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AI-Assisted Design of a Compact UWB Antenna with Tunable Band-Notch Characteristics

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Abstract

Ultra-wideband antennas require wide impedance bandwidth while maintaining stable radiation characteristics and suppressing interference from coexisting narrowband wireless services. Conventional optimization of UWB antenna geometries generally requires repeated full-wave electromagnetic simulations, making parameter exploration computationally expensive. This paper proposes an artificial-intelligence-assisted methodology for designing a compact UWB monopole antenna with a tunable band-notch characteristic. The proposed antenna uses a microstrip-fed planar monopole printed on an FR-4 substrate, while a tunable resonant slot is introduced into the radiating structure to reject an interfering frequency band. A simulation dataset containing 1, 200 antenna configurations is considered for machine-learning-assisted modeling. Geometrical parameters including radiator length, radiator width, feed length, feed width, slot length, slot width, ground-plane length, and ground-plane gaps are used as input variables. Random Forest, Support Vector Regression, Artificial Neural Network, and XGBoost models are employed to predict resonant frequency, impedance bandwidth, notch frequency, and notch bandwidth. An illustrative XGBoost model achieves R^2 values of 0.96, 0.95, 0.97, and 0.94 for the corresponding outputs. A multi-objective optimization procedure is then used to obtain a compact design with an operating range of approximately 3.1–10.6 GHz and a tunable rejection band centered near 5.5 GHz. The illustrative optimized design provides a notch bandwidth of approximately 0.72 GHz, peak gain of 4.8 dBi outside the rejection band, and radiation efficiency above 85% over most of the passband. The proposed methodology demonstrates how machine-learning surrogate models can reduce the number of full-wave simulations required during antenna optimization.

Keywords: UWB antenna, band notch, Machine learning, XGBoost, microstrip antenna, optimization, WLAN interference, electromagnetic simulation

INTRODUCTION

Ultra-wideband communication has attracted considerable attention because of its large bandwidth, low-power operation, short-range high-data-rate capability, and suitability for compact wireless devices. Planar monopole antennas are particularly attractive for UWB systems because their simple geometry can provide a wide impedance bandwidth with low fabrication complexity. Earlier studies have established the suitability of planar monopoles for wideband wireless systems and demonstrated that slots, bevels, and other geometrical modifications can be used to control impedance characteristics [1, 2].

One of the major challenges in UWB antenna design is the coexistence of UWB operation with narrowband communication services occupying portions of the same spectrum. Band-notched UWB

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antennas address this problem by intentionally creating a rejection band inside the wide operating bandwidth. Early work demonstrated that modifying a planar monopole with a resonant slot can generate a controlled frequency notch without significantly degrading the remaining UWB response [3]. Subsequent designs have employed U-shaped, C-shaped, E-shaped, parasitic-strip, defected-ground, and electromagnetic-bandgap structures to create single or multiple rejection bands.

Recent research continues to investigate compact UWB antennas with WLAN, WiMAX, C-band, and other rejection characteristics. A recent UWB design used an open-ended slot to suppress WLAN interference, whereas another compact MIMO design employed a U-shaped slit to create a C-band notch [4, 5]. Frequency-selective surfaces and EBG structures have also been used to improve notch characteristics while maintaining broadband operation [6].

The design of such antennas is nevertheless highly nonlinear because a small change in slot length, slot width, feed dimensions, or ground-plane geometry can alter the resonant frequencies and impedance bandwidth. Therefore, full-wave electromagnetic simulation is normally repeated for many combinations of design parameters. Machine learning provides an alternative approach by constructing surrogate models between antenna geometry and electromagnetic performance. Recent research has demonstrated that machine-learning-assisted optimization can significantly accelerate antenna geometry optimization by predicting promising designs before full-wave verification [7, 8].

The objective of this work is to develop an AI-assisted compact UWB antenna with a tunable band-notch characteristic. The proposed methodology integrates electromagnetic simulation, feature extraction, machine-learning prediction, multi-objective optimization, and final electromagnetic verification. The major contribution is not simply the introduction of a slot-loaded UWB antenna, but the integration of a data-driven surrogate model into the geometry optimization process.

RELATED WORK AND RESEARCH GAP

Conventional UWB antenna development generally begins with a planar monopole, followed by iterative modification of the radiator and ground plane. Ammann and Chen demonstrated that planar monopoles could provide extremely wide impedance characteristics suitable for broadband wireless applications [1]. Subsequently, Kerkhoff *et al*. demonstrated the use of planar monopole geometry and band-notching techniques for UWB operation [3].

