Design a Slotted Patch Antenna by Using Deep Learning Algorithms for Mobile Communication

Saad Wasmi Osman Luhaib, and Sawsan N. Abdullah

***Abstract*—A structured machine-learning-assisted methodology is proposed for designing and predicting slotted microstrip patch antenna performance. The antenna targets mobile communication applications in the S- and lower C-bands. A rectangular FR-4 patch is loaded with a single parametric rectangular slot. The slot is defined by length L_g, width W_g, and position X_0. These parameters perturb the surface current distribution and effective electrical length in a controlled manner. A comprehensive dataset of 250 full-wave configurations was generated in HFSS using waveguide excitation and open boundary conditions, with resonant frequency f_r extracted at $S_{11} < -10\,\mathrm{dB}$, impedance bandwidth BW defined at the same threshold, and peak realized gain G obtained from far-field patterns at f_r. The nonlinear mapping between aperture geometry $[L_g, W_g, X_0]$ and antenna responses $[f_r, BW, G]$ was modeled using four regression algorithms. Fully connected neural network (FCNN), linear regression, decision tree regressor, and support vector machine (SVM)—have been used to train and predict the antenna parameters. The models show a substantial agreement between the results obtained by HFSS software and ML. The FCNN demonstrated superior predictive accuracy with a mean absolute error below 1% across all targets. The proposed technique achieves a frequency tuning range of 1.52–4.18 GHz, a bandwidth enhancement of up to 47%, and gain control from -3 dBi to 3 dBi.**

***Index Terms*—Design Patch Antenna, Deep Learning Algorithms, Slotted Antenna, Mobile Communication.**

I. Introduction

DUE to the small size of the patch antenna, its simple construction, and its ease of manufacture, microstrip patch antennas are widely used in wireless communication systems and are compatible with integrated circuits [1]–[3]. However, there are limitations that prevent its application in dynamically reconfigurable communication systems, and for this reason most of the research work has been directed towards improving the performance of patch antennas through modifications to the antenna structure, including the use of apertures [4]–[7]. Among these techniques, inserting slots on the patch has been shown to be an effective way to distribute current, which leads to control of electromagnetic parameters such as radiation gain, resonant frequency, and bandwidth [8]–[10]. Different geometric shapes have been studied to make slots in the antenna, including the letter U [5], slots in the shape of E [6], and also in the shape of L [8]. These studies have shown that all these modifications cause a defect or disturbances that affect the radiation efficiency and bandwidth, as in [9]. It has also been shown that making a rectangular slotting loaded centrally improves the bandwidth by a percentage of up to 45%. Asymmetrically placed openings were used to direct the gain and divide the frequency, as in [10].

Although there are many studies on split-patch antennas, most have focused on design iterations through full-wave simulation to explore the effects of geometric modifications on performance. This process can be time-consuming. In addition, most of the work or studies have focused on specific performance metrics such as bandwidth and resonant frequency without focusing on the beam pattern or beams. Recently, developments in design have brought about a paradigm shift in component modelling for microwaves. Various machine learning algorithms, such as support vector machines (SVM), decision trees (DT), and neural networks, have been used to predict S-parameters [11], optimize matching networks [12], and perform the reverse design of antenna geometries [13], [14]. Artificial neural networks have been used to model the main frequency of slotted antennas, reducing the use of a repetitive full wave in simulation. Gaussian regression has been used for the fast and probabilistic modeling of fine-scale filters [15]. Most of the research has focused on the narrow bandwidth, and few studies have considered the resonant frequency, gain, and frequency bandwidth based on comprehensive geometric descriptions of the slots or have validated the approach by comparing it with synthetic models. In addition, there are few current studies that compare machine learning methods to evaluate performance.

The main contributions of this work are summarized as follows:

- Development of a parametric slotted microstrip patch antenna model incorporating three independent geometric variables: slot length (L_g), slot width (W_g), and slot position (X_0).
- Generation of a structured dataset comprising 250 full-wave HFSS-simulated antenna configurations to capture the nonlinear relationship between slot geometry and antenna performance parameters.
- Implementation of a multi-output regression framework to simultaneously predict resonant frequency (f_r), -10 dB impedance bandwidth (BW), and peak realized gain (G).
- Comparative evaluation of four machine learning algorithms—Fully Connected Neural Network (FCNN), Lin-

Manuscript received April 9, 2026; revised April 27, 2026. Date of publication August 17, 2026. Date of current version August 17, 2026. The associate editor prof. Zoran Blažević has been coordinating the review of this manuscript and approved it for publication.

Authors are with the Department of Electrical Engineering, College of Engineering, University of Mosul, Mosul, Iraq (e-mails: s.w.o.luhaib@uomosul.edu.iq, sawsannajeebabdullah@ntu.edu.iq).

