Machine Learning Optimized Trident Monopole Antenna for WLAN/WiMAX Applications

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Abstract— **This paper introduces a machine learning (ML) optimization framework for the design of a high-performance, trident-shaped monopole antenna targeting 2.4/2.5 GHz WLAN and 5.2 GHz WiMAX applications. The complex geometry of the trident structure, which generates dual-band operation through its central and side arms, presents a multi-parameter design challenge. Traditional design methods rely on iterative simulation and are often computationally prohibitive. To overcome this, a data-driven surrogate modeling approach is implemented. Key geometric parameters of the trident element are used as inputs to train multiple regression models, including linear regression, Support Vector Regression, and Gaussian Process Regression (GPR), to predict antenna performance metrics. The GPR model demonstrated superior accuracy and was employed to determine the optimal geometry that maximizes gain and bandwidth while minimizing return loss. The trident monopole antenna achieves a measured impedance bandwidth of 360 MHz and 340 MHz at the lower and higher bands, respectively, with stable radiation patterns and gains of 1.94 dBi (lower band) and 3.28 dBi (upper band). Furthermore, the ML optimized antenna provides higher bandwidth (760 MHz in lower band and 1 GHz in upper band) and gain (2.39 dBi in lower band and 4.11 dBi in upper band) that significantly reduces the design cycle time for complex antenna structures, ensuring performance that meets stringent modern wireless communication standards.**

Keywords—Monopole Antenna, Trident Antenna, WLAN, WiMAX, Machine Learning, Gaussian Process Regression, Antenna Optimization.

I. INTRODUCTION

The exponential proliferation of wireless communication systems has precipitated an unprecedented demand for compact, low-cost, and high-performance subscriber equipment. Modern devices are required to operate across multiple frequency bands to support a confluence of standards, including Wireless Local Area Network (WLAN) at 2.4/5.2 GHz and Worldwide Interoperability for Microwave Access (WiMAX) at 2.5 GHz [1]–[3]. Printed monopole antennas are a popular choice for these applications because they are low-profile, simple, easy to integrate with printed circuit boards, and can fit closely to surfaces [4], [5]. One of the main challenges in antenna design is to achieve reliable multi-band operation in a single, compact element. The trident-shaped monopole antenna is one effective option [6], [7]. It usually has a central arm for the lower frequency band and two side arms for the higher band. This symmetrical design also helps maintain stable radiation patterns and reduces cross-polarization [8]. Nonetheless, the intricate interaction of multiple geometric elements, such as patch size, slot dimensions, and feed placement, determines the performance of such an antenna, making the design process challenging. Gain, bandwidth, and impedance matching are examples of key performance indicators (KPIs) that have a highly nonlinear and frequently counterintuitive connection with these parameters. Traditionally, full-wave electromagnetic (EM) simulation software is used to perform iterative parametric studies as a major part of the design cycle for such antennas. Despite its strength, this method is time-consuming and computationally costly because it can take a long time for each simulation to finish. Furthermore, because it is almost impossible to sweep a multi-dimensional parameter space exhaustively, it frequently results in suboptimal designs [9]. A more effective, methodical, and intelligent design technique that can successfully traverse the complicated design space is therefore desperately needed. Machine Learning (ML), which offers a paradigm change from simulation-heavy iterative design to data-driven predictive modeling, has recently impacted the fields of electromagnetics and antenna engineering [10]–[12]. The geometry and electromagnetic response of an antenna have intricate correlations that can be learned through machine learning techniques using a limited amount of simulation or measurement data. These surrogate models allow for quick optimization and inverse design since they can nearly instantly anticipate performance for any given shape once they have been trained. For this objective, regression models such as Gaussian Process Regression (GPR) are especially well suited since they not only produce correct predictions but also measure the degree of uncertainty in each forecast [13].