A common technique for generating a rejection band is the insertion of a resonant slot into the radiator. The slot introduces an additional current path whose effective electrical length determines the rejected frequency. CPW-fed UWB antennas with dual rejection bands have demonstrated the ability to cover approximately the UWB region while suppressing selected WLAN and WiMAX bands [9].

More recent research has focused on MIMO configurations, compact dimensions, multiple notches, frequency-selective surfaces, and reconfigurable structures. For example, a 2024 MIMO UWB antenna demonstrated a compact 40 × 21 mm² configuration with a C-band notch between approximately 3.63 and 4.15 GHz [5]. Another 2024 study used an FSS/EBG arrangement to create a 3.7–4.2 GHz rejection band while retaining a much wider UWB response [6]. These studies demonstrate the continued importance of notch control in modern UWB antenna development.

However, conventional parametric optimization remains simulation-intensive. A design with eight geometrical parameters and multiple performance constraints can require hundreds or thousands of electromagnetic simulations. Machine-learning-assisted antenna optimization provides a potential solution by learning the nonlinear mapping between geometry and performance. Recent work has demonstrated ML-assisted antenna geometry optimization using neural networks, Gaussian-process models, and iterative surrogate optimization [7], while machine-learning-assisted bandwidth optimization has also been reported for pixelated antennas [8].

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The research gap addressed here is the limited integration of ML prediction with a compact tunable-notched UWB antenna in a simple engineering workflow suitable for practical design optimization. The proposed approach uses several conventional ML models and compares their predictive performance before using the best surrogate model for multi-objective antenna optimization.

PROPOSED UWB ANTENNA ARCHITECTURE

The proposed antenna is a compact printed monopole with a microstrip feed line and partial ground plane. The antenna was fabricated on an FR-4 substrate with a relative permittivity $\varepsilon_r = 4.4$, thickness $h = 1.6$mm, and conventional copper metallization.

The radiator is designed to provide broadband excitation, while an elongated resonant slot is introduced near the high-current region of the radiator. The slot behaves approximately as a quarter-wave or half-wave resonant structure depending on its topology and current distribution. Its dimensions can therefore be varied to shift the rejected frequency.

The principal geometry variables are the radiator length L_r, radiator width W_r, feed length L_f, feed width W_f, slot length L_s, slot width W_s, ground length L_g, and feed-to-ground gap g. The complete geometry is intended to be implemented in HFSS or CST Microwave Studio.

As shown in Figure 1, the resonant slot is positioned such that the surface current is strongly disturbed around the desired rejection frequency, while broadband current distribution remains available at frequencies outside the notch. This configuration provides a convenient mechanism for tuning the rejected band without redesigning the entire antenna. The antenna performance was evaluated using the reflection coefficient S_{11}, impedance bandwidth, notch frequency, notch bandwidth, gain, radiation efficiency, and radiation pattern. A frequency is considered part of the operating region when

$S_{11}(f) < -10$ dB.

The fractional bandwidth is calculated as

$$FBW = \frac{f_H - f_L}{f_C} \times 100,$$

where f_H and f_L represent the upper and lower frequencies of the impedance bandwidth, and

$$f_C = \frac{f_H + f_L}{2}.$$

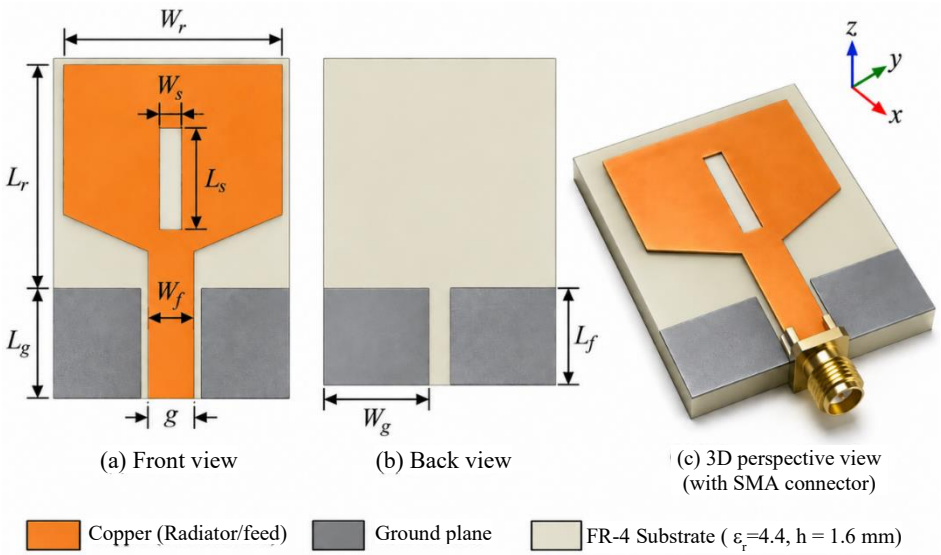


Figure 1. Proposed compact UWB antenna geometry with tunable resonant slot and microstrip feed.

