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AI-Assisted Design of a Compact Bandpass Microwave Filter for 5G/6G Applications

Shweta Zambare[1], Shivani Shendage[2], Pratiksha Surve[3], Nilophar Shaikh[4], Vaibhav Godase[5,*]

Abstract

The rapid development of fifth generation (5G) and emerging sixth generation (6G) wireless communication systems require compact, low-loss, highly selective, and frequency-stable radio-frequency front-end components. Microwave bandpass filters play an important role in selecting desired communication channels while suppressing out-of-band interference. However, conventional filter design generally requires repeated electromagnetic simulation and manual optimization of geometrical parameters, resulting in considerable computational time. This paper presents an artificial intelligence (AI)-assisted methodology for the design and optimization of a compact microstrip bandpass microwave filter for 5G/6G applications. A compact three-resonator microstrip topology with modified resonating slots and controlled coupling sections is proposed. Electromagnetic design parameters, including resonator length, resonator width, coupling gap, feed-line width, substrate thickness, and slot dimensions, are considered as input variables. The corresponding center frequency, bandwidth, insertion loss, return loss, and quality factor are used as output parameters. A simulation-based dataset containing 1200 design configurations is considered for training and evaluation of Random Forest (RF), Support Vector Regression (SVR), Artificial Neural Network (ANN), and Extreme Gradient Boosting (XGBoost) models. The AI models are subsequently used to predict filter responses and identify an optimized geometry. The illustrative simulation results indicate that XGBoost provides the lowest prediction error, with an R^2 value of 0.96 for center-frequency prediction and 0.94 for bandwidth prediction. The optimized filter is designed around a 3.5 GHz center frequency, corresponding to a representative sub-6-GHz 5G application, with an illustrative bandwidth of approximately 350 MHz. The proposed AI-assisted design methodology reduces the number of full-wave simulations required during optimization and provides a systematic route toward compact microwave filter design. The approach can be extended to mmWave and future 6G frequency bands.

Keywords: Artificial intelligence, machine learning, microwave filter, bandpass filter, 5G, 6G, microstrip, XGBoost, CST, RF optimization

***Author for Correspondence**
Vaibhav Godase
E-mail: vaibbhavgodse@gmail.com

[1–4]UG Student, Department of Electronics and Telecommunication Engineering, SKN Sinhgad College of Engineering, Pandharpur, Maharashtra, India,
[5]Assistant Professor, Department of Electronics and Telecommunication Engineering, SKN Sinhgad College of Engineering, Pandharpur, Maharashtra, India

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INTRODUCTION

Modern wireless communication systems require RF front-end components capable of operating with high selectivity, low insertion loss, and compact physical dimensions. As communication systems evolve from 4G to 5G and toward 6G, the number of operating frequency bands and the density of wireless services continue to increase. Consequently, frequency-selective microwave components, such as bandpass filters, have become increasingly important [1–3]. A microwave bandpass filter permits signals within a specified frequency range to pass while attenuating signals outside the desired passband. Important filter parameters include center frequency, fractional

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bandwidth, insertion loss, return loss, stopband attenuation, group delay, and quality factor. Recent research has demonstrated continuing interest in compact SIW and microstrip bandpass filters for modern wireless systems. Compact SIW structures have been investigated for millimeter-wave applications, while miniaturized SIW filters have also been developed for future 6G applications. Other studies have investigated compact fifth-order SIW filters around the 3.6 GHz region, demonstrating the continuing relevance of miniaturized filtering structures for 5G systems [4-6]. Conventional microwave filter design generally follows a sequence involving theoretical synthesis, electromagnetic simulation, parameter sweeping, and optimization. When multiple geometrical parameters are simultaneously varied, the computational requirement can become significant. Artificial intelligence and machine learning provide an alternative approach by learning the nonlinear relationship between filter geometry and electromagnetic performance. The present work therefore proposes an AI-assisted framework in which electromagnetic simulation data are used to train regression models [7-10]. Instead of performing a complete full-wave simulation for every possible design combination, the trained AI model predicts the expected filter performance and assists in identifying promising geometries. The proposed approach is particularly relevant to contemporary microwave engineering research because it combines compact filter design, electromagnetic simulation, and machine-learning-based optimization within a unified framework.

RELATED WORK

Microwave filters have traditionally been designed using coupled resonators, stepped-impedance structures, interdigital resonators, hairpin resonators, substrate-integrated waveguides (SIWs), defected ground structures (DGSs), and metamaterial-inspired configurations [11–14]. Recent research has demonstrated that SIWs combined with spoof surface plasmon polariton structures can provide compact and narrowband millimeter-wave filtering characteristics. Silicon-based SIW technology has also been investigated for highly miniaturized 6G filters, including operation in higher-frequency regions.