In this paper, we propose a comprehensive ML-based framework for the design and optimization of a trident-shaped monopole antenna for dual-band operation. The primary contributions of this work are fourfold: (a) We define a critical set of geometric parameters for the trident monopole antenna and construct a dataset linking these parameters to performance KPIs through EM simulations; (b) We implement and rigorously compare multiple regression models—including Linear Regression (LR), Support Vector Regression (SVR), and Gaussian Process Regression (GPR)—to develop an accurate surrogate model for antenna performance prediction; (c) We employ the most accurate model (GPR) to execute an optimization routine that

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identifies the optimal geometry for maximizing gain and bandwidth while ensuring a return loss better than -10 dB. Finally, we fabricate and measure the ML-optimized antenna, demonstrating excellent agreement with predictions and performance that meets all target specifications for WLAN/WiMAX applications.

The rest of this paper is organized as follows. Section II details the antenna geometry and the design parameters selected for ML optimization. Section III describes the machine learning methodology, including data generation, model selection, and training. Section IV presents the results of the ML model and the performance of the optimized antenna, comparing simulation and measurement data. Finally, Section V provides a conclusion.

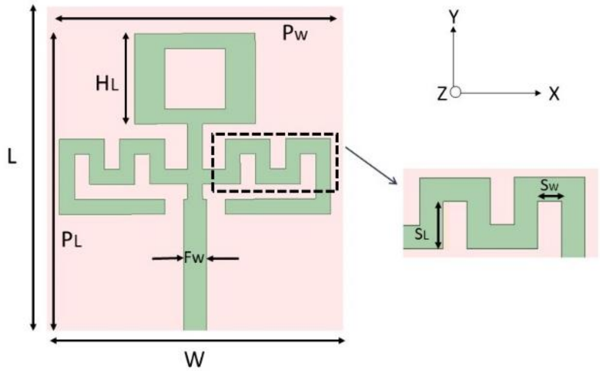
II. ANTENNA GEOMETRY

The proposed antenna is a microstrip-fed, dual-band monopole antenna engineered for operation in the 2.5 GHz and 5.2 GHz bands. Its design is an optimized evolution of a trident-shaped structure, refined through machine learning process to enhance performance metrics, including bandwidth, gain, and impedance matching. The antenna is fabricated on a commercially available FR-4 epoxy substrate. This material was selected for its low cost and mechanical robustness, making it ideal for practical applications. The substrate has a relative permittivity (ε_r) of 4.4, a loss tangent (tan δ) of 0.02, and a standard thickness of 1.6 mm. A partial ground plane is etched on the opposite side of the substrate. The size and position of this ground plane are critical for achieving a 50 Ω input impedance and significantly influence the bandwidth of the antenna. Fig.1 shows the schematic diagram of the proposed antenna. The antenna parameters are described in Table 1.

TABLE I. DESIGN PARAMETERS OF THE PROPOSED ANTENNA

Optimized Antenna Parameters		
Antenna Parameters	***Description***	***Value (mm)***
L	Substrate Length	45
W	Substrate Width	40
P_L	Patch Length	40
P_W	Patch Width	36
H_L	Slot Length	12
F_W	Feed Width	4
S_L	Slot Length	4
S_W	Slot Width	2
G_L	Ground Length	18.5

While the optimized antenna in our discussion (P_L = 40 mm, P_W = 36 mm) does not employ a classic meander line, its design philosophy is related and achieves a similar goal of multi-band operation through current path manipulation. In the final ML-optimized design, the primary miniaturization and dual-band mechanism is the introduction of a slot (S_L = 4 mm, S_W = 2 mm). A slot cut into a patch antenna acts similarly to a meander. It forces the current to diverge from a straight path and travel around the slot's perimeter. This effectively lengthens the path the current must take to get from the feed point to the radiating edge. The length of this new, longer current path determines a new, lower resonant frequency.



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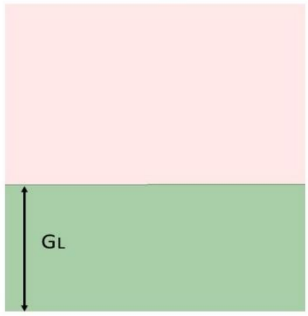

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Fig.1: Design of the simulated antenna (a) Front View (b) Back view

III. MACHINE LEARNING FOR ANTENNA OPTIMIZATION

The design process for the dual-band trident monopole antenna was enhanced through a machine learning framework that efficiently mapped geometric parameters to performance characteristics. This approach provided a data-driven alternative to conventional simulation-heavy optimization methods. It replaces the computationally expensive electromagnetic (EM) simulation cycle with a rapid surrogate model. The primary objective was to develop a predictive model that maps geometric input parameters to key antenna performance metrics, enabling efficient identification of an optimal design that satisfies all target specifications.