Digital Object Identifier (DOI): 10.24138/jcomss-2026-0074

ear Regression (LR), Decision Tree (DT), and Support Vector Machine (SVM)—under identical preprocessing and training conditions.
- Demonstration that the FCNN model achieves superior predictive accuracy with $R^2 > 0.95$ for all output parameters and low mean absolute error values (0.028 GHz, 14 MHz, and 0.22 dBi).
- Validation that a single-slot configuration enables wide tunability across 1.52–4.18 GHz frequency range, 5–160 MHz bandwidth variation, and -6 to 3 dBi gain control.
- Significant reduction in computational design time by replacing iterative full-wave optimization with an accurate machine learning-based surrogate model.

In this paper, a new method and a new approach combining apertures and performance prediction are used to be able to tune the resonant frequency, bandwidth, and adjustable gain through aperture-based structure reconfiguration for machine learning to design patch antennas. A rectangular patch antenna with a single parametric slot and variable aperture dimensions is designed. Four machine learning algorithms were used to analyze the effect of the slot to compare the antenna performance. Four automated algorithms, including fully connected neural network (FCNN), linear regression (LR), decision trees (DT), and permanent vector machines (SVM), were used to determine the resonant frequency, bandwidth at 4 dB, and maximum gain as a function of the aperture slot. The main points of this paper are to demonstrate a compact engineering method for predicting the performance of a single-aperture antenna and create a dataset that relates the dimensions of a single-aperture antenna using simulation software HFSS. The machine learning models have been compared to choose the most appropriate algorithm for predicting the antenna parameters. The validity of the design is verified by comparison with simulation results from HFSS.

The remainder of this paper is organized as follows. Section II describes the antenna design methodology, including slot configuration, simulation setup, and machine learning framework. Section III presents the HFSS simulation results and parametric analysis of slot effects on antenna performance. Section IV evaluates and compares the predictive performance of the machine learning models. Finally, Section V concludes the paper and summarizes the main findings.

II. Design Methodology

A. Antenna Design and Slot Configuration

The basic structure consists of a rectangular microstrip patch antenna as shown in figure 1, designed for S-band and lower C-band operation, fabricated on an FR-4 substrate with a relative transmittance ϵ_r = 4.4, loss tangent $tan\delta$ = 0.02, and thickness h = 1.6 mm. The patch dimensions (Wp, Lp) were initially determined using the classical transmission line model [1], [16].

$$f_r = \frac{c}{2L_{eff}\sqrt{\varepsilon_{eff}}} \quad (1)$$

where f_r is the resonant frequency, c is speed of light in vacuum,L_{eff} is effective length of the patch and ε_{eff} is effective dielectric constant.

$$\varepsilon_{eff} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2}\frac{1}{\sqrt{1 + \frac{12h}{W_p}}} \quad (2)$$

where h is the height of the substrate and Wp is the width of the patch. To facilitate tuning, a rectangular slot with variable length (Lg), width (Wg), and position x0 is added along the radiating patch. This slot affects the surface current distribution, changing the effective electrical length of the antenna and adding additional resonance modes. A parametric survey was conducted in the HFSS program by changing the length (Lg), width (Wsg), values, and position of the aperture, and through this, its effect on both the resonant frequency and the bandwidth at -10 dB of S_{11} and the peak gain was observed. 250 different geometric shapes were simulated to cover the antenna areas and obtain data.

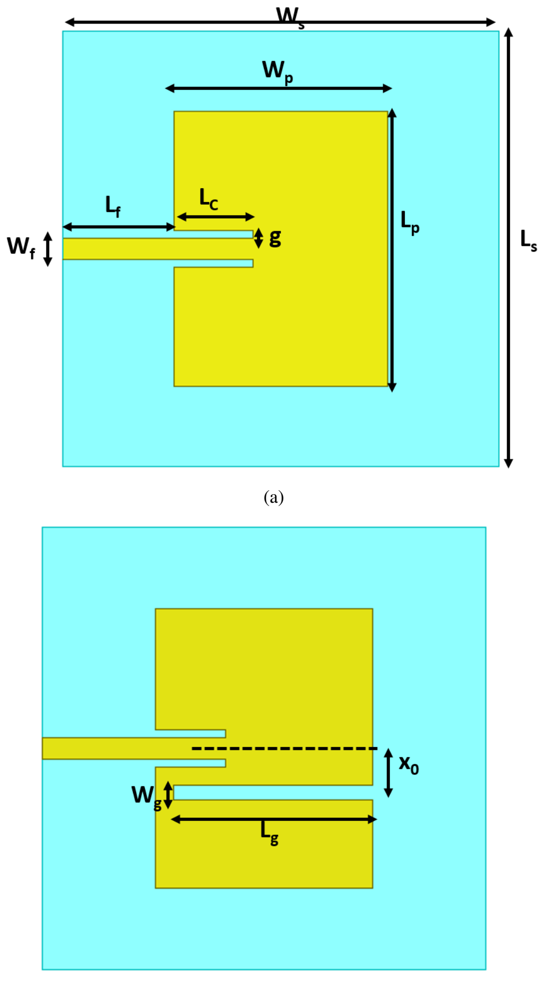


Fig. 1. Illustration of the geometric of Patch antenna (a) classical design,(b) proposed slotted patch antenna.