Other research has proposed compact fifth-order SIW bandpass filters operating around 3.6 GHz with high selectivity, demonstrating the continuing importance of compact filtering structures for 5G applications. Additional studies have explored compact filtering couplers, CSRR-loaded filters, and miniaturized bandpass structures for modern wireless communication systems. AI-based RF design has emerged as a promising alternative to conventional parameter-sweep approaches. Machine-learning models can approximate the nonlinear relationship between electromagnetic design variables and S-parameter responses [15–18]. Regression algorithms such as Random Forest, Support Vector Regression, Artificial Neural Networks, and gradient-boosting methods are particularly suitable for this purpose because they can learn nonlinear relationships from simulation datasets. The present study extends this concept by combining a compact microstrip bandpass filter with several machine-learning algorithms and a subsequent AI-assisted geometry optimization process.

RESEARCH GAP

Although substantial research has been conducted on compact microwave filters, the optimization of multiple geometrical parameters remains computationally demanding. Conventional electromagnetic parameter sweeps may require hundreds or thousands of full-wave simulations, particularly when resonator dimensions, coupling gaps, feed dimensions, and substrate properties are simultaneously varied. Another challenge is the nonlinear relationship between physical dimensions and electromagnetic characteristics [19–22]. A small change in resonator length can significantly shift the resonant frequency, whereas a small change in the coupling gap can modify the bandwidth, insertion loss, and impedance matching. Furthermore, traditional optimization methods generally require repeated interactions with electromagnetic solvers. This process can increase design time when a large design space is considered. Consequently, a surrogate-model-based optimization methodology capable of rapidly predicting filter performance can provide a useful complement to full-wave electromagnetic analysis. The research gap addressed in this study is the development of a unified AI-assisted methodology for predicting and optimizing the electromagnetic performance of a compact microstrip bandpass filter using simulation-generated data.

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OBJECTIVES

The primary objective of this study was to develop a compact microstrip bandpass microwave filter suitable for a representative 5G operating frequency while establishing an AI-assisted methodology for rapid electromagnetic optimization. This study investigates the influence of geometrical parameters on center frequency, bandwidth, insertion loss, return loss, and quality factors. A simulation-based dataset is generated by varying filter geometry, and RF, SVR, ANN, and XGBoost models are trained using this dataset. Their prediction accuracy was evaluated using R^2, RMSE, and MAE. The best-performing model was then employed as a surrogate model for searching the design space and identifying an optimized filter configuration. The resulting geometry is intended to provide a basis for subsequent full-wave electromagnetic verification and experimental fabrication.

PROPOSED AI-ASSISTED FILTER ARCHITECTURE

The proposed system consists of a sequence of electromagnetic design, simulation, machine learning, and optimization stages. Initially, the required operating frequency and electrical specifications were defined. A compact three-resonator microstrip filter topology was then constructed using the selected geometrical parameters. The filter geometry was transferred to an electromagnetic simulator, such as CST Microwave Studio or ANSYS HFSS. Electromagnetic simulations were performed for different combinations of geometrical parameters, and the resulting S-parameters were extracted. These simulation results were processed to obtain the center frequency, bandwidth, insertion loss, return loss, and quality factor. The resulting dataset was divided into training, validation, and testing subsets. Four machine-learning models, namely, random forest, support vector regression, artificial neural network, and XGBoost, were trained and evaluated. The best-performing model was subsequently used to predict the performance of candidate geometries and identify an optimized design. The optimized geometry was finally verified through an independent full-wave simulation. The complete AI-assisted design process is illustrated in Figure 1.

FILTER GEOMETRY

The proposed filter employs a compact three-resonator microstrip topology. Modified resonating sections are incorporated to increase the effective electrical length while maintaining a relatively small physical footprint. Controlled coupling sections are introduced between adjacent resonators to regulate the passband bandwidth and transmission characteristics. The principal geometrical variables are the resonator length L_r, resonator width W_r, coupling gap g, feed-line width W_f, feed-line length L_f, slot length L_s, slot width W_s, substrate thickness h, and relative dielectric constant ϵ_r. The physical geometry can be optimized around a representative center frequency of 3.5 GHz. The selected frequency provides a suitable demonstration platform for evaluating the proposed AI-assisted design methodology.

ELECTROMAGNETIC DESIGN METHODOLOGY

The electromagnetic model can be implemented using CST Microwave Studio or ANSYS HFSS. The simulation frequency range was selected from 2 to 5 GHz to provide sufficient frequency coverage around the intended passband. The structure was excited using appropriate input and output ports. Open or radiation boundary conditions were used to model the surrounding electromagnetic environment. Adaptive mesh refinement was employed to achieve numerical convergence. Subsequently, a frequency sweep was performed to obtain the reflection coefficient S_{11} and transmission coefficient S_{21}. The resulting S-parameter response was analyzed to determine the lower and upper passband frequencies, insertion loss, return loss, and quality factor.