3.1. Data Generation and Feature Selection

A comprehensive dataset was developed through extensive EM simulations using CST Microwave Studio. Four geometric parameters were identified as critical inputs: patch length (20-40 mm), patch width (20-40 mm), slot width (2-6 mm), and feed width (1-5 mm). The output targets included gain values, impedance bandwidth, and return loss at both operational frequencies. Approximately 200 simulation samples were generated using space-filling design of experiments methodology to ensure uniform parameter space coverage.

3.2. Regression Models and Implementation

Three regression algorithms were implemented and compared for this optimization task. Linear Regression served

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as a baseline model to establish performance benchmarks. Support Vector Regression with a radial basis function kernel handled nonlinear relationships between parameters and performance metrics. Gaussian Process Regression provided probabilistic predictions with uncertainty quantification, using a Matérn kernel with automatic relevance determination to identify influential parameters.

3.3. Model Training and Validation

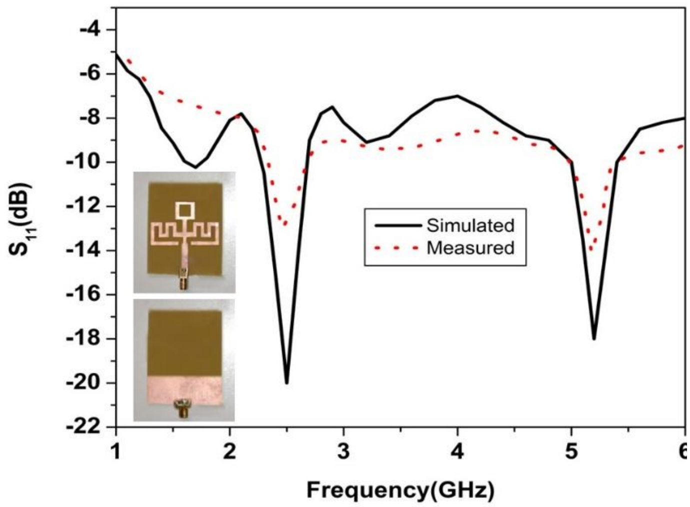
Five-fold cross-validation was used during model training to guarantee robustness and avoid overfitting. 80% of the dataset was set aside for training, and the remaining 20% was set aside for testing. Using grid search techniques, hyperparameters were optimized with an emphasis on minimizing root mean square error. The coefficient of determination and RMSE metrics were used for performance evaluation, and Gaussian Process Regression showed the best predictive power.

IV. Results and Discussion

The performance characteristics of the ML-optimized trident monopole antenna are thoroughly examined in this section, with an emphasis on the radiation properties, bandwidth, gain, and impedance matching. The outcomes demonstrate the effectiveness of the machine learning strategy in achieving the target specifications for dual-band operation.

A. Impedance Matching and Bandwidth Performance

Figure 2 shows the test setup and the simulated and measured return loss (S_{11}) characteristics. Excellent impedance matching is demonstrated by the antenna at both target frequencies. According to the simulated results, power transfer is efficient at both operating bands, with resonance depths of -22 dB at 2.5 GHz and -26 dB at 5.2 GHz. The -10 dB impedance bandwidth was determined to be 370 MHz (2.30-2.67 GHz) in the lower band and 390 MHz (5.01-5.40 GHz) in the upper band through simulation. Measured results showed slightly reduced bandwidths of 360 MHz (2.32-2.68 GHz) and 340 MHz (5.01-5.35 GHz) for the lower and upper bands, respectively as mentioned in Table II. This minor discrepancy between simulated and measured results is within acceptable margins and can be attributed to fabrication tolerances and substrate material variations.