B. Simulation and Performance Measurement

The antenna models were simulated using the program HFSS with waveguide ports and open boundary conditions.

The output parameters for each configuration were the resonant frequency (f_r), which was set at the threshold of S_{11} and less than -10 dB, the bandwidth (BW), and the peak gain, using the extracted pattern in the far field at the resonant frequency. The aperture dimensions were standardized relative to the patch antenna size to allow generalization of the results. All simulations were performed with local refinements around the aperture area to ensure accuracy. The performance of the models was evaluated for the data using the following methods: Mean absolute error (MAE), Root mean square error (RMSE), R^2 score. Since these methods measure the accuracy of prediction and have the ability to generalize each model, the model with the root mean square error (RMSE) and R^2 score was chosen, considering that it is the most appropriate in the antenna design process.

C. Machine Learning Algorithms

To facilitate the process of predicting antenna performance, four automated algorithms were applied. The fully connected neural network (FCNN), linear regression (LR), decision tree regressor (DT), and support vector machine (SVM) were evaluated methodologically. Each method was selected based on its ability to model nonlinear relationships, interpret the importance of features, or provide basic comparisons [17]–[24]. The dataset consists of 250 unique antenna configurations, where each input vector x=[Lg, Wg, X0] represents the calibrated geometric parameters of the aperture, while the output vector y=[fr,BW,G] corresponds to the simulated resonant frequency, -10 dB bandwidth, and peak gain. The dataset was split into training (80%) and testing (20%) sets. All input features were standardized to zero mean and unit variance before training [23], [24].

D. Fully Connected Neural Network (FCNN)

A fully connected neural network algorithm (FCNN), also known as a multilayer neural network (MLP), is a non-linear function. It can teractions of variables and their electromagnetic responses and consists of several fully connected layers, where each cell in a layer receives inputs from all cells of the previous layer with weights or weight coefficients for each connection, and then the output is passed through a nonlinear function such as ReLU, Sigmoid, or Tanh [17], [18], [21], [22]. This method is characterized by building a model for nonlinear relationships and being highly flexible in using different data. But this method is slow and prone to overfitting, especially for small data. In this study, it was designed as follows: The input layer was four neurons corresponding to parameters, while the hidden layer was two layers containing 64 and 32 neurons, respectively, and the modeling was done using the rectified linear unit activation (ReLU) for non-linear inputs, while the output layer was three neurons with linear activation for continuous outputs, which are [fr, Bw, G], and the network was trained using the Adam optimizer at a rate of 0.001 and using the mean square error loss function (MSE), and this method showed strong performance in generalization, outperforming other methods used in this study [20], [21].

E. Linear Regression (LR)

This method assumes a linear relationship between the input and output parameters.

$$Y = W^T X + b \tag{3}$$

where (W, T and b) are the weights and stimuli learned from the training data. Although the method is simple and easy to analyze and interpret, it offers perspectives on the relative influence of the aperture parameters. However, this method is complex when modeling intricate electromagnetic interactions and is limited in its applications, which makes it primarily useful for comparing and estimating the importance of features [23], [24].

F. Decision Tree (DT)

This method is non-parametric, where the data space is repeatedly divided into regions or sub-spaces, and the output is assumed to be constant within each sub-region (node), where the outputs are evaluated as constant for each sub-leaf node. The performance prediction in this method is formed by following the tree path and the interactions of the features [19], [20], but it may tend to cause a variance imbalance unless modified or applied according to precise criteria to adjust the proportionality. It was used in this study by choosing the maximum depth of the tree and the minimum splitting of the sample through five-fold cross-validation to balance the variance and bias, as it showed low accuracy compared to other methods in regions with sparse training data [24].

G. Support Vector Machine (SVM)

This method is used for non-linear data, where the data cannot be separated in a straight line, using a technique called the (kernel trick) it converts the data to a higher-dimensional space, where it can be separated. One of the most famous types of functions that were used in this study is the Radial Basis Function (RBF), and the advantages of this method are that it is effective in high-dimensional spaces [17], [18], [22]. It works well when there is a clear difference between classes, and it also reduces the prohibition of overgeneralization (overfitting), especially when using appropriate (kernel) functions. Among the disadvantages of this method is that it does not work well when the classes overlap greatly, and its performance is slow in large databases [21], [24].