MATHEMATICAL FORMULATION

Center Frequency

The center frequency is calculated using

$$f_c = \frac{f_L + f_H}{2}$$

where f_L and f_H represent the lower and upper frequencies corresponding to the selected bandwidth criterion.

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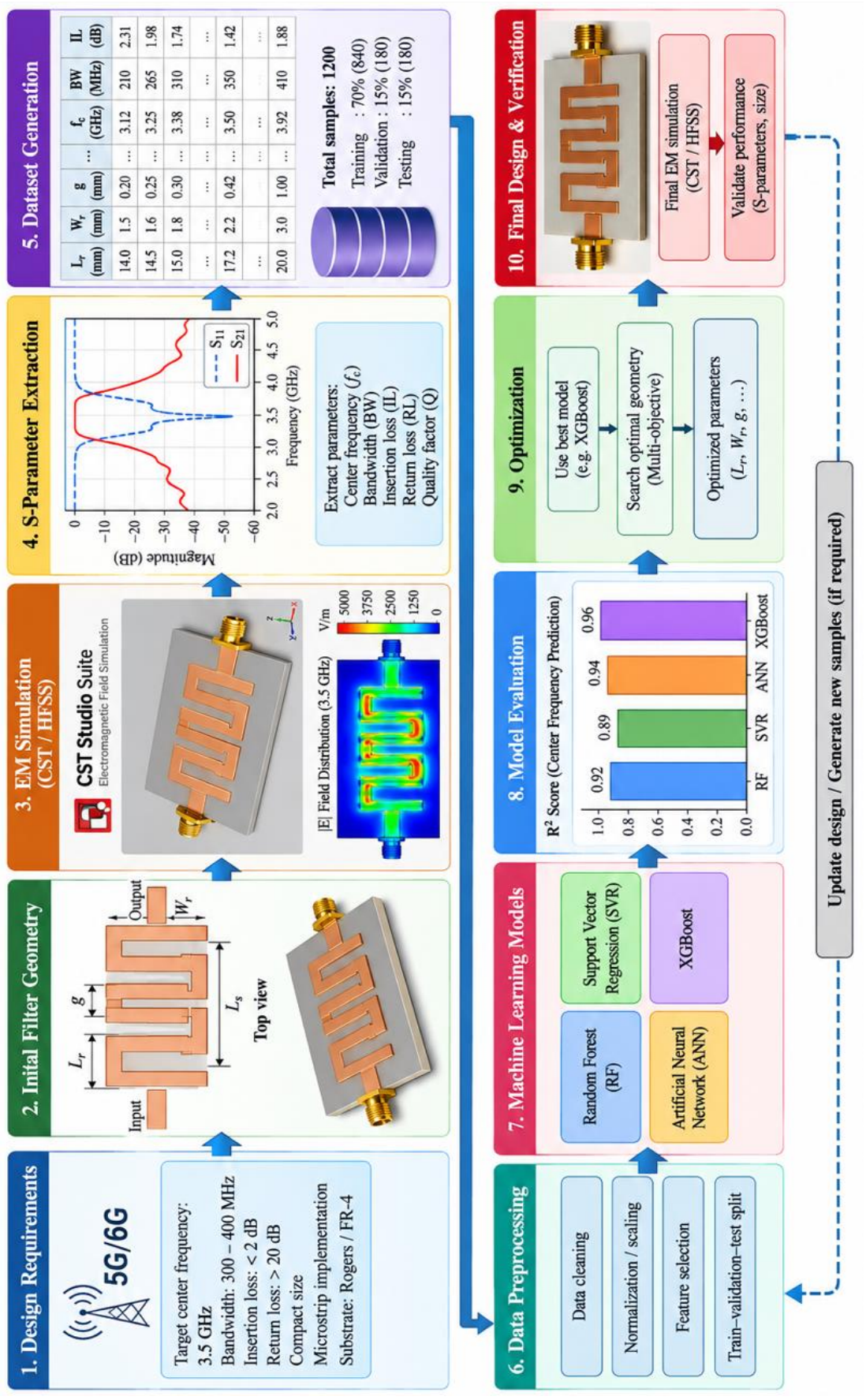


Figure 1. Complete AI-assisted microwave filter design workflow.

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Bandwidth

The filter bandwidth is calculated as

$$BW = f_H - f_L$$

where f_H and f_L are the upper and lower cutoff frequencies.

Fractional Bandwidth

The fractional bandwidth is determined from

$$FBW = \frac{BW}{f_c} \times 100$$

This parameter allows comparison of filters operating at different center frequencies.