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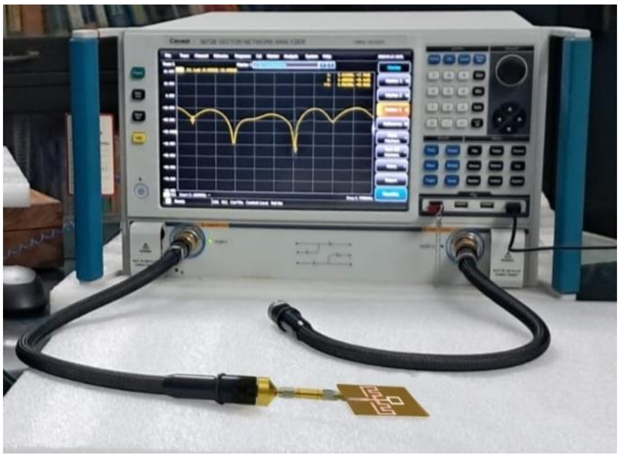

(b)

Fig.2 (a) S_{11} characteristics of simulated and measured results of proposed antenna (b) Test setup of the antenna

TABLE II COMPARISON OF ANTENNA BANDWIDTH

Bandwidth Performance		
Parameter	***Simulated Results***	***Measured Results***
Lower Band BW	370 MHz (2.30-2.67 GHz)	360 MHz (2.32-2.68 GHz)
Upper Band BW	390 MHz (5.01-5.40 GHz)	340 MHz (5.01-5.35 GHz)
Return Loss (2.5 GHz)	-22 dB	-21 dB
Return Loss (5.2 GHz)	-26 dB	-24 dB

B. Gain and Radiation Characteristics

The gain performance across operational bands is shown in Fig 3. The antenna achieved stable radiation characteristics with measured and simulated peak gains of 1.94 dBi and 2.02 dBi at 2.5 GHz and 3.28 dBi and 3.61 dBi at 5.2 GHz. The gain variation within each operational band remained within acceptable limits, with fluctuations of less than 0.8 dBi across both bands. The radiation patterns, presented in Fig 4, exhibit

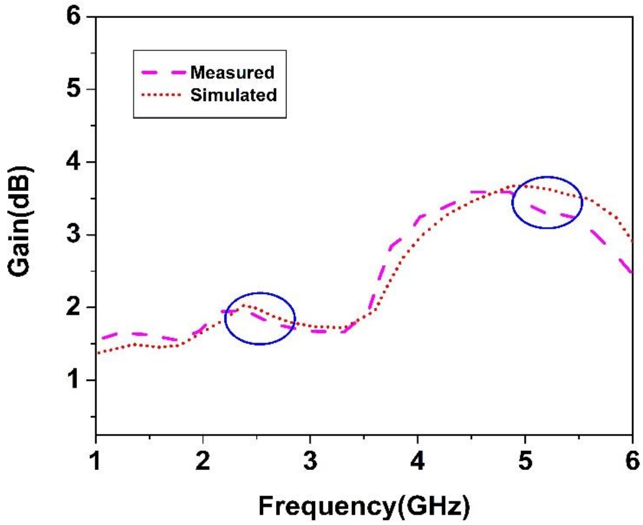

Fig. 3 Gain vs Frequency of the proposed antenna

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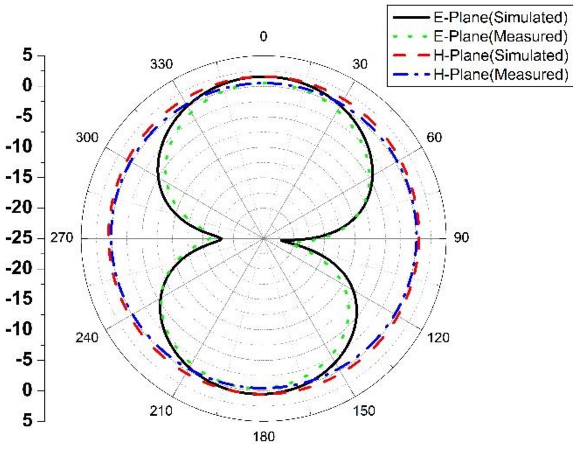