III. Simulation Results

To study the effect of the slot on the antenna, a comprehensive survey of the parameters was conducted using the program HFSS, where the antenna dimensions were maintained while changing the slot dimensions. The main performance indicators were extracted, which are the resonant frequency (fr), bandwidth (BW) of -10 dB, and peak gain (G).

Figure 2 shows the HFSS-simulated S-parameter responses for selected aperture configurations. The results demonstrate that changing the aperture parameters produces a clear tuning of the resonance frequency from 1.52 to 4.18 GHz. Increasing the aperture length shifts the resonance frequency downward

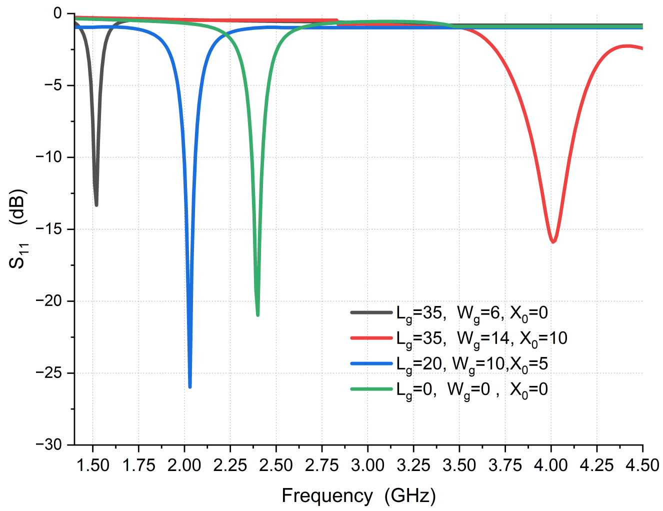


Fig. 2. HFSS-simulated S_{11} responses showing resonance tuning from 1.52 to 4.18 GHz for different geometrical parameters.

due to the increase in the effective current path, while changing the aperture width modifies the impedance matching and affects the bandwidth.The slot position modifies the response by changing the coupling strength near high-current regions. Across valid simulated cases, the impedance bandwidth ranges from 30 to 260.4 MHz. The simulated peak gain varies from approximately -3.03 to 3 dBi. These results confirm that aperture parameters provide substantial control over antenna performance. Therefore, they can be effectively integrated with data-driven optimization.

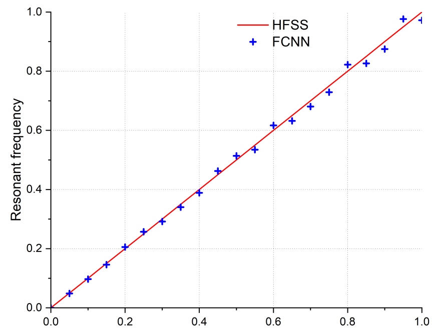
IV. Machine Learning Model Performance

Figures 3–6 compare the predicted antenna responses with the HFSS-simulated results. Four regression models are evaluated: FCNN, LR, DT, and SVM. The predicted outputs include resonant frequency, bandwidth, and peak gain. The resonant frequency is evaluated over 1.52–4.50 GHz, the bandwidth is calculated at 2.4 GHz and ranges from 30 to 260.4 MHz, and the gain varies from -3 to 3 dBi. The diagonal line shows the ideal prediction condition, where the predicted and simulated values are equal.

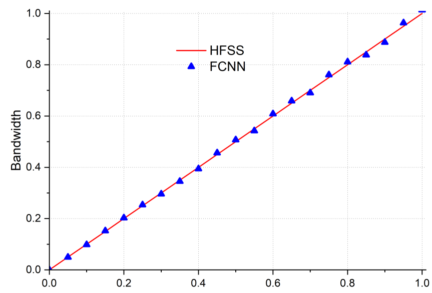
Figure 3 shows that FCNN provides the closest agreement with HFSS results. Most data points are concentrated near the ideal line, especially for resonant frequency and bandwidth. The corresponding MAE values are 0.028 GHz, 14 MHz, and 0.22 dBi for resonant frequency, bandwidth, and gain, respectively. This confirms the ability of FCNN to model nonlinear relationships between antenna geometry and electromagnetic response.

Figure 4 shows that LR produces larger deviations from the ideal line. Its MAE values are 0.062 GHz, 30 MHz, and 0.46 dBi for resonant frequency, bandwidth, and gain, respectively. This indicates that a linear model is less effective for representing the coupled electromagnetic behavior.