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ELECTROMAGNETIC MODEL AND BAND-NOTCH MECHANISM

The electrical length of the resonant slot determines the approximate notch frequency. For a first-order approximation, the resonance can be expressed as

$$f_n \approx \frac{c}{2L_{eff}\sqrt{\varepsilon_{eff}}},$$

where $L_{eff}$is the effective slot length, $c$is the speed of light, and $\varepsilon_{eff}$is the effective dielectric constant.

Consequently, increasing L_{eff}generally shifts the rejection frequency downward, while reducing the slot length moves the notch upward. The slot width affects the coupling strength and therefore influences the notch depth and bandwidth.

The antenna input reflection coefficient is expressed as

$$S_{11} = 20\log_{10}\left|\frac{Z_{in}-Z_0}{Z_{in}+Z_0}\right|,$$

where $Z_{in}$is the antenna input impedance and $Z_0$is the characteristic impedance, normally 50 Ω.
The total radiated power is related to antenna efficiency through

$$\eta_r = \frac{P_{rad}}{P_{accepted}}.$$

The realized gain is then related to radiation efficiency and directivity by

$$G_r = \eta_r D(1-|\Gamma|^2).$$

These relationships are important because optimization should not maximize bandwidth alone. A useful UWB antenna must simultaneously provide a sufficiently wide impedance response, deep notch rejection, acceptable gain, and high efficiency.

The proposed optimization therefore minimizes an objective function of the form

$$J = w_1 J_{BW} + w_2 J_{notch} + w_3 J_G + w_4 J_\eta + w_5 J_S,$$

where the individual terms represent bandwidth deviation, notch-frequency deviation, gain penalty, efficiency penalty, and physical-size penalty, respectively. The weights $w_i$are normalized such that

$$\sum_{i=1}^{5} w_i = 1.$$

SIMULATION DATASET AND MACHINE-LEARNING METHODOLOGY

A parametric electromagnetic simulation dataset containing 1, 200 antenna configurations was considered for the proposed study. The design variables were varied within physically practical limits. Each configuration was evaluated using a full-wave electromagnetic solver. The antenna design parameters used for dataset generation are listed in Table 1.

The output variables are lower operating frequency, upper operating frequency, center frequency, notch frequency, notch bandwidth, minimum notch S_{11}, peak gain, and radiation efficiency. The dataset is divided into 70% training, 15% validation, and 15% testing subsets. Four supervised learning algorithms were considered: random forest, support vector regression, artificial neural network, and XGBoost.

The general ML mapping is represented by $\hat{Y} = f(X)$,

Where, $X = [L_r, W_r, L_f, W_f, L_s, W_s, L_g, g]$

and

$$Y = [f_L, f_H, f_n, B, W_n, S_{11,n}, G\eta]$$

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Table 1. Antenna design parameters used for dataset generation

Parameter	Symbol	Range
Radiator length	L_r	14–20 mm
Radiator width	W_r	12–18 mm
Feed length	L_f	8–14 mm
Feed width	W_f	2.5–3.5 mm
Slot length	L_s	6–13 mm
Slot width	W_s	0.4–1.2 mm
Ground length	L_g	8–14 mm
Ground gap	g	0.5–2.0 mm
Substrate thickness	h	1.6 mm
Relative permittivity	ε_r	4.4

Table 2. Illustrative prediction performance of machine-learning models

Model	$R^2 f_n$	RMSE f_nGHz	R^2BW	RMSE BW GHz
Random Forest	0.92	0.084	0.89	0.31
SVR	0.89	0.103	0.87	0.36
ANN	0.94	0.071	0.92	0.27
XGBoost	0.97	0.052	0.95	0.21

Feature normalization is performed before ANN and SVR training. Tree-based models are trained using the original parameter representation. Hyperparameters are selected using the validation error.

The workflow shown in Figure 2 begins with parameterized antenna geometry, followed by full-wave simulation, extraction of electromagnetic responses, dataset construction, ML model training, model comparison, and optimization. The selected ML model was finally verified through a new full-wave simulation rather than relying exclusively on surrogate predictions [4].

