing with the parameters n_jobs=-1 and cross-validation parameters CV=5 [29].

$$y = w * x + b \qquad (12)$$

where the bias term (b), the input vector (x), and the weight vector (w) are defined.

4.2.3. Linear Regression (LR)

Fitting data to a linear equation allows LR to model the dependent variable's relationship with one or more independent variables. The approach presupposes that the output is directly proportional to the square of the input variables [30].

$$y=\beta0+\beta1x+\epsilon y \qquad (13)$$

Where ϵ represents the error term, β0 stands for the intercept, and β1 is the coefficient for the independent variable x.

4.2.4. Artificial Neural Network (ANN)

The objective of building an ANN is to simulate the way the human brain works by simulating its architecture and connections between neural layers. A weight is assigned to each link and is fine-tuned throughout training to reduce prediction error [31].

In the ANN model, each neuron's output is computed using the following formula:

$$aj = f\left(\sum_{i=1}^{n} w_{ij} * x_i + b_j\right) \qquad (14)$$

Where aj is the activation of neuron j, f is used for activation, w_{ij} are the weight x_i are the inputs, and b_j is the bias term for this research, use ANN with three models and each model has a different hidden layer as shown in Table 3.

Table 3: Artificial Neural Network (ANN) models

No. of model	Hidden layer size	Activation function	Max. iteration
Model 1	(128,64,64), (256,128,64)	[relu, tanh]	[5000]
Model 2	(64,32), (128,64)	[relu, tanh]	[3000, 5000]
Model 3	(32,16), (16,8)	[relu, tanh]	[3000, 5000]

Where:

Max_iter: This indicates how many times the neural network model will update its weights and parameters during training. These iterations are necessary for the algorithm to converge toward the best possible solution that minimizes prediction error. If the value is too low, training may stop before reaching optimal performance, resulting in an underfitting model. If the value is too large, training time may increase without any real improvement in performance, and may also lead to overfitting.

hidden_layer_sizes: Refers to the structure of the neural network, specifically the number of neurons in each hidden layer. In this thesis, two hidden layers were used, each with a different number of neurons.

5. RESULTS AND DISCUSSIONS

The goal of this research is to use ANN, DT, LR, and SVM as examples of machine learning methods to obtain expected values for the length and width dimensions of the filter circuit elements that are close to the real and optimized values to save effort and time during the design process and provide a stable and ready structure to predict values at any frequency without the need to refer to mathematical equations. To implement these algorithms, the Python programming language was used with some of its libraries such as pandas, sklearn, and numpy. The percentage of test data was 30%, while the percentage of training data was 70%.

After implementing the mentioned algorithm codes using Python, the expected values were obtained based on the rules that were created. These values were recorded in Tables 4 to 7, and the filter response was taken for each algorithm. Separately using the simulation program ADS as shown in 3,4,5,6,7,8,9, and 10 figures.

Table 4: The prediction data of used ML algorithms according to Dataset 1

parameters	True values	DT	LR	SVM
Wo(mm)	3.1901	3.177	3.173	3.180
WL1,3 (mm)	0.4174	0.416	0.417	0.417
WC2(mm)	11.653	11.673	11.701	11.683
Lo(mm)	5.6300	5.917	5.418	5.690
LL1,3 (mm)	3.1888	3.338	3.057	3.210
LC2(mm)	5.3707	5.700	5.215	5.477
S11 (dB)	-3.208	-2.587	-3.567	-3.004
S21 (dB)	-2.875	-3.542	-2.566	-3.073
fc (GHz) at -3 dB	3.640	3.441	3.748	3.577
Average error (%)		2.63%	2.02%	0.71%
Training time (sec.)		0.004	0.024	11.79

Table 5: The prediction data of ANN models according to Dataset 1

parameters	True values	Model 1	Model 2	Model 3
Wo(mm)	3.1901	3.179	3.178	3.173
WL1,3 (mm)	0.4174	0.417	0.417	0.417
WC2(mm)	11.653	11.684	11.691	11.689
Lo(mm)	5.6300	5.709	5.524	5.413
LL1,3(mm)	3.1888	3.217	3.236	3.266
LC2(mm)	5.3707	5.493	5.479	5.518
S11 (dB)	-3.208	-2.975	-2.961	-2.868
S21 (dB)	-2.875	-3.103	-3.117	-3.216
fc (GHz) at -3 dB	3.640	3.568	3.563	3.534
Average error (%)		0.86%	1.02%	1.71%
Training time (sec.)		273.63	9.06	10.53

Tables 4 and 5 show the prediction accuracy, error rates, and training times for Dataset 1 for different algorithms. In terms of the cutoff frequency (fc at -3.00 dB), the true value was 3.640 GHz. The SVM model achieved the closest prediction at 3.577 GHz, and the ANN-based models (Models 1, 2, and 3) also provided relatively close estimates (3.577, 3.568, and 3.534 GHz, respectively), indicating their ability to generalize well to this parameter. The DT algorithm gave the lowest estimate (3.441 GHz), demonstrating a significant underestimation compared to the true value.