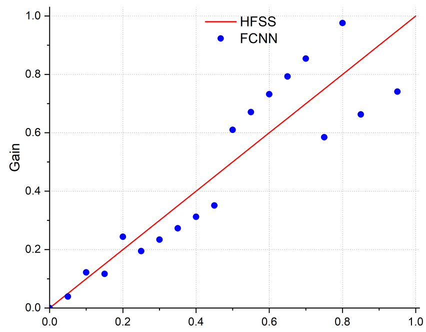
Figure 5 demonstrates that DT provides moderate prediction accuracy. The MAE values are 0.037 GHz, 19 MHz, and 0.31 dBi for the three output parameters. However, higher



(a)



(b)



(c)

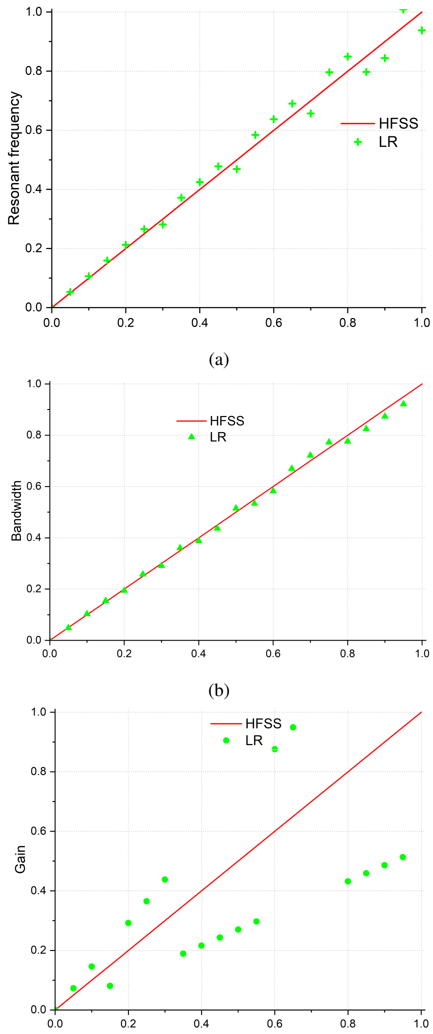
Fig. 3. FCNN predictions vs. HFSS-simulated results for (a) resonant frequency, (b) bandwidth, and (c) gain.

scatter is noticed in gain prediction, indicating lower reliability for this target.

Figure 6 presents the SVM results, which are comparable to DT. The obtained MAE values are 0.043 GHz, 21 MHz, and 0.35 dBi. Although SVM provides acceptable prediction accuracy, gain estimation remains less consistent than frequency and bandwidth estimation.

Overall, FCNN achieves the best prediction performance among all models. DT and SVM provide intermediate accuracy, while LR gives the largest prediction errors. These results confirm the suitability of nonlinear learning models for high frequency prediction applications.

Table I summarizes the test-set performance of four supervised regression models: Fully Connected Neural Network (FCNN), Linear Regression (LR), Decision Tree (DT), and Support Vector Machine (SVM). The models were trained to predict three antenna responses: resonant frequency f_r (GHz), -10 dB impedance bandwidth BW (MHz), and peak realized gain G (dBi). Their performance was evaluated using mean absolute error (MAE), root mean square error (RMSE), and

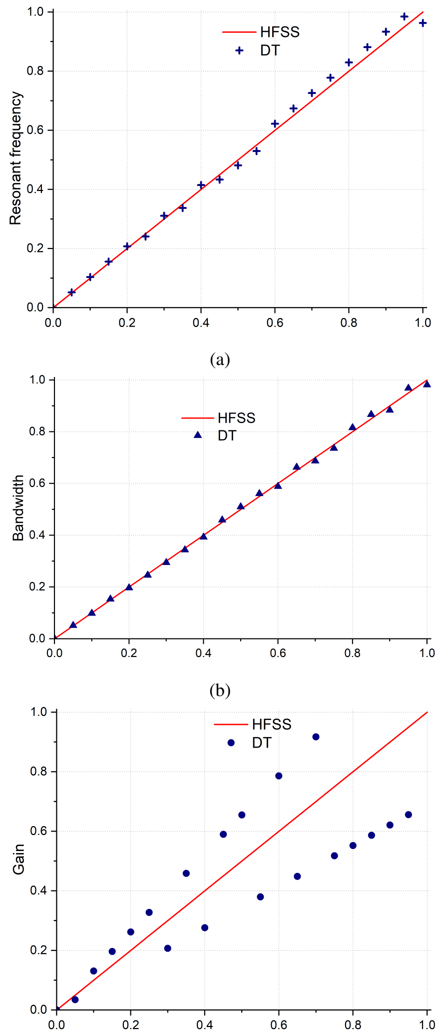


(a)

(b)

(c)

Fig. 4. LR predictions vs. HFSS-simulated results for (a) resonant frequency, (b) bandwidth, and (c) gain.