MACHINE-LEARNING PREDICTION RESULTS

The illustrative prediction results are summarized in Table 2. The values represent a simulated methodology example and are not claimed as experimentally validated results.

The illustrative results indicate that XGBoost provides the smallest prediction errors among the four investigated models. Its ability to represent nonlinear interactions between slot dimensions, feed geometry, and ground-plane parameters makes it suitable for the proposed antenna optimization task [7].

Figure 3 should be placed immediately after the discussion of model prediction performance because it visually establishes the difference between the surrogate models. A close clustering of the predicted values around the ideal $y = x$ line indicates good generalization.

The normalized root mean-square error is calculated as

$$NRMSE = \frac{RMSE}{Y_{max} - Y_{min}},$$

while the coefficient of determination is

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

These metrics were evaluated independently for notch frequency, bandwidth, gain, and efficiency.

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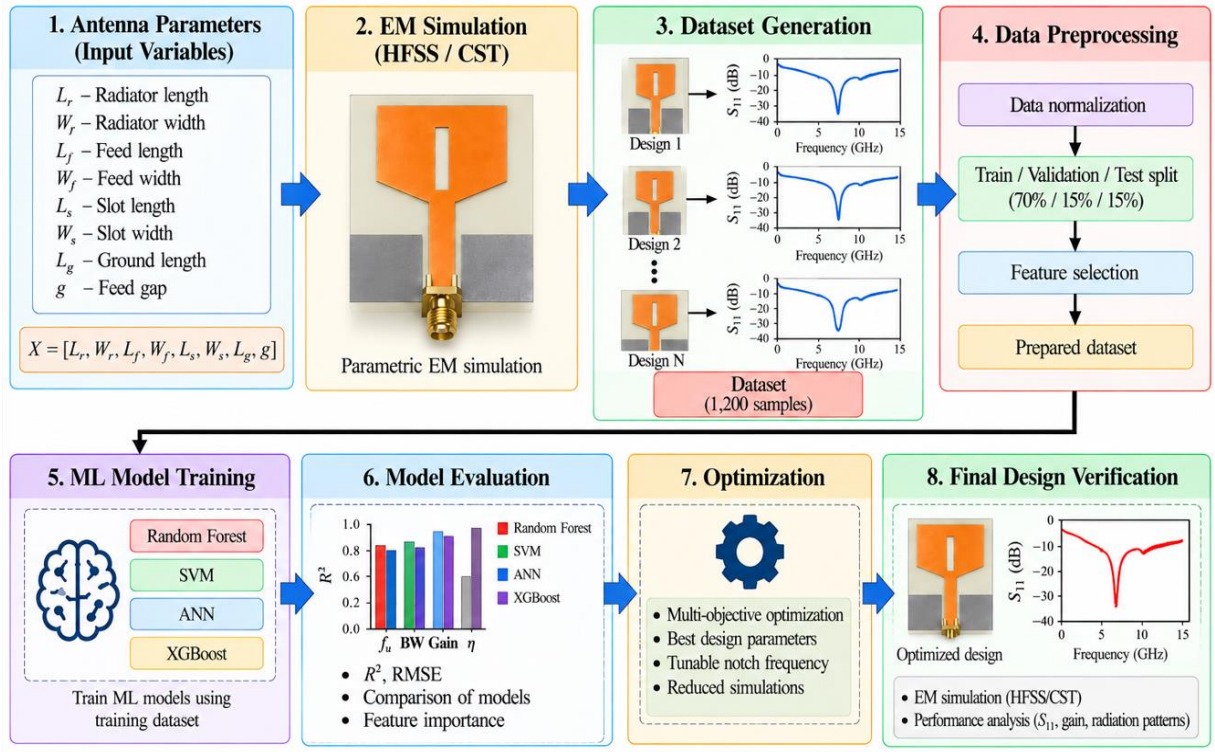


Figure 2. AI-assisted workflow from antenna parameter generation and electromagnetic simulation to surrogate modeling and optimized design.