Meanwhile, the LR algorithm predicted a frequency of 3.748 GHz. The 0.71% error rate and 11.79 seconds training time for the SVM represented a good balance between accuracy and training time. The artificial neural network (ANN) algorithm with Model 1 was the most accurate among the three models, with an error rate of 0.86%, but it took the longest training time (273.63 seconds). The DT algorithm had the highest error rate (2.63%), meaning its predictions were less reliable.

However, it was the fastest to train, taking only 0.004 seconds, compared to the LR algorithm, which achieved a training time of 0.024 seconds and an error rate of 2.02%. The results demonstrate that the SVM method can be used to make accurate and efficient predictions. To select the best algorithm for practical applications in microwave filter design.

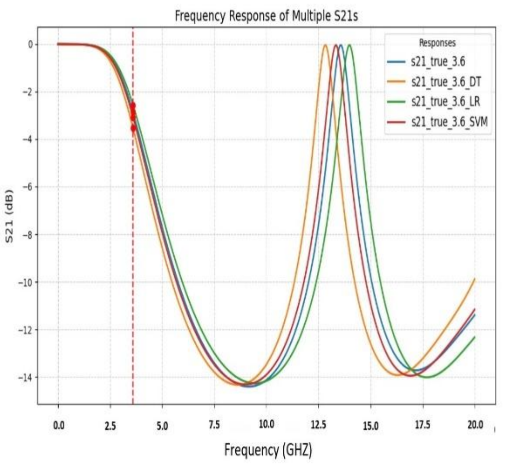

Fig. 3 The response of S21 for true and prediction values of all ML algorithms at dataset 1 and fc=3.600 GHZ

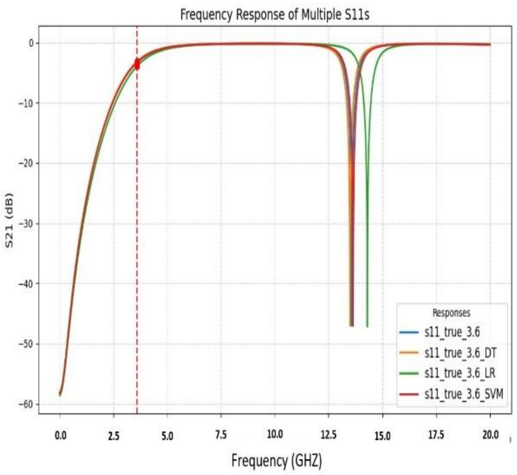

Fig. 4 The response of S11 for true and prediction values of all ML algorithms at dataset 1 and fc=3.600 GHZ

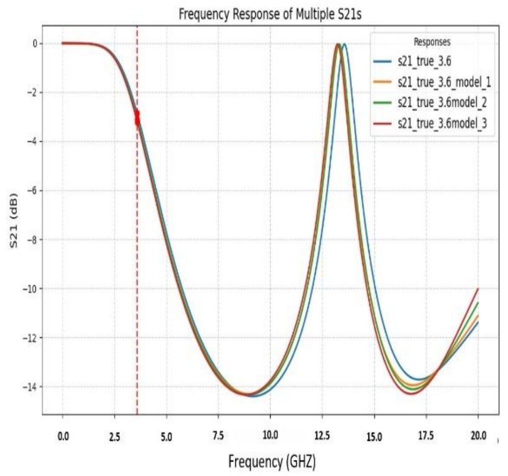

Fig. 5 The response of S21 for true and prediction values of ANN models at dataset1 and fc=3.600 GHZ.