(a)

(b)

(c)

Fig. 5. DT predictions vs. HFSS-simulated results for (a) resonant frequency, (b) bandwidth, and (c) gain.

coefficient of determination (R^2).

The FCNN achieves the best overall prediction performance, with the lowest MAE and RMSE values for all three targets. Specifically, it obtains MAE values of 0.028 GHz, 14 MHz, and 0.22 dBi, with corresponding RMSE values of 0.035 GHz, 17.5 MHz, and 0.28 dBi for f_r, BW, and G, respectively. It also achieves the highest R^2 scores of 0.985, 0.973, and 0.952, indicating strong generalization capability.

In contrast, LR shows the largest prediction errors, with RMSE values of 0.078 GHz, 37.5 MHz, and 0.58 dBi, confirming that a purely linear model is less suitable for capturing the nonlinear relationship between aperture geometry and antenna response. DT and SVM provide intermediate performance, with DT slightly outperforming SVM in most cases. Overall, the gain prediction shows relatively lower R^2 values compared with f_r and BW, indicating that gain is more sensitive to complex geometry–field interactions.

Table II compares the proposed approach with several recent machine learning–assisted antenna designs. Most existing studies focus on mmWave antennas, wearable structures, or inverse design methods [25]– [30]. In contrast, the proposed work considers a slotted microstrip patch antenna operating in the S- and lower C-bands and employs multiple machine learning algorithms to predict key antenna parameters, including resonant frequency, bandwidth, and gain. The results demonstrate that the proposed framework provides wide frequency tunability (1.52–4.18 GHz) while maintaining a compact antenna structure and reliable predictive performance.

V. Conclusion

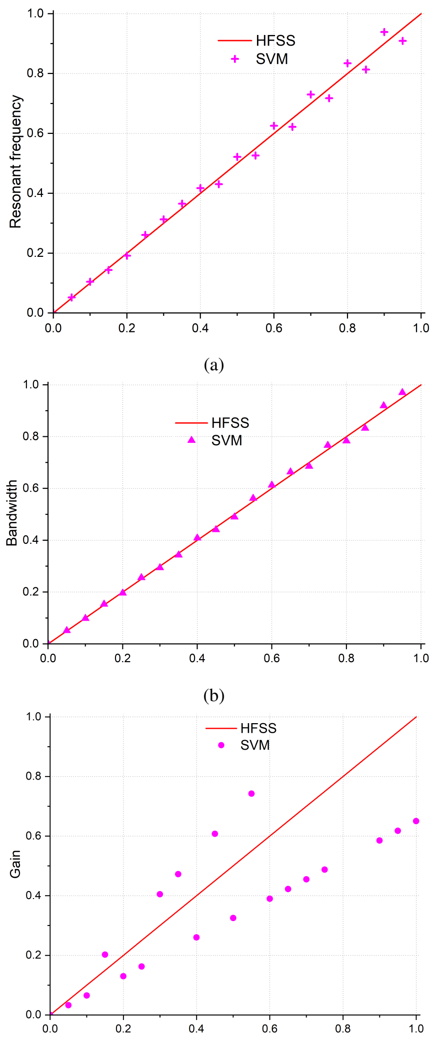
A structured machine learning–assisted design framework for slotted microstrip patch antennas has been presented, enabling direct prediction of key electromagnetic performance parameters—resonant frequency, -10 dB impedance bandwidth, and realized gain—from parametric aperture geometry. A dataset consisting of 250 full-wave HFSS-simulated antenna configurations was constructed to establish the nonlinear mapping between slot dimensions and antenna response. Four supervised regression models—Fully Connected Neural Network (FCNN), Linear Regression (LR), Decision Tree (DT), and

TABLE I
PREDICTION PERFORMANCE OF MACHINE LEARNING MODELS ON UNSEEN TEST DATA.

Model	MAE			RMSE			R^2		
	f_r (GHz)	BW (MHz)	G (dBi)	f_r (GHz)	BW (MHz)	G (dBi)	f_r	BW	G
FCNN	0.028	14	0.22	0.035	17.5	0.28	0.985	0.973	0.952
LR	0.062	30	0.46	0.078	37.5	0.58	0.903	0.874	0.819
DT	0.037	19	0.31	0.046	23.8	0.39	0.958	0.937	0.883
SVM	0.043	21	0.35	0.054	26.3	0.44	0.945	0.915	0.864

