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MACHINE LEARNING BASED DESIGN AND INVERSE OPTIMIZATION OF PATCH ANTENNAS FOR 5G APPLICATIONS

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Abstract

In this work, a machine learning (ML) assisted approach is proposed for the design and optimization of compact inset-fed microstrip patch antenna (MPA) intended for 28 GHz 5G applications. First, the antenna design and simulation are carried out using HFSS for symmetrical semicircular notches to obtain better impedance matching over 24-31GHz. Then, HFSS generated dataset are obtained for varying dimensions of patch width, substrate height, semicircle radius and inset feed depth. These datasets are used on four different machine learning (ML) models for prediction of antenna performance indices such as (a) return loss, (b) resonant frequency and (c) gain. However, the best estimations with regard to accuracy has been obtained from the (i) Extra Trees Regressor model for (a) and (ii) Random Forest Regressor model for both (b) and (c). The optimized design has resulted -49.08 dB return loss at 27.97 GHz, 7.16 dBi gain and 4.7 GHz bandwidth which implies a good agreement with the HFSS simulations. Moreover, it is seen that the ML integrated electromagnetic simulation significantly accelerates the antenna design by preserving the predictive accuracy.

Keywords — 5G communications, Patch Antenna, Machine Learning (ML), Antenna Optimization (AO), Inverse Design, HFSS,28GHz.

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1. INTRODUCTION

The growth in wireless communication technologies has demanded for antennas that can support a wider spectrum of upcoming high frequency (HF) applications. These include 5G Wireless (FR2), Vehicle-to-Everything (V2X) communication in automotive systems, smart city Internet of Things (IoT) networks, low Earth orbit (LEO) satellite links, high resolution radar imaging, fixed wireless access, and industrial millimetre wave (mmWave) systems [1,2]. Working with the mmWave spectrum offers several unique benefits when compared to sub-6GHz frequencies, which includes reduced inter cell interference, ultra-low latency, and enhanced data security [3]. Such features make mmWave communication a fundamental enabler for the ultra-reliable low-latency communications (URLLC) and enhanced mobile broadband (eMBB) services in next generation wireless networks. In recent years, the studies have proposed different antenna designs to these applications, like high gain vehicular antennas for autonomous driving, compact base-station arrays for 5G backhaul, short-range IoT access points, and lightweight directional antennas for unmanned aerial vehicles (UAVs).

To overcome atmospheric effects path loss and attenuation at mmWave frequencies, high gain and narrow beam antennas are needed for 5G. So, towards this [4] introduced a novel hook shaped antenna array operating at 28GHz, designed for enhancing gain and efficiency in compact form. Authors in [5] proposed a compact multiband folded dipole mmWave antenna using coplanar waveguide (CPW) feeding designed on Rogers TMM4 substrate. The antenna covers multiple 5G and beyond 5G bands with high gain and efficiency. Recent advancements in wireless technology have encouraged the design of microstrip antennas for LTE applications. The study [6] investigates antenna performance using simulations, measurements and machine learning techniques, focusing on gain, directivity and efficiency. This paper [7] targets high band mmWave 5G applications by designing a microstrip patch antenna resonating at 26GHz and 28GHz, which are used in 5G deployment. The authors [8] present a rectangular microstrip patch antenna with a slot, designed for 28GHz 5G applications. The antenna uses microstrip line feeding and improves performance through the slot design.

5G wireless technology operates in the mmWave band with 28GHz being a key frequency. Antenna performance is crucial for reliable communication. A quasi-Yagi slotted array antenna operating at 28GHz is proposed to meet these requirements, offering wide beam coverage and effective gain for mobile communication [9]. This [11] study presents microstrip patch antenna designs, single to eight elements, optimized for 5G using RT Duroid5880 substrate and corporate feeding networks. The work in [12,13] presents a microstrip patch array antenna designed to operate at 28GHz for 5G KA band. The design in [14] incorporates a square patch with parasitic elements and slots to enhance bandwidth and gain, optimized for 28GHz operation. This [15] paper presents a compact patch antenna design for 5G and future mmWave communication systems and built on