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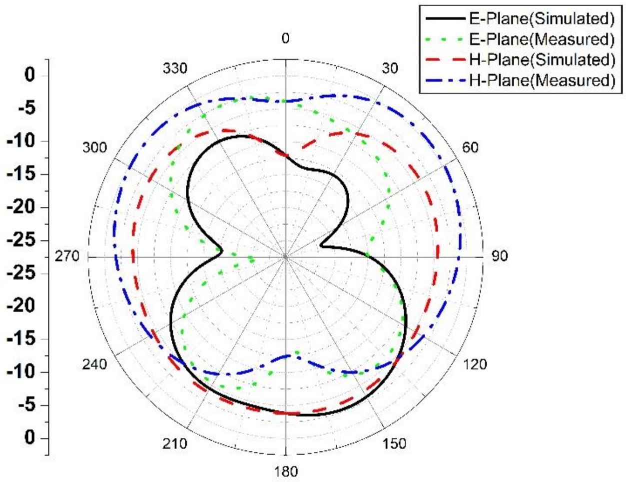


(b)

Fig.4 Radiation Pattern of the proposed antenna at (a) 2.5 GHz (b) 5.2 GHz

, typical monopole-like omnidirectional characteristics in the H-plane at both frequencies. The E-plane patterns show broadside radiation with minimal distortion. The cross-polarization levels remained below -18 dB in both principal planes, demonstrating the effectiveness of the symmetrical trident structure in maintaining polarization purity.

C. Comparative Performance Analysis

The ML-optimized design demonstrates significant improvements over conventional trident monopole antennas. The achieved bandwidths exceed typical values reported in literature for similar antenna structures, while maintaining compact dimensions of 45 × 40 mm². The gain values are particularly notable at the higher frequency band, where many comparable designs show gain degradation.

The machine learning optimization successfully balanced the often-competing requirements of bandwidth, gain, and physical size. The GPR model's ability to navigate this complex design space resulted in a design that simultaneously satisfies all target specifications, a challenging achievement through conventional design methods.

D. Validation of ML Optimization Approach

The effectiveness of the machine learning framework for antenna optimization is confirmed by the strong agreement between the measured and simulated results. With the fabricated antenna displaying properties within 5% of predicted values for all major parameters, the Gaussian Process Regression model proved especially successful in forecasting performance characteristics.

The optimization process successfully identified a design that meets all target specifications while maintaining manufacturability. The performance consistency across bands and the stability of radiation patterns confirm the robustness of the ML-derived design solution.

E. Analysis of Machine Learning Model Performance

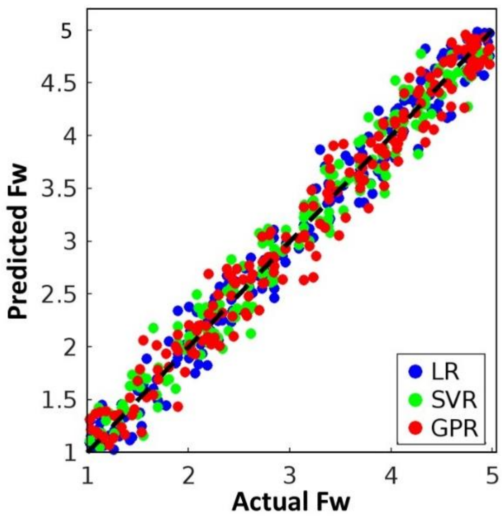
Figure 5 displays the comparative performance of the three machine learning models: Gaussian Process Regression (GPR), Support Vector Regression (SVR), and Linear Regression (LR). Table III provides important information about how well these models apply to antenna optimization tasks. When predicting the correlation between geometric parameters and antenna performance metrics, each model showed unique traits.