TABLE II
COMPARISON WITH RECENT MACHINE LEARNING–ASSISTED ANTENNA DESIGN STUDIES

Ref.	Antenna Type	Frequency (GHz)	Bandwidth	Gain (dBi)	ML Technique
[25]	Circularly polarized patch antenna	29.5–34	14%	6.4–7.6	ANN prediction
[26]	MEMS-based reconfigurable slot antenna	41–57	1.43–2.63 GHz	6.2–7.9	Optimization-based design
[27]	Dual-band microstrip patch antenna	3.45 / 5.9	160–220 MHz	0.57–3.83	Conventional EM design
[28]	Metamaterial-based reconfigurable antenna	Sub-6 GHz	Improved multiband BW	–	Extra Tree Regression
[29]	Wearable frequency reconfigurable patch	3.5 / 28	25–73%	3.6–6.2	ML optimization
[30]	CNN-based inverse-designed microstrip antenna	2.8 / 3.7	–	6.8–7.0	CNN + optimization
This work	Slotted microstrip patch antenna	1.52–4.18	5–160 MHz	-3 to 3	FCNN, LR, DT, SVM



(a)

(b)

(c)

Fig. 6. SVM predictions vs. HFSS-simulated results for (a) resonant frequency, (b) bandwidth, and (c) gain.

Support Vector Machine (SVM)—were trained and systematically evaluated using standard statistical metrics.The comparative analysis shows that FCNN provides the highest predictive accuracy. Its R^2 values exceed 0.95 for all target variables. This confirms its ability to capture coupled geometric–electromagnetic interactions. Nonlinear learning models provide higher fidelity than linear and shallow methods. This advantage is especially important for multi-parameter antenna prediction. The proposed surrogate model reduces the need for repeated full-wave optimization. It therefore accelerates antenna design while maintaining high predictive reliability.

REFERENCES

[1] K. R. Carver and J. W. Mink, "Microstrip antenna technology," *IEEE Trans. Antennas Propag.*, vol. 29, no. 1, pp. 2–24, 1981.
[2] M. Gupta and V. Mathur, "Koch fractal-based hexagonal patch antenna for circular polarization," *Turk. J. Electr. Eng. Comput. Sci.*, vol. 25, no. 6, pp. 4474–4485, 2017.
[3] S. Farhat *et al.*, "Wideband patch array antenna using superstrate configuration for future 5g applications," *Turk. J. Electr. Eng. Comput. Sci.*, vol. 28, no. 3, pp. 1673–1685, 2020.
[4] J. R. James and P. S. Hall, *Handbook of Microstrip Antennas*. London, UK: Peter Peregrinus, 1989, vol. 1.
[5] R. Chair, A. A. Kishk, and K. F. Lee, "Ultra-wideband coplanar waveguide-fed rectangular slot antenna," *IEEE Antennas Wireless Propag. Lett.*, vol. 3, pp. 227–229, 2004.
[6] M. T. Islam, M. N. Shakib, and N. Misran, "Broadband e-shaped patch antenna for wireless systems," *Prog. Electromagn. Res.*, vol. 98, pp. 163–173, 2009.
[7] R. Sahoo and D. Vakula, "Bow-tie-shaped wideband conformal antenna with wide-slot for gps application," *Turk. J. Electr. Eng. Comput. Sci.*, vol. 27, no. 1, pp. 80–93, 2019.
[8] S. H. Yang, K. F. Lee, A. A. Kishk, and A. Elsherbeni, "Design and study of wideband single-layer rectangular u-slot microstrip patch antenna," *IEEE Antennas Propag. Mag.*, vol. 49, no. 1, pp. 102–114, 2007.
[9] B. Sanz-Izquierdo, J. C. Batchelor, and M. I. Sobhy, "Compact dual-band wearable textile antenna for rfid and wlan applications," *Electron. Lett.*, vol. 42, no. 8, pp. 447–449, 2006.
[10] M. Ojaroudi, "Compact uwb monopole antenna with enhanced bandwidth using rotated l-shaped slots and parasitic structures," *Microw. Opt. Technol. Lett.*, vol. 55, no. 7, pp. 1647–1650, 2013.
[11] M. Z. H. Noori, S. F. Jilani, and H. M. H. Shakir, "A machine learning approach for fast and accurate s-parameter modeling of reconfigurable antennas," *IEEE Access*, vol. 9, pp. 10 463–10 474, 2021.
[12] D. Das, A. Sahu, and S. K. Behera, "Design and optimization of a compact microstrip filter using neural network and particle swarm optimization," *IET Microw. Antennas Propag.*, vol. 13, no. 6, pp. 732–738, 2019.