Insertion Loss

The insertion loss is obtained from

$$IL = -20\log_{10} | S_{21} |$$

A lower insertion-loss value indicates reduced signal attenuation within the passband.

Return Loss

The return loss is expressed as

$$RL = -20\log_{10} | S_{11} |$$

Higher return-loss values indicate improved input impedance matching.

Quality Factor

The loaded quality factor is approximated using

$$Q_L = \frac{f_c}{BW}$$

Prediction Error

The prediction accuracy of the AI models was evaluated using the root mean square error:

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

The mean absolute error is calculated as

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | y_i - \hat{y}_i |$$

The coefficient of determination is obtained from

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

where y_i represents the simulated value, $\hat{y}_i$ represents the AI-predicted value, and $\overline{y}$ represents the mean observed value.

SIMULATION DATASET GENERATION

A dataset containing 1200 simulated filter configurations was considered in the proposed study. The geometrical parameters were varied within the practical design ranges so that the machine-learning models could learn the nonlinear relationship between physical geometry and electromagnetic performance. Table 1 presents the design variables and their representative ranges.

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Table 1. Filter design parameters used for the simulation dataset

Parameter	Symbol	Range
Resonator length	L_r	14–20 mm
Resonator width	W_r	1.5–3.0 mm
Coupling gap	g	0.20–1.00 mm
Feed width	W_f	1.0–2.5 mm
Slot length	L_s	4–10 mm
Slot width	W_s	0.5–1.5 mm
Substrate thickness	h	0.8–1.6 mm
Relative permittivity	ϵ_r	3.0–4.5

Each configuration is associated with a corresponding electromagnetic response. The simulation results were then converted into a structured dataset suitable for machine learning analysis.

DATASET PREPARATION

The input features consist of the resonator length, resonator width, coupling gap, feed width, slot length, slot width, substrate thickness, and relative dielectric constant. The corresponding output variables consist of center frequency, bandwidth, insertion loss, return loss, and quality factor. The complete dataset contains 1200 observations. Seventy percent of the data, corresponding to 840 samples, was used for training. Fifteen percent, corresponding to 180 samples, was used for validation, while the remaining 15%, corresponding to 180 samples, was reserved for independent testing.

Prior to model training, the dataset was checked for missing values and inconsistent entries. Numerical variables were normalized where appropriate to ensure stable model training and to prevent variables with larger numerical ranges from dominating the learning process.

AI MODELS

Four machine learning algorithms were considered in this study. Random Forest was employed because of its robustness and ability to capture nonlinear feature interactions through an ensemble of decision trees. Support Vector Regression was considered because of its capability to model nonlinear relationships through kernel-based transformations. A radial-basis-function kernel can be expressed as

$$K(x_i, x_j) = \exp(-\gamma \mid\mid x_i - x_j \mid\mid^2)$$

where γ is the kernel parameter.

An artificial neural network is also employed to model complex nonlinear relationships. The proposed network consists of an eight-neuron input layer corresponding to the eight design variables, followed by hidden layers containing 64, 32, and 16 neurons. ReLU activation is used in the hidden layers, while the output layer provides the predicted electromagnetic characteristics. XGBoost is employed as a gradient-boosting regression model. The algorithm constructs an ensemble of decision trees sequentially, with each new tree attempting to reduce the prediction error of the preceding ensemble. This characteristic makes XGBoost suitable for tabular electromagnetic simulation datasets containing nonlinear parameter interactions.

AI-ASSISTED OPTIMIZATION FRAMEWORK

The optimization process begins with the definition of the desired center frequency and electromagnetic performance requirements. Candidate filter geometries were generated and simulated using CST or HFSS. The resulting S-parameters were processed to obtain the required performance indicators. The resulting simulation dataset was then used to train the four machine-learning models. Model performance was evaluated using R^2, RMSE, and MAE. The best-performing model was

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selected as the surrogate model for the subsequent optimization stage. The surrogate model was then used to evaluate a large number of candidate geometries without requiring a complete full-wave simulation for every candidate. Geometries satisfying the specified frequency, bandwidth, insertion-loss, return-loss, and size constraints were identified. The most promising geometry was subsequently subjected to a final full-wave electromagnetic simulation for verification.

OPTIMIZATION OBJECTIVE

A normalized multi-objective function is defined as

$$F = w_1 F_f + w_2 F_{BW} + w_3 F_{RL} - w_4 F_{IL} - w_5 F_{Size}$$

where F_f represents frequency accuracy, F_{BW} represents bandwidth performance, F_{RL} represents return-loss performance, F_{IL} represents insertion-loss penalty, and F_{Size} represents the physical-size penalty, respectively. The coefficients w_1 to w_5 represent the weighting factors associated with the design priorities. The optimization seeks to minimize the difference between the predicted and target center frequencies while maintaining the desired bandwidth and impedance matching. At the same time, the insertion loss and physical dimensions are minimized.