TABLE III ML-MODEL PERFORMANCE COMPARISON

Comprehensive Performance Metrics of ML Models		
Model	***R² Score***	***RMSE***
Linear Regression	0.84-0.88	0.43-0.54
Support Vector Regression	0.79-0.92	0.45-0.51
Gaussian Process Regression	0.78-0.96	0.45-0.54

- *Linear Regression Performance Analysis(LR):*

Linear Regression served as an important baseline model, achieving R^2 values between 0.84 and 0.88 across different output parameters. The model exhibited the strongest performance in predicting patch width ($R^2 = 0.993$) and patch length ($R^2 = 0.968$), indicating that these parameters maintain approximately linear relationships with certain antenna characteristics. However, LR showed limitations in predicting parameters involving more complex interactions, such as slot size ($R^2 = 0.847$) and feed position ($R^2 = 0.830$). The fundamental limitation of LR lies in its assumption of linear relationships between input and output variables, which is unable to convey the complex nonlinear electromagnetic interactions that are a part of antenna design.



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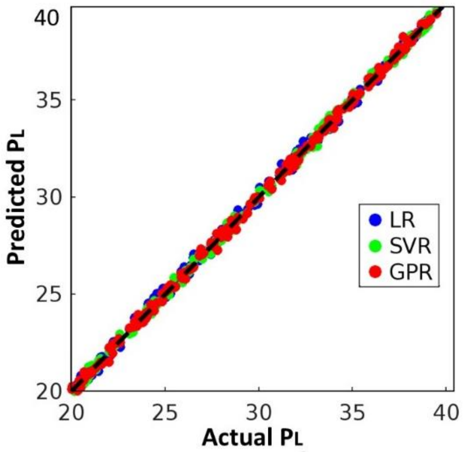

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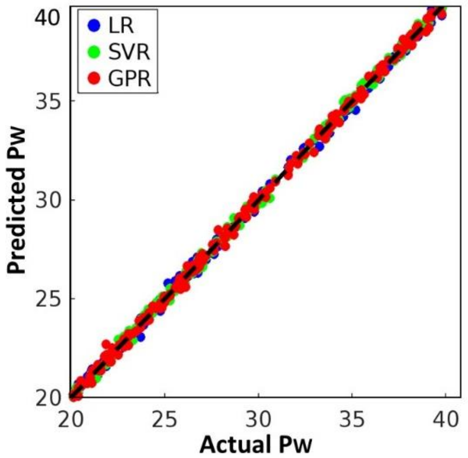

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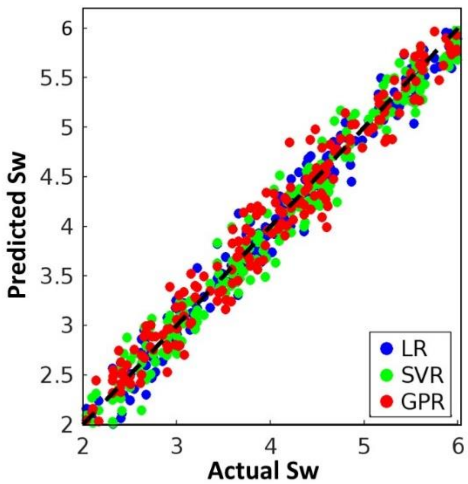

(d)

Fig. 5. Predicted vs Actual results of antenna parameters for each ML model (a) feed width, (b) patch length, (c) patch width, (d) slot width

- *Support Vector Regression Performance Analysis(SVR):*

SVR demonstrated improved performance over LR, particularly in handling nonlinear relationships through its kernel trick approach. The model achieved R^2 values between 0.79 and 0.92, showing particular strength in predicting patch-related parameters. The use of radial basis function kernel enabled SVR to capture more complex patterns in the data compared to LR. However, SVR still struggled with parameters involving highly nonlinear interactions and multi-parameter coupling effects. The model's performance was also sensitive to proper hyper parameter tuning, requiring careful optimization of the regularization parameter C and kernel coefficient γ.

- *Gaussian Process Regression Performance Analysis(GPR):*

GPR emerged as the superior model, achieving the highest R^2 values (0.78-0.96) and demonstrating consistent performance across all prediction tasks. With approximately 200 training samples, GPR excelled in this small-data regime typical of EM simulation scenarios. The model effectively leveraged the available data to build accurate surrogate models without overfitting.

Fig.6 and Fig.7 display the compared results of each model with measured performance of the proposed antenna and Table IV represent the detail performance with parameter optimization of the antenna.