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an FR4 substrate and uses specially shaped slots to improve performance. The authors [16] present two antenna designs using Substrate Integrated Waveguide (SIW) and microstrip technologies at 28GHz for 5G wireless networks. Both antennas are implemented on Rogers RT5880 substrates and analysed for performance through parametric studies. The work in [17] investigates the performance of microstrip antennas with various shapes rectangular, circular, and triangular at 28GHz using Finite Integration Technique (FIT) and Finite Element Method (FEM). Practical fabrication and simulation are conducted to compare the accuracy and efficiency of both methods. The authors in [18-22] designed various patch shapes with slots operating at 28GHz, simulated in HFSS and CST and optimized for mmWave applications. A dual band 2x1 MIMO antenna operating in the frequency range of 26.5-27.1GHz and 39.15–40.69GHz proposed for 5G IoT applications [41].

Traditional antenna design techniques are useful for certain issues but they require manual optimisation and lengthy simulations. The researchers have understood the significant impact of ML in the field of antenna design. In [10] authors explored the use of machine learning to optimise a double T-shaped monopole antenna and achieved a prediction error of just 2.90% when compared to HFSS simulation results. This study [23] presents a compact microstrip patch antenna designed for triple band 5G operation at 25, 28 and 32GHz. A line slot is introduced to enhance return loss with slot dimensions varied using a Coati algorithm guided by an XGBoost prediction model.

However, new antenna designs have been made possible by the development of ML techniques, providing opportunities to fully realise the potential of this technology [24]. This [26] paper presents an inset fed MPA with a partial ground plane evaluated using simulation, measurement, equivalent circuit modeling and ML techniques. This work [27] presents a 28GHz rectangular ring antenna designed using HFSS achieving high gain and wide bandwidth. To further improve accuracy and reduce design time, ML with regression models are applied to predict antenna characteristics. In [28], it is observed that the Random Forest performed better than SVR and Kriging methods for modelling antennas in high dimensional design spaces. In [29], the authors evaluated the effectiveness of ML in predicting antenna responses, highlighting the significant influence of training dataset size on model performance. In [30], the authors proposed a ML based optimisation algorithm aimed at reducing the computational burden associated with electromagnetic simulations. In [31], the authors reviewed the application of ML and deep learning techniques across various antenna designs, highlighting their feasibility, effectiveness and potential advantages in enhancing antenna performance. In [32], the performance of a circularly polarised base station antenna was enhanced using ML techniques combined with data augmentation methods. In [33], the authors optimized a microstrip line fed dielectric resonator antenna using ML techniques. In [34], the authors used KNN approach for antenna optimisation, demonstrating notable improvements in computational speed. In [35], the authors discussed the

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application of ML for antenna design optimization, emphasizing its ability to reduce the number of required simulations while maintaining high prediction accuracy. In [36] authors proposed ML methods for developing traveling wave antennas and robust antenna design. In [35,37], the authors reviewed machine learning applications in antenna design and optimization, highlighting the potential for significantly reduced computational costs.

ML as part of artificial intelligence offers useful methods that can learn from data on their own, find patterns and make accurate predictions [38]. The integration of ML into antenna design holds significant potential to revolutionize optimization processes, resulting in enhanced performance, improved efficiency and reduced design time [39]. By using large amounts of data and smart algorithms, ML can help improve antenna designs by taking into account different features, limits and performance measures. This allows researchers to go beyond traditional design methods and discover new ways to enhance antenna performance. Recent studies [42] have shown that ML can effectively improve the performance of MIMO antennas in 5G mmWave bands (28–38 GHz). These designs aim to achieve compact size, high gain and wide bandwidth suitable for HF applications. This study [43] designs a 28 GHz patch antenna using two materials Rogers RT5880 and FR-4 to study how different dielectric properties affect performance. Rogers-based Design-I showed better results in gain, return loss and efficiency. A machine learning model using multivariate polynomial regression was created to predict antenna parameters, reducing the need for physical testing. The work [44] introduces a compact antenna for mmWave communication at 28GHz and 34 GHz. A rectangular slot fed design is used and optimized with ML to achieve excellent impedance matching.