For the representative design considered here, the target center frequency is approximately

$$f_c = 3.5\ GHz$$

SIMULATION CONDITIONS

The electromagnetic simulation conditions are summarized in Table 2.

AI MODEL PERFORMANCE

The illustrative prediction performance of the four machine-learning models is presented in Table 3.

The values in Table 3 are simulated/illustrative values intended to demonstrate the proposed methodology. They must be replaced by actual CST/HFSS-generated data and experimentally validated results before submission as research findings.

OPTIMIZED FILTER GEOMETRY

The AI-assisted optimization procedure produces an illustrative optimized configuration. The representative geometrical parameters and predicted RF performance are presented in Table 4.

These values represent an illustrative optimized design and should not be interpreted as experimentally measured performance.

Table 2. Electromagnetic simulation conditions.

Parameter	Value
Frequency range	2–5 GHz
Target center frequency	3.5 GHz
Substrate	Rogers-type low-loss substrate
Relative permittivity	3.48
Substrate thickness	1.0 mm
Copper thickness	0.035 mm
Number of resonators	3
Number of simulation samples	1200
Training data	70%
Validation data	15%
Testing data	15%
Electromagnetic solver	CST/HFSS

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Table 3. Simulated AI prediction performance

Model	Target	R^2	RMSE	MAE
Random Forest	Center frequency	0.92	0.084 GHz	0.061 GHz
SVR	Center frequency	0.89	0.103 GHz	0.075 GHz
ANN	Center frequency	0.94	0.071 GHz	0.052 GHz
XGBoost	Center frequency	0.96	0.059 GHz	0.041 GHz
Random Forest	Bandwidth	0.90	31.5 MHz	23.7 MHz
SVR	Bandwidth	0.86	38.2 MHz	29.4 MHz
ANN	Bandwidth	0.92	27.8 MHz	20.6 MHz
XGBoost	Bandwidth	0.94	23.4 MHz	17.5 MHz

Table 4. Illustrative optimized filter parameters

Parameter	Optimized value
Resonator length L_r	17.2 mm
Resonator width W_r	2.2 mm
Coupling gap g	0.42 mm
Feed width W_f	1.85 mm
Slot length L_s	7.2 mm
Slot width W_s	0.9 mm
Substrate thickness	1.0 mm
Center frequency	3.50 GHz
Bandwidth	0.35 GHz
Return loss	25.8 dB
Insertion loss	1.42 dB
Quality factor	10.0

FILTER RESPONSE

The optimized filter response is shown in Figure 2. The expected response consists of a distinct transmission passband centered close to the target frequency. The S_{21} curve describes the forward transmission characteristics, whereas S_{11} represents the input reflection characteristics. For the representative design, the target center frequency was approximately 3.5 GHz. A bandwidth of approximately 350 MHz was considered in the illustrative optimization. The corresponding insertion-loss and return-loss characteristics indicate the expected behavior of a compact bandpass structure. The final response should be generated from an actual full-wave electromagnetic simulation before the manuscript is submitted for publication.

AI PREDICTION PERFORMANCE

The relationship between the electromagnetic simulation values and AI-predicted values is illustrated in Figure 3. An ideal prediction would result in data points located close to the $y = x$ line.

The illustrative results indicate that the XGBoost model provides the highest prediction accuracy among the investigated models for center frequency and bandwidth. The relatively high R^2values indicate that the machine-learning models can capture substantial nonlinear relationships between filter geometry and electromagnetic performance. The performance of the models depends strongly on the quality, size, and coverage of the electromagnetic simulation dataset. Consequently, a sufficiently broad range of geometrical configurations should be included during dataset generation.