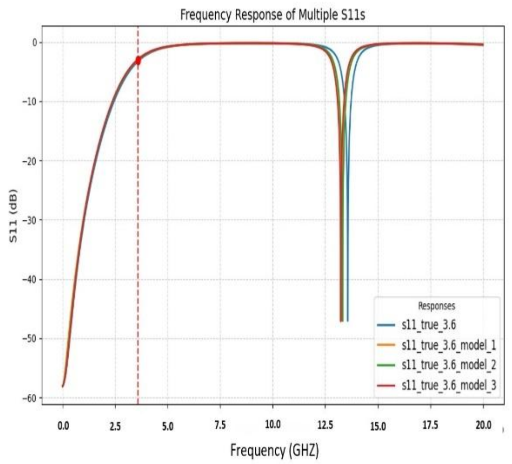

Fig. 6 The response of S11 for true and prediction values of ANN models at data set 1 and fc=3.600 GHZ

Figures 3 and 4 show the filter response of the values of S21 and S11 based on the true values and the predicted values of ML algorithms. The excellent ability of SVM in estimating the filter response shows strong congruence among the principles calculated by different methods and the actual values. Where the DT and LR algorithms have a lesser degree of agreement with the actual values. It can be seen that the values estimated by different ML algorithms were very close to the actual values. Figures 5 and 6 illustrate the filter response to the values of S11 and S21, compared to the results of the ANN with different numbers of hidden layers (models 1, 2, and 3) in a simulation run using the ADS program. The ANN shows convergence in performance and a close relationship with the actual values. Conclude from observing all the figures that model1 and model2 give the best filter response and are very close to the actual response.

Table 6: The prediction data of used ML algorithms according to Dataset 2

parameters	Optimize values	DT	LR	SVM
Wo(mm)	3.181	3.177	3.173	3.180
WL1,3 (mm)	0.417	0.416	0.417	0.417
WC2 (mm)	11.738	11.67	11.70	11.68
Lo(mm)	5.630	5.838	5.341	5.603
LL1,3 (mm)	3.196	3.321	3.040	3.191
LC2(mm)	5.412	5.628	5.131	5.408
S11 (dB)	-3.077	-2.68	-3.72	-3.12
S21 (dB)	-3.000	-3.42	-2.44	-2.96
fc (GHz)	3.600	3.474	3.792	3.613

at -3 dB				
Average error (%)		2.04%	2.63%	0.21%
Training time (sec.)		0.009	0.015	13.41

Table 7: The prediction data of used ANN models according to Dataset 2

parameters	Optimize. values	Mode1	Model2	Model3
Wo(mm)	3.181	3.179	3.178	3.173
WL1,3 (mm)	0.417	0.417	0.417	0.417
WC2(mm)	11.738	11.683	11.690	11.689
Lo(mm)	5.630	5.6336	5.448	5.343
LL1,3 (mm)	3.196	3.2037	3.224	3.252
LC2 (mm)	5.412	5.4240	5.413	5.448
S11 (dB)	-3.077	-3.081	-3.061	-2.995
S21 (dB)	-3.000	-2.996	-3.016	-3.081
fc(GHz) at -3 dB	3.600	3.601	3.595	3.575
Average error (%)		0.17%	0.77%	1.35%
Training time(sec.)		267.7	8.49	10.46

In Tables 6 and 7, the ADS program's optimization method was used to improve the results in Dataset 2. With the error rate of the majority of algorithms drastically decreased, these tables show a notable improvement in prediction accuracy. In terms of the cutoff frequency (fc at -3.00 dB), the optimized value obtained from ADS was 3.600 GHz. The SVM algorithm provided the closest estimation at 3.792 GHz, which demonstrates its ability to predict this critical parameter with high accuracy after optimization. The ANN-based models (Models 1, 2, and 3) also produced very close estimates of 3.613, 3.601, and 3.595 GHz, respectively, further confirming the models' capacity to adapt and align with optimized data.

The DT and LR models predicted 3.474 and 3.792 GHz, respectively, showing slightly more deviation, especially for LR, which tends to overestimate. As for the error rates and training time, although the training period was lengthy at 267.7 seconds, the ANN algorithm with model 1 achieved the lowest error rate of 0.17%, indicating good accuracy. With a training time of 13.41 seconds and an error rate of 0.211%, the SVM algorithm demonstrated a reasonable compromise between speed and precision. While the LR and DT algorithms had the lowest training time, they had the highest error rates, which were 2.04 and 2.63, respectively, which gives the impression of an unreliable inability to deduce predictions close to the required values.

These findings demonstrate how optimization techniques in ADS can greatly improve the model accuracy and stress the significance of striking a balance between accuracy and training time when selecting the best ML algorithm.