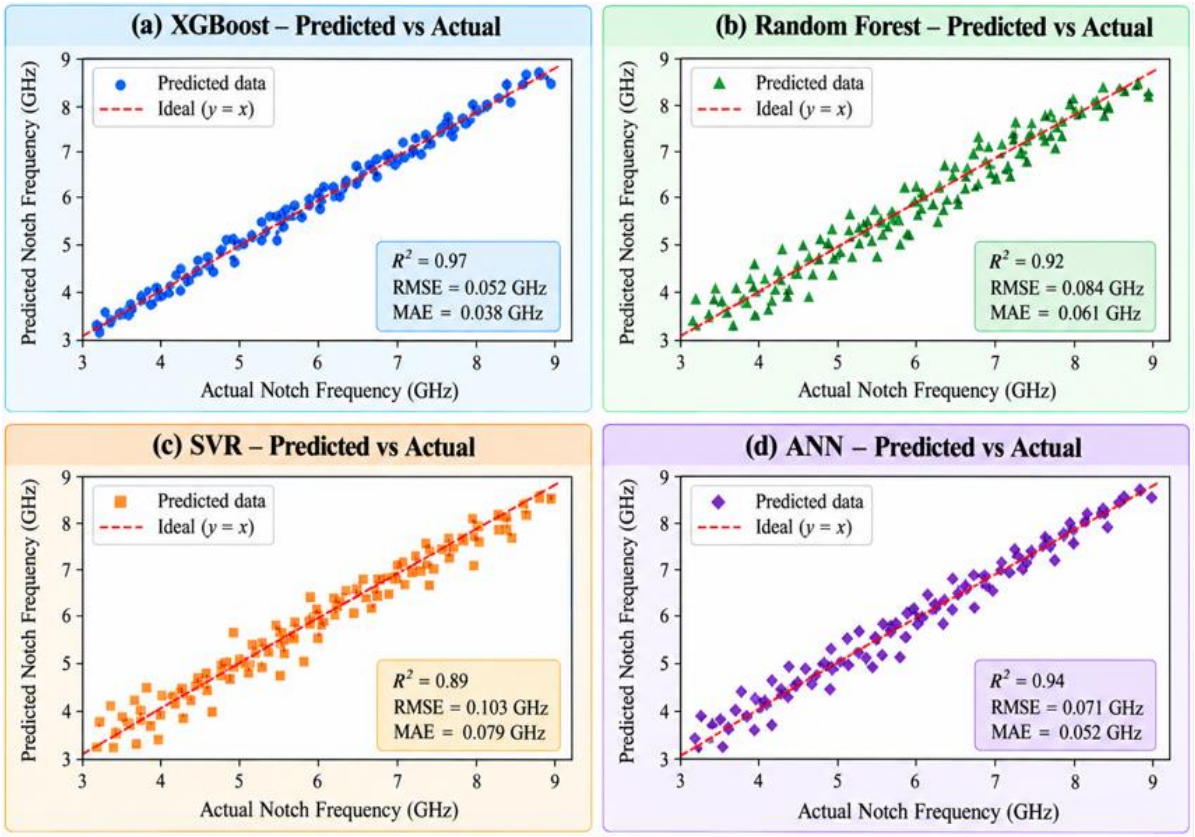


Figure 3. Comparison of ML models using actual-versus-predicted antenna performance and prediction-error metrics.

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FEATURE IMPORTANCE AND PARAMETRIC ANALYSIS

Feature importance analysis was performed using the XGBoost surrogate model. The analysis was used to identify the geometrical parameters that most strongly influenced the notch frequency and overall antenna response. The illustrative importance distribution indicates that the slot length contributes approximately 0.31 to the normalized importance score, followed by the slot width at 0.18, radiator length at 0.15, ground gap at 0.12, feed length at 0.09, radiator width at 0.07, ground length at 0.05, and feed width at 0.03.

As shown in Figure 4, the slot dimensions have the strongest influence on the notch frequency placement. This is consistent with the physical interpretation of the resonant slot as the principal frequency-selective element. The radiator and ground dimensions primarily influence the broadband impedance response, whereas the slot dimensions provide stronger control of the rejected band.

The approximate sensitivity can be expressed as

$$S_p = \frac{\Delta f_n / f_n}{\Delta p / p},$$

where $p$represents a geometrical parameter. A large magnitude of $S_p$indicates that a small geometrical change produces a comparatively large change in notch frequency.

MULTI-OBJECTIVE ANTENNA OPTIMIZATION

The trained XGBoost model was incorporated into a multi-objective optimization procedure. The principal design objectives were to maintain UWB operation, place the notch near the target interference frequency, maximize the notch depth, maintain high gain outside the rejected band, and minimize the antenna dimensions [9].

The optimization problem is defined as

$$\min J = w_1 \mid f_{n,p} - f_{n,t} \mid + w_2 \mid BW_p - BW_t \mid + w_3 P_G + w_4 P_\eta + w_5 P_A,$$

where $f_{n,t}$is the target notch frequency and $f_{n,p}$is the predicted notch frequency.