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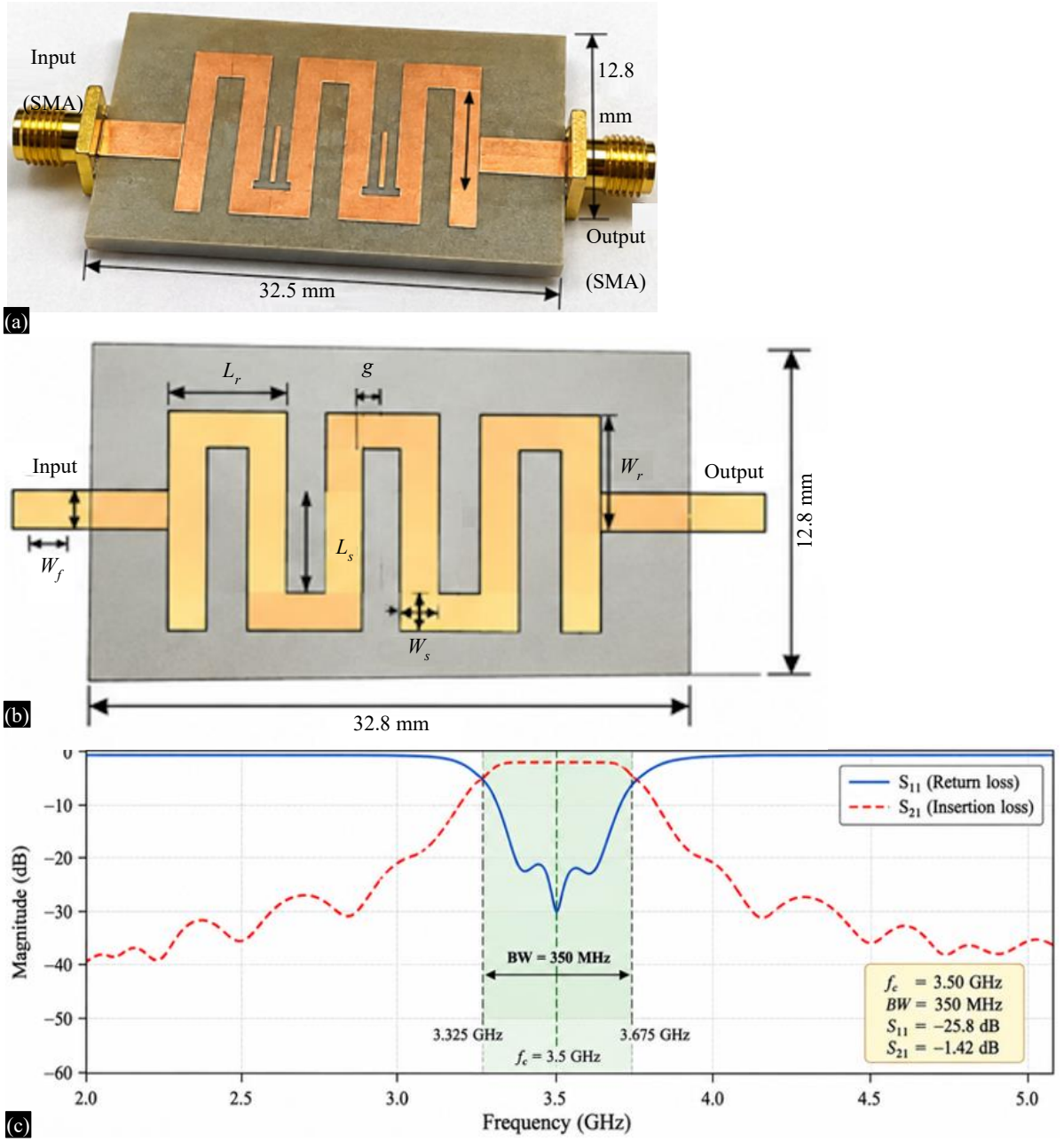


Figure 2. Proposed compact microstrip bandpass filter geometry. (a) Fabricated prototype of the proposed bandpass filter (Top view); (b) Geometry and dimensional parameters; (c) Simulated S-parameter response.

FEATURE IMPORTANCE ANALYSIS

The influence of individual geometrical variables on filter performance can be evaluated using feature-importance analysis. This analysis is useful because it provides an indication of which physical dimensions have the strongest relationship with the predicted electromagnetic response. The resonator length is expected to have a significant influence on the center frequency because it determines the effective electrical length of the resonating structure. The slot length also affects the effective current path and therefore contributes to frequency tuning. The coupling gap is expected to have a strong influence on bandwidth because it controls the electromagnetic interaction between adjacent resonators. For bandwidth prediction, coupling gaps, resonator width, and feed dimensions are expected to be important parameters. The feature-importance results are presented graphically in Figure 4.