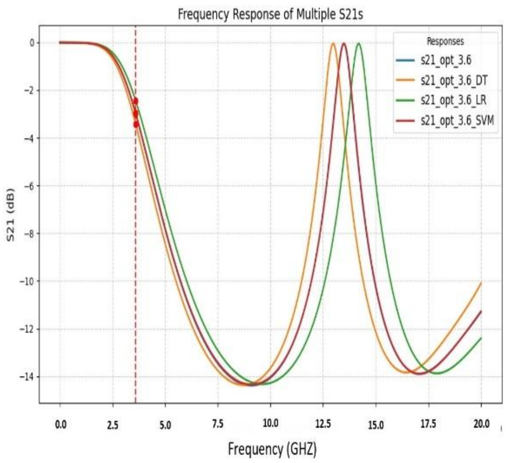

Fig. 7 The response of S21 for optimization and prediction values of all ML algorithms at dataset 2 and fc=3.600 GHZ

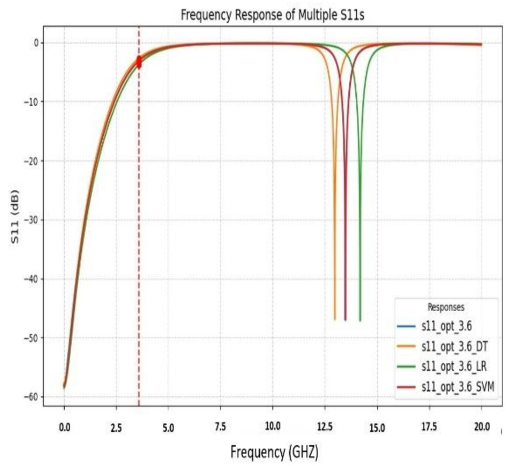

Fig. 8 The response of S11 for optimization and prediction values of all ML algorithms at dataset 2 and fc=3.600 GHz

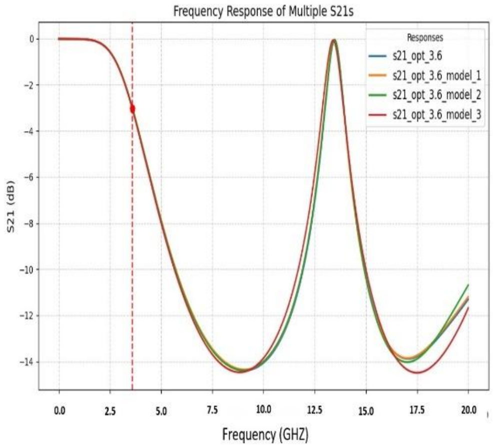

Fig. 9 The response of S21 for optimization and prediction values of ANN models at dataset 2 and fc=3.600 GHZ

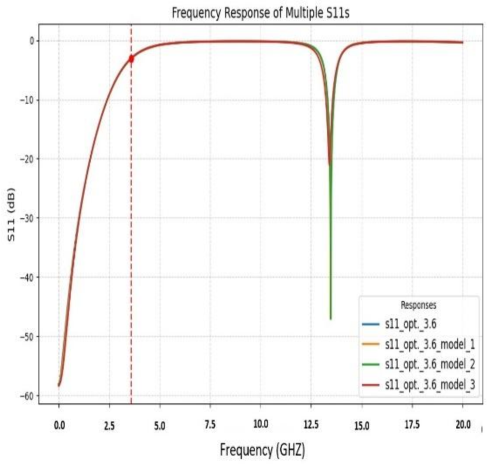

Fig. 10 The response of S11 for optimization and prediction values of ANN models at dataset 2 and fc=3.600 GHZ

Figures 7,8,9, and 10 show the response of S21 and S11 parameters of a filter after optimizing the length and width dimensions at data set 2 using ADS software. Figures 5 and 7 show the response of S21 of the filter using different techniques (such as SVM and ANN), showing better performance improvement around the center frequency of 3.6 GHz. Figures 6 and 8 reflect the response of S11, showing good agreement and achieving loss reduction at the center frequency. The results show that choosing the appropriate ML algorithm, such as ANN or SVM, significantly improves the performance, which is consistent with the results of Tables 5 and 6, which show a significant improvement in S11 and S21 values after applying the optimization. While Figures 8 and 9 indeed shows convergence in S-parameters results, the training time and prediction error vary notably between the models as shown in Table 8. For instance, although the ANN and SVM show similar S-parameters values, the computational cost of achieving that accuracy differs significantly, which can influence the model choice in real-world applications.

5.1 Algorithm Improvement Rates and Optimal Selection Conditions

The improvement rates for each algorithm were calculated based on the accuracy of their predictions and training times, as summarized in Table 8 below:

Table 8: Algorithm Improvement Rates

Algorithm	Average Error at dataset1	Average Error at dataset2	Training Time at dataset1	Training Time at dataset2
DT	2.63%	2.04%	0.004	0.009
LR	2.02%	2.63%	0.024	0.015
SVM	0.71%	0.21%	11.79	13.41
Model 1	0.86%	0.17%	273.63	267.7
Model 2	1.02%	0.77%	9.06	8.49
Model 3	1.71%	1.35%	10.53	10.46

From Table 8, it is clear that the ANN (Model 1) provided the highest accuracy with an average error as low as 0.17%, but at the cost of significantly longer training times. In contrast, SVM also achieved high accuracy (0.21% error) with a more balanced training time, making it suitable for many practical applications. The DT and LR algorithms had the lowest training time, but with less accuracy making it advantageous for rapid prototyping and simpler designs, though it sacrifices accuracy. This detailed analysis provides the necessary guidance for researchers to select the most appropriate algorithm based on their specific design requirements.