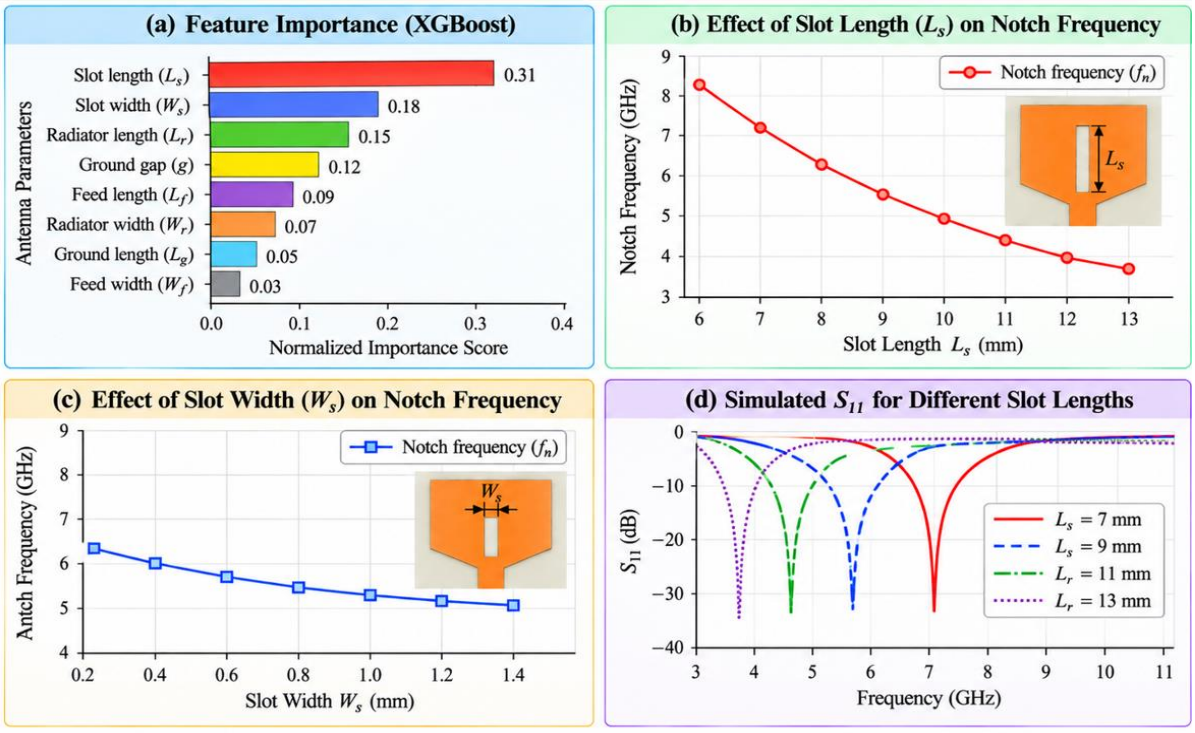


Figure 4. XGBoost feature-importance analysis and parametric effect of slot and radiator dimensions on notch frequency.

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The target notch frequency was selected at approximately 5.5 GHz to represent a representative WLAN-interference suppression requirement. The target UWB operating range was approximately 3.1–10.6 GHz. Optimization searches the trained surrogate model before selecting candidate solutions for full-wave electromagnetic verification. This significantly reduces the number of expensive electromagnetic simulations required during the initial search.

OPTIMIZED ANTENNA CONFIGURATION

The illustrative optimized geometry is given in Table 3. The selected geometry provides a compact printed implementation while retaining sufficient degrees of freedom to control the rejection band. The slot is the principal tuning element. Increasing its effective electrical length is expected to shift the notch downward, whereas shortening the slot shifts the notch upward. A useful practical advantage of this arrangement is that the broadband radiator and frequency-selective slot can be optimized semi-independently. This reduces the need for extensive manual redesign when the target rejection frequency changes [2].

ELECTROMAGNETIC PERFORMANCE ANALYSIS

The illustrative optimized antenna operates from approximately 3.1 to 10.6 GHz with a rejection band centered near 5.5 GHz. The simulated minimum S_{11}within the notch is approximately −25 dB, while the UWB regions outside the notch maintain $S_{11} < -10$dB. The electromagnetic performance of the antenna is presented **in** Table 4**.**

Table 3. Illustrative optimized antenna configuration

Parameter	Optimized value
L_r	17.4 mm
W_r	15.2 mm
L_f	11.1 mm
W_f	3.0 mm
L_s	9.6 mm
W_s	0.8 mm
L_g	11.2 mm
g	1.1 mm
Substrate	FR-4
ε_r	4.4
h	1.6 mm