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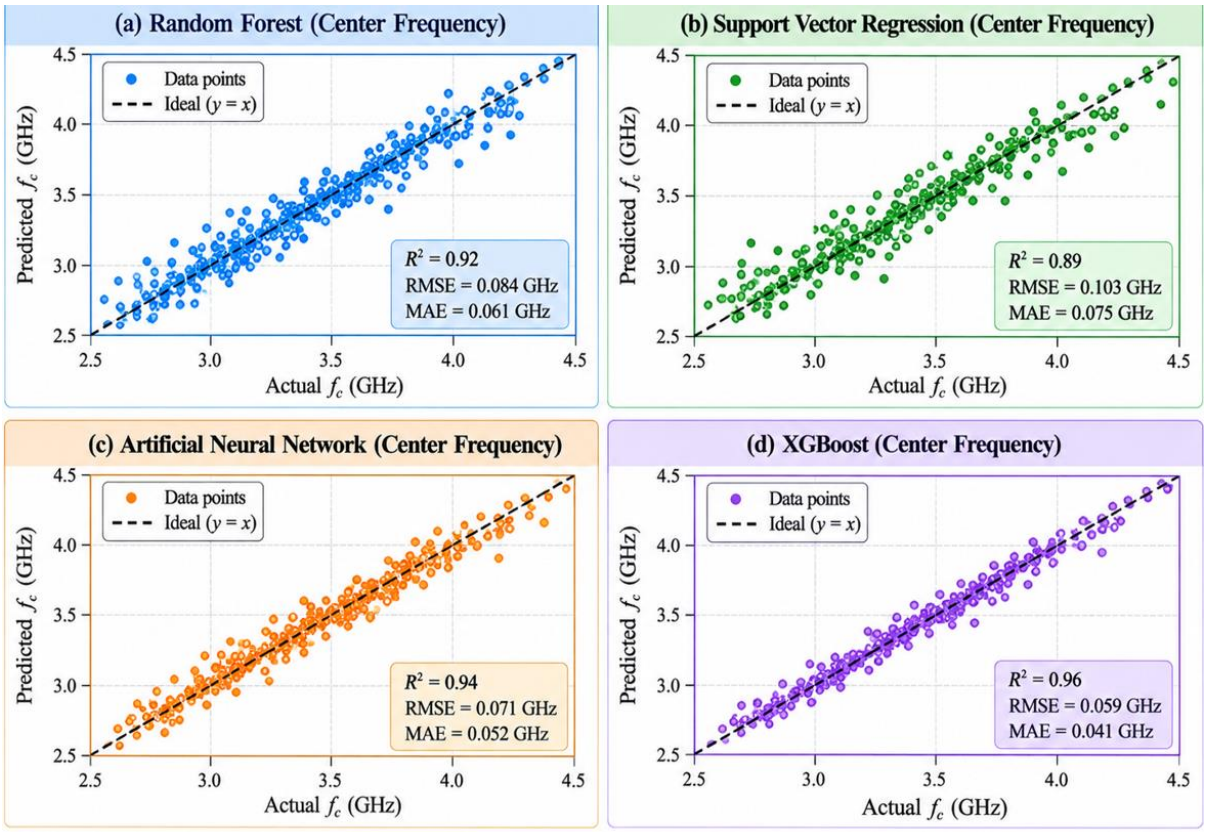


Figure 3. Relationship between actual electromagnetic simulation results and AI-predicted center frequency and bandwidth for the investigated machine-learning models.