[13] T. Huang, Y. Li, and D. Liu, "Inverse design of patch antennas using deep neural networks," *IEEE Access*, vol. 7, pp. 116 830–116 838, 2019.
[14] M. J. Lancaster and J. Powell, "Computer-aided design of microstrip patch antennas using artificial neural networks," *Microw. Opt. Technol. Lett.*, vol. 20, no. 3, pp. 191–196, 1999.
[15] J. Guo, S. Sun, and X. Sun, "Fast modeling of rf/microwave devices using gaussian process regression with adaptive sampling," *IEEE Microw. Wireless Compon. Lett.*, vol. 28, no. 4, pp. 310–312, 2018.
[16] F. E. Mahmood and S. W. O. Luhaib, "Semi-circular compact cpw-fed antenna for ultra-wideband applications," *TELKOMNIKA*, vol. 20, no. 6, pp. 1200–1205, 2022.
[17] A. A. E. Ali, A. R. Sebak, and T. A. Denidni, "Reconfigurable slot-loaded patch antenna with multi-band operation using machine learning-assisted optimization," *IEEE Trans. Antennas Propag.*, vol. 70, no. 8, pp. 6564–6575, 2022.
[18] F. Qamar, M. H. Jamaluddin, M. Khalily, and M. F. Jamlos, "Artificial intelligence empowered predictive modeling for tunable microstrip patch antennas," *IEEE Access*, vol. 11, pp. 31 479–31 490, 2023.
[19] L. Li, Y. Wang, and H. Zhang, "Fast prediction of resonant frequency and bandwidth for slot antennas using convolutional neural networks," *Electronics*, vol. 12, no. 4, pp. 715–725, 2023.
[20] C. Shi, X. Yang, and Y. Zhang, "Hybrid learning model for high-fidelity prediction of antenna gain and bandwidth," *IEEE Open J. Antennas Propag.*, vol. 3, pp. 450–460, 2022.
[21] A. Roy, S. S. Mahapatra, and B. Majhi, "Design automation of slotted microstrip antennas using gradient-boosted regression and explainable ai," *IEEE Trans. Antennas Propag.*, vol. 71, no. 1, pp. 324–336, 2023.
[22] P. Xu, Y. Lu, and W. Hong, "Machine learning-based surrogate modeling of wideband antennas using generative design approach," *IEEE Trans. Antennas Propag.*, 2024, early Access.
[23] J. Ahmed, M. K. Hasan, and N. Misran, "A comprehensive survey on machine learning for antenna design: Trends, challenges, and opportunities," *IEEE Access*, vol. 11, pp. 56 789–56 810, 2023.
[24] A. Sharma, H. J. Song, and C. A. Balanis, "Recent advances in ai-assisted antenna design: A review of methods, tools, and open problems," *IEEE Antennas Propag. Mag.*, vol. 66, no. 2, pp. 22–39, 2024.
[25] M. N. Uddin, M. K. Islam, M. Ortiz, and E. A. Alwan, "Intelligent design prediction of a circularly polarized antenna for cubesat application using machine learning algorithms," *Electronics*, vol. 12, no. 20, p. 4195, 2023.
[26] Y. Chen, H. Guo, Y. Liu, J. Li, Y. Zhan, Q. Wu, and M. Li, "An l-slot frequency reconfigurable antenna based on mems technology," *Micromachines*, vol. 14, no. 10, p. 1945, 2023.
[27] S. K. Noor, M. N. Islam, and N. Misran, "A patch antenna with enhanced gain and bandwidth for sub-6 ghz and sub-7 ghz 5g wireless applications," *Electronics*, vol. 12, no. 12, p. 2555, 2023.
[28] S. K. Patel, A. Sharma, and B. Majhi, "Machine learning assisted metamaterial-based reconfigurable antenna for portable wireless devices," *Scientific Reports*, vol. 12, pp. 1–12, 2022.
[29] A. Salisu, M. A. Abdullahi, and S. A. Musa, "Machine learning optimized compact wearable frequency reconfigurable antenna for sub-6 ghz/mm-wave 5g integration," *Scientific Reports*, vol. 15, 2025.
[30] S. Chen, Y. Li, and H. Wang, "Inverse design of microstrip antennas based on deep learning," *Electronics*, vol. 14, no. 13, p. 2510, 2025.

Saad Wasmi Osman Luhaib received the B.Sc. and M.Sc. degrees in Electronic and Communication Engineering from the University of Mosul, Iraq, in 2004 and 2007, respectively, and the Ph.D. degree in Communication Engineering from the University of Leeds, U.K., in 2018. He is currently an Assistant Professor with the Department of Electrical Engineering, University of Mosul. His research interests include microwave engineering, antennas, filters, multimode resonators, and communication systems.

Sawsan N. Abdullah received the B.Sc. degree in Electrical Engineering (Electronics and Communications) and the M.Sc. degree in Electrical Engineering from the University of Mosul, Iraq, in 2009 and 2021, respectively. She is currently a Lecturer Assistant with the Department of Electrical Engineering Technologies, Northern Technical University, Mosul, Iraq. Her research interests include wireless communication systems, microwave engineering, and antennas.