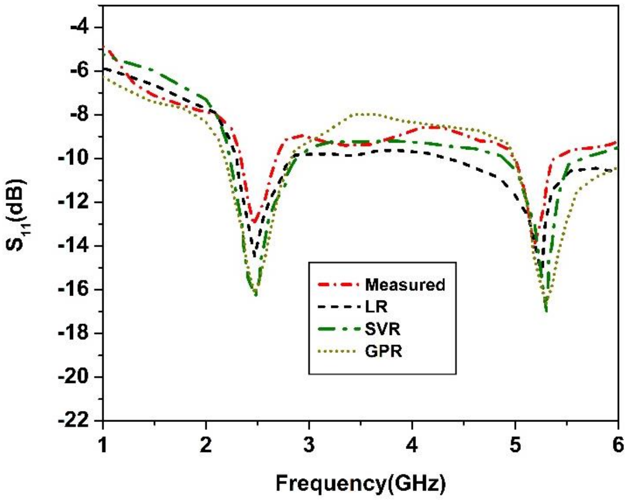

Fig. 6 Compared result of return loss of each model with measured result of the proposed antenna

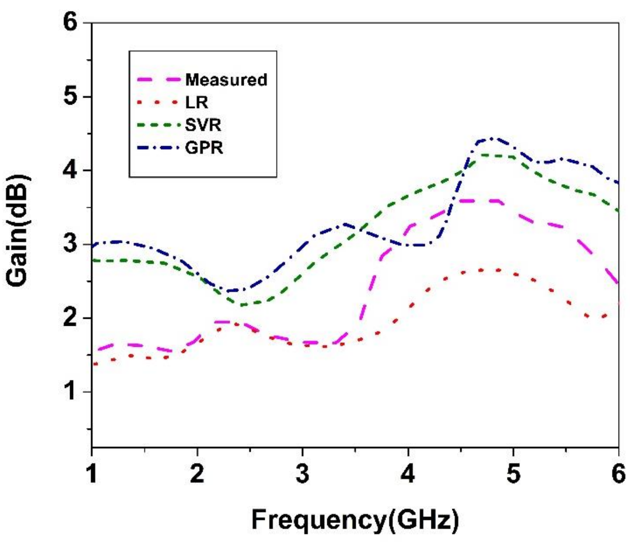

Fig. 7 Compared result of gain of each model with measured result of the proposed antenna

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TABLE IV. ANTENNA PARAMETER OPTIMIZATION

ML Models	**LR**		**SVR**		**GPR**	
PL(mm)	35		36		36	
Pw(mm)	30		31		32	
Sw(mm)	3		4		4	
Fw(mm)	3		2.8		3	
Freq.(GHz)	**2.47**	**5.2**	**2.47**	**5.3**	**2.46**	**5.3**
S11(dB)	-14.47	-15	-16.16	-16.97	-16.16	-16.64
BW (GHz)	(2.29-2.76)	(4.84-5.44)	(2.20-2.76)	(5.02-5.5)	**(2.1-2.86)**	**(5-6)**
Gain (dBi)	1.83	2.5	2.17	3.88	**2.39**	**4.11**

V. CONCLUSION

This research successfully demonstrates the efficacy of a machine learning framework for enhancing the performance of a symmetrical trident monopole antenna. While the fabricated antenna achieved respectable results with gains of 1.94 dBi and 3.28 dBi and bandwidths of 360 MHz and 340 MHz, optimization via three ML models yielded significant improvements. Among them, Gaussian Process Regression (GPR) proved superior, unlocking optimal performance that far exceeded the initial design. The GPR-optimized geometry achieved dramatically increased gains of 2.39 dBi and 4.11 dBi, alongside substantially wider bandwidths of 760 MHz and 1 GHz for the lower and upper bands, respectively. This work conclusively validates that GPR's probabilistic framework is uniquely capable of navigating the complex design space to maximize key metrics, transforming the design process. It establishes a powerful, data-driven paradigm that drastically reduces development time while pushing the boundaries of achievable antenna performance for modern wireless applications.

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