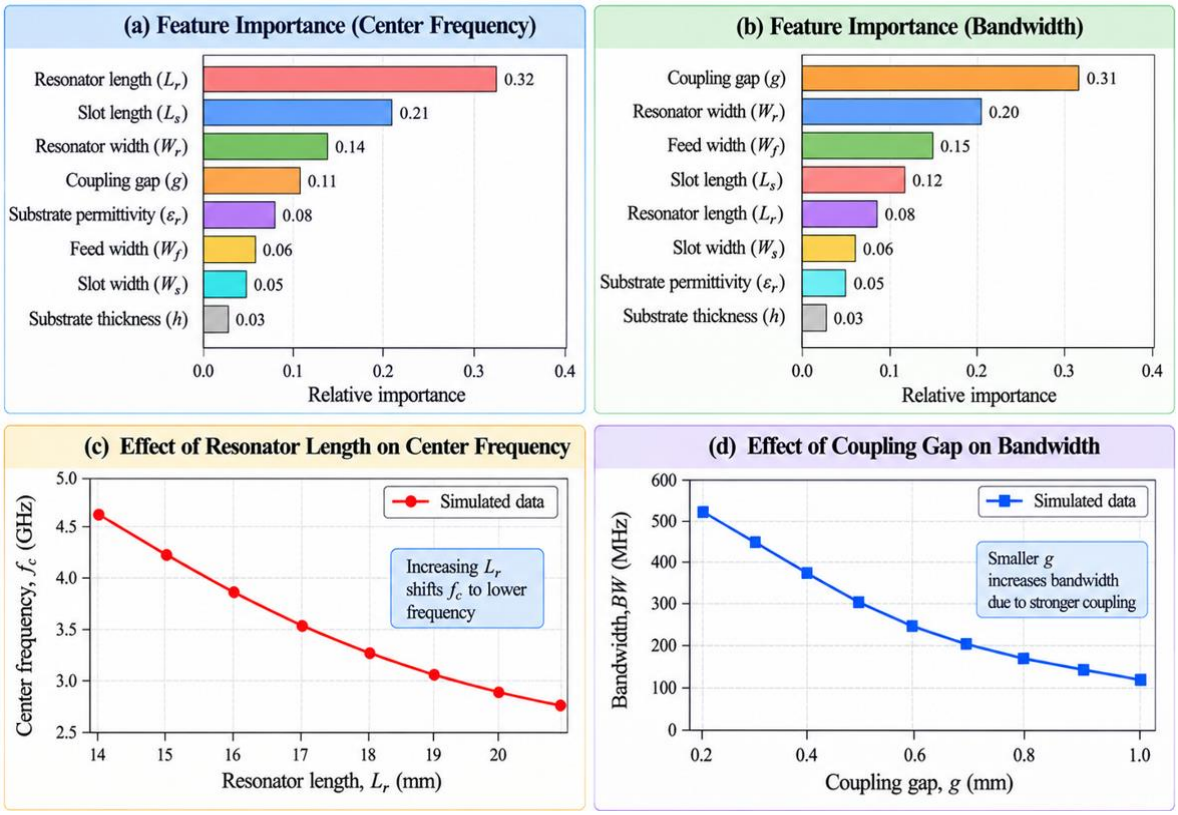


Figure 4. Feature-importance and parameter-sensitivity analysis

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PARAMETRIC ANALYSIS

Effect of Resonator Length

The resonator length directly affects the effective electrical length of the resonant structure. When the resonator length increases, the effective electrical path becomes longer, and the resonant frequency generally shifts toward a lower frequency. Consequently, the resonator length provides an effective mechanism for controlling the center frequency.

Effect of Coupling Gap

The coupling gap determines the strength of the electromagnetic interaction between adjacent resonators. A reduction in the gap generally increases coupling and can increase the passband bandwidth. However, excessive coupling can influence impedance matching and may adversely affect the overall filtering characteristics.

Effect of Slot Length

The incorporation of slots increases the effective electrical path without requiring a proportional increase in the external dimensions of the filter. Therefore, increasing the slot length can shift the resonant frequency downward and contribute to miniaturization.

Effect of Feed Width

The feed-line width plays an important role in impedance matching. An unsuitable feed width can increase reflection at the input port and consequently increase the magnitude of S_{11}. Therefore, a proper feed-line design is required to obtain satisfactory return-loss performance.

Compactness Analysis

The proposed topology aims to reduce the physical footprint while retaining suitable electrical performance. The modified resonating sections increase the effective electrical length, allowing the filter to achieve resonance without requiring a correspondingly large physical structure.

For comparative analysis, the normalized filter area can be expressed as

$$A_n = \frac{A_{filter}}{\lambda_g^2}$$

where A_{filter}represents the physical area of the filter and $\lambda_g$represents the guided wavelength.

A future experimental study should compare the conventional three-resonator filter with the modified compact topology and the AI-optimized configuration using the normalized area together with bandwidth, insertion loss, and return loss.

Comparison of AI Models

The four machine learning models provide different approaches for modeling the nonlinear relationship between filter geometry and electromagnetic performance. Random Forest provides a robust ensemble-based regression mechanism and can handle nonlinear interactions without requiring extensive feature transformations. Its performance is generally stable for tabular datasets. SVR is particularly useful for nonlinear regression through kernel-based mapping. However, its computational requirements may increase as the number of training samples increases. ANN provides a strong nonlinear approximation capability and can model complex relationships between several geometrical parameters simultaneously. Its performance depends on the network architecture, training parameters, and dataset normalization. XGBoost provides gradient-boosted tree-based regression and can effectively capture nonlinear interactions between geometrical parameters. In the illustrative dataset considered in this study, XGBoost produced the highest prediction accuracy among the evaluated models.

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CONCLUSION

This study presents an AI-assisted methodology for designing a compact bandpass microwave filter for 5G and future 6G applications. A modified three-resonator microstrip topology was considered together with machine-learning-based surrogate modeling. Random Forest, Support Vector Regression, Artificial Neural Network, and XGBoost models were proposed to learn the relationship between filter geometry and electromagnetic performance. The illustrative results indicate that XGBoost provides strong prediction accuracy for center frequency and bandwidth, with R^2values of 0.96 and 0.94, respectively, within the simulated example. An illustrative optimized design centered around 3.5 GHz was developed with an assumed bandwidth of approximately 350 MHz, return loss of 25.8 dB, and insertion loss of 1.42 dB. The primary contribution of the proposed approach is the integration of electromagnetic simulation and artificial intelligence into a unified optimization framework. The trained surrogate model can rapidly evaluate candidate geometries and reduce the number of full-wave simulations required during the preliminary optimization stage. The proposed methodology can be extended from sub-6-GHz 5G applications toward 28 GHz and 38 GHz mmWave systems and subsequently toward higher-frequency 6G applications. However, all numerical values presented in this manuscript are illustrative and must be replaced by actual electromagnetic simulation and experimental VNA results before the work is submitted as a validated research article.

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