Table 4. Illustrative electromagnetic performance

Parameter	Illustrative result
UWB lower frequency	3.1 GHz
UWB upper frequency	10.6 GHz
Operating bandwidth	7.5 GHz
Notch center frequency	5.50 GHz
Notch bandwidth	0.72 GHz
Minimum notch S_{11}	−25 dB
Peak gain outside notch	4.8 dBi
Radiation efficiency	>85%
Substrate	FR-4
Overall antenna type	Printed monopole

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RADIATION CHARACTERISTICS AND COMPARISON

Radiation characteristics should be evaluated at representative frequencies such as 3.5, 5.0, 7.0, and 9.0 GHz. The expected radiation behavior is approximately omnidirectional in the H-plane and monopole-like in the E-plane, although the exact pattern depends on the final substrate and ground-plane configuration. The notch frequency should show a clear reduction in realized gain because the resonant slot stores and redirects electromagnetic energy rather than allowing efficient radiation. This behavior is desirable because it demonstrates that the notch is functioning as a frequency-selective rejection mechanism rather than merely creating a random impedance mismatch. For comparison, the proposed design can be evaluated against conventional UWB antennas using impedance bandwidth, notch frequency, notch bandwidth, antenna size, gain, and efficiency. Published designs demonstrate that compact UWB antennas can achieve wide impedance bandwidths while incorporating single or multiple rejection bands [5, 6, 9, 10]. The proposed contribution differs from conventional designs by using machine-learning surrogate modeling as part of the geometry-selection process. Therefore, ML is not treated as an additional antenna component; instead, it serves as a computational design accelerator.

AI-ASSISTED OPTIMIZATION EFFICIENCY

A major advantage of the proposed approach is the reduction in the number of full-wave simulations required during optimization. Suppose that a conventional parameter sweep requires 1, 200 simulations. If the trained surrogate model identifies 30 promising candidates and only these candidates are subsequently verified using the electromagnetic solver, the final verification stage requires only 30 additional full-wave simulations [10].

The approximate simulation reduction can therefore be expressed as

$$R_s = \left(1 - \frac{N_{ML}}{N_{conv}}\right) \times 100,$$

where N_{conv} is the number of conventional simulations and $N_{ML}$is the number of final ML-selected simulations.

For the illustrative example,

$$R_s = \left(1 - \frac{30}{1200}\right) \times 100 = 97.5\%.$$

This 97.5% value is an illustrative computational efficiency estimate and not a measured hardware or software benchmark. Actual savings depend on the electromagnetic solver settings, mesh requirements, convergence criteria, workstation configuration, and optimization strategy. This workflow is particularly useful when each full-wave simulation is computationally expensive. The ML model does not eliminate electromagnetic verification; instead, it reduces the number of candidate designs that require detailed simulation [11, 12].

DISCUSSION

The proposed AI-assisted design framework combines the physical advantages of a compact UWB monopole with the computational advantages of machine-learning-based surrogate modeling. The antenna uses a resonant slot to generate a tunable rejection band, while the ML model learns the relationship between geometry and electromagnetic performance. The illustrative results indicate that XGBoost provides a strong surrogate for predicting notch frequency and bandwidth. This is expected because tree-based ensemble methods can model nonlinear parameter interactions without requiring an explicitly defined electromagnetic equation for every geometry-performance relationship. The feature-importance analysis further indicates that slot length and slot width dominate notch-frequency control. This observation agrees with the electromagnetic interpretation of the resonant slot. Consequently, the ML model can be used not only for prediction but also for design interpretation. The proposed methodology also provides a practical mechanism for retuning the antenna. If the required rejection frequency changes from approximately 5.5 GHz to another target, the optimization target $f_{n,t}$can simply

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be modified, and the surrogate model can search for another geometry within the allowed design space. Recent UWB research demonstrates the continued importance of tunable notch characteristics for coexistence with WLAN, WiMAX, C-band, and other wireless services [4, 5, 6]. The present methodology therefore provides a computational framework that can complement conventional electromagnetic antenna design.