6. CONCLUSION

In this paper, several ML methods were used to design (LPF) with a cutoff frequency of 3.6 GHz. A variety of ML methods were employed, including SVM, LR, ANN, and DT. The ADS software was used to simulate the designed filter, exploiting the optimization feature of the ADS software to optimize the dimensions of the filter circuit elements. A dataset used for training and calculations was used to replicate the suggested filter separately. ML algorithms can greatly enhance the design's validity, according to the simulation results. Time and effort savings, improved accuracy, and smaller microstrip lines are all benefits. This study focused on applying and evaluating established machine learning (ML) algorithms to optimize the design of microwave low-pass filters, rather than developing new ML techniques. The key contribution lies in combining simulation-generated data with ML-driven predictive modeling to streamline the filter design process within a practical framework using ADS and an FR4 substrate. Although the ML methods used are well-known, their application to this specific 5G-relevant design problem offers valuable insights and demonstrates a practical approach to improving design efficiency and accuracy. Finally, at this stage, the filter design could not be fabricated due to limited access to specialized fabrication facilities capable of handling the sub-millimeter scale dimensions of the proposed layout. The filter's miniaturized structure, designed for operation at 3.6 GHz using an FR4 substrate, involves very fine transmission line widths and spacings, which exceed the resolution of most standard PCB manufacturing services currently available to us.

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تحليل أداء خوارزميات التعلم الآلي لتصميم مرشح الترددات المنخفضة للميكروويف في أنظمة الاتصالات الحديثة

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الملخص

أدى الاعتماد المتزايد على الشبكات اللاسلكية لنقل البيانات إلى زيادة الطلب على مرشحات الموجات الدقيقة التي تتميز بالكفاءة العالية والحجم الصغير والتكلفة المنخفضة. تقدم هذه الدراسة تصميمًا محسنًا لمرشح تمرير منخفض من نوع باتر وورث، يمكن استخدامه في شبكات الجيل الخامس عند تردد قطع 3.6 جيجا هرتز. تم تطوير التصميم باستخدام برنامج محاكاة نظام التصميم المتقدم (ADS) باستخدام ركيزة عازلة FR4. تتطلب الاتصالات الحديثة تصميمات دقيقة لتقديمها في وقت وجهد أقل، وتحقيق أداء أفضل. لذلك، تم استخدام العديد من خوارزميات التعلم الآلي (ML)، مثل الشبكات العصبية الاصطناعية (ANNs) وأشجار القرار (DTs) والانحدار الخطي (LRs) وآلات المتجهات الداعمة (SVMs)، لتحسين تصميمات LPF. تم إنشاء مجموعة بيانات تضمنت معلمات طول وعرض خطوط نقل المرشح عند ترددات مختلفة. ثم تم تدريب خوارزميات التعلم الآلي عن طريق إنشاء الكود الخاص بها في لغة بايثون. توضح النتائج تحسينات كبيرة في دقة التنبؤ والكفاءة الحسابية للخوارزميات المختلفة. حققت الشبكة العصبية الاصطناعية (النموذج 1) أقل متوسط خطأ بنسبة 0.17%، ولكن مع أطول مدة تدريب، بينما وفرت آلة الدعم المتجه (SVM) توازنًا بين الدقة ومدة التدريب بخطأ بنسبة 0.21%. في المقابل، حققت تقنية DT أسرع أوقات تدريب، ولكن بمتوسط خطأ أعلى بنسبة 2.63%. قلل هذا النهج بشكل كبير من الحاجة إلى الضبط اليدوي وتكرارات المحاكاة. تُبرز هذه النتائج إمكانات تقنيات التعلم الآلي في تحسين تصميمات مرشحات الموجات الدقيقة، مما يوفر للمهندسين أدوات مرنة وعالية الدقة لتطبيقات الاتصالات الحديثة.

الكلمات الدالة:

مرشح الترددات المنخفضة باتر وورث، التعلم الالي، الشبكة العصبية الاصطناعية، شجرة القرار، الة دعم المتجهات، الانحدار الخطي.