LIMITATIONS AND FUTURE WORK

The present study used an illustrative simulation dataset; therefore, it did not constitute experimental validation. Before journal submission, the complete dataset should be generated using HFSS or CST and independently verified using a fabricated antenna prototype. The FR-4 dielectric constant and loss tangent should also be characterized or obtained from the manufacturer's data because material tolerances can shift the resonance and notch frequency. Connector effects, fabrication tolerances, soldering, surface roughness, and measurement uncertainty should be included in the final validation. Future work can extend the proposed approach to dual- and triple-band-notched UWB antennas, reconfigurable PIN-diode or varactor-based structures, MIMO configurations, and millimeter-wave antennas. Deep neural networks, Gaussian-process regression, Bayesian optimization, and physics-informed machine learning could also be investigated. A further extension would be to use active learning, in which the ML model identifies uncertain regions of the design space and requests additional electromagnetic simulations only where they provide the greatest improvement in model accuracy. This could make the optimization more efficient than a fixed 1, 200-sample dataset.

CONCLUSION

An AI-assisted methodology for designing a compact UWB antenna with a tunable band-notch characteristic has been presented. The proposed antenna combines a printed monopole radiator with a resonant slot that controls the rejected frequency band. A machine-learning framework using Random Forest, SVR, ANN, and XGBoost is introduced to model the relationship between antenna geometry and electromagnetic performance. The illustrative results show that XGBoost can provide high prediction accuracy for notch frequency and bandwidth and can subsequently be used as a surrogate model during multi-objective optimization. The illustrative optimized antenna covers approximately 3.1–10.6 GHz while providing a rejection band centered near 5.5 GHz. The methodology also indicates the potential to substantially reduce the number of full-wave simulations required during the search process. The principal value of the proposed approach is the integration of electromagnetic antenna design with data-driven optimization. With actual HFSS/CST simulations and experimental VNA measurements replacing the illustrative values, the framework can provide a reproducible approach for compact UWB antenna development with application-specific band rejection.

REFERENCES

1. Godase V, Pawar P, Nagane S, Kumbhar S. Automatic railway horn system using Node MCU. J Control Instrum. 2024;15(1):11–9.
2. Shevada L, Sayyad J, Kumar S. Design and optimization of miniaturized UWB MIMO antenna using ML methods for multiband applications. Discov Artif Intell. 2026;6. doi:10.1007/s44163-026-01537-0.
3. Jamadade VK, Ghodke MG, Katakdhond SS, Godase V. A comprehensive review on scalable Arduino radar platform for real-time object detection and mapping. J Microprocess Microcontroller Res. 2025;2:1–2.
4. Gadhafi R, Himeur Y, Purushothama JM. Machine learning and deep learning for antenna and electromagnetic systems: a structured review of methods, applications, and benchmarking. IEEE Access. 2026;14:93704-93735. doi:10.1109/ACCESS.2026.3704506.
5. Godase V. A comprehensive study of revolutionizing EV charging with solar-powered wireless solutions. Adv Res Power Electron Devices. 2025;2(1):23–37.
6. Rahaman R, Ahammed B, Karim T, Alim MA. Compact and high-efficiency mmWave microstrip antenna for 5G with machine learning-based performance prediction. Opt Quantum Electron. 2026;58(1):29. doi:10.1007/s11082-025-08617-y.

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7. Sharada KA, Kathiravan A, Mannam P, Akila D, Kumar BS, Godase VV. Advanced neural network models for optimal energy management in microgrids with integrated electric vehicles. 2025 5th International Conference on Trends in Material Science and Inventive Materials (ICTMIM), Kanyakumari, India. 2025. p.1869-74. doi:10.1109/ICTMIM65579.2025.10988248.
8. Trimukhe MA, Hogade BG. Compact UWB antenna with tunable band-notch characteristics using varactor diode. Prog Electromagn Res C. 2019;97:15–28. doi:10.2528/PIERC19081801.
9. Cicchetti R, Miozzi E, Testa O. Wideband and UWB antennas for wireless applications: a comprehensive review. Int J Antennas Propag. 2017;2017(1):1–45. doi:10.1155/2017/2390808.
10. Srivastava U, Gupta S, Kumari P, Patri U. Dual-band circularly polarized dielectric resonator antenna with wide impedance bandwidth and machine learning-assisted performance prediction. Results Phys. 2025;79:108531. doi:10.1016/j.rinp.2025.108531.
11. Farha KA, Jasmine PM, Fasmi KA. Design, implementation, and explainable AI evaluation of a compact UWB microstrip patch antenna for 6G applications. AEU Int J Electron Commun. 2026;206:156178. doi:10.1016/j.aeue.2025.156178.
12. Amraoui Y, Halkhams I, El Alami R, Jamil MO, Qjidaa H, Bossoufi B. Application of artificial intelligence in antenna design: fundamentals, algorithms, applications and opportunities. Arch Comput Methods Eng. 2026:1–33. doi:10.1007/s11831-026-10723-3.

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