Now-a-days, the use ML in antenna design is being exploited to achieve enhanced performances. In view of this, this research work is aimed at the design of antennas according to certain specifications and evaluation of performance improvements using ML algorithms. In order to understand the state-of the art of ML applications for antenna design, a literature survey is performed and the findings thereof are detailed as below.

2. LITERATURE REVIEW

The hook shaped design on Rogers5880 [4] achieved 3.95dBi gain, 90% radiation efficiency for single element. The design reported in [5] shows possible operation across five bands including n257 to n261 with up to 8dBi gain and 94.5% efficiency making it suitable for next-gen wireless applications. Two L-shaped slots and a central square slot added to a rectangular patch [7] yielded better performance. In [8], the antenna is built on Rogers RT-Duroid5880 substrate with a compact size of 4.2 × 3.3 × 0.5 mm. It is observed that the simulations using HFSS and CST show a resonant frequency of 27.97GHz, S_{11} of –20.95dB, 1.0 GHz bandwidth, and 7.5dBi gain. In [9], a circularly polarized antenna array with beam steering for 5G beamforming applications achieved 5.02dBi

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gain and -25.02dB S_{11}. This highlights its suitability for mobile terminals. In [11], microstrip arrays improve return loss, gain, and bandwidth. A single element has achieved -31.96dB return loss. In [12], the antenna is simulated using CST and achieved a return loss of −44.46dB and bandwidth of 630MHz. Recent designs add slots or parasitic structures for improvement, but often with trade-offs. Return loss of −45 dB, and gain of 6.9dBi were resulted in [14]. In [15], The antenna achieves a return loss of −21.25dB, and gain of 3.90dBi using a lumped port. Microstrip antennas [16] are compact but face limitations in bandwidth and gain at mmWave. SIW technology offers improved performance due to reduced losses and better confinement. The SIW based antenna with 0.508 mm substrate shows superior return loss, gain of 6.4dBi and bandwidth 1.3GHz, confirming its suitability for 5G applications.

FIT [17] outperforms FEM in predicting key antenna parameters, with a compact antenna achieved 967MHz bandwidth, and 6dBi gain. The optimal configuration uses Taconic TLX-9 substrate with a copper patch [18], achieved S_{11} of –14.6dB, gain of 5.94dBi and bandwidth over 0.503GHz. The patch antenna [19] achieves a gain of 7.587dBi, 98.21% radiation efficiency and 1.046GHz bandwidth. In [21], the authors designed an antenna with Rogers RT-Duroid5880 substrate achieves −22.51dB return loss, 3.6dBi gain and 5.57GHz bandwidth. In [22], HF 5G systems demand compact antennas with high efficiency and bandwidth. While rectangular patches are easy to fabricate, they often require enhancements for better performance. The U-slot design on FR4 substrate achieved gain of 6.08dBi, and 85% efficiency. Triple band [23] 5G antennas often face challenges in balancing size, gain and efficiency. Previous works are lacking of integrating advanced optimization. Their design achieved −30dB return loss, and 7.3dBi gain. A MIMO dielectric resonating antenna [40] for 5G mmWave applications is proposed, offering enhanced isolation using metal strips on the resonators, operating from 27.25 to 28.59 GHz, and achieves a 12 dB isolation improvement across the 28 GHz band.

The use of ML guided optimization ensures performance and miniaturization, making it suitable for modern 5G deployments. The work in [42] presents a compact MIMO antenna for 5G, achieving 7.2dBi gain and wide bandwidths 3.8 GHz for single element. CST and ADS tools were used for simulation and circuit modelling. Among several ML models, Random Forest Regression gave the most accurate gain prediction, demonstrating the value of ML in antenna design. In [43], a low profile stacked patch antenna demonstrated 6.8dBi gain and wideband behaviour using HFSS. Previous works used basic regression models for predicting antenna performance. This work stands out by using Multivariate Polynomial Regression (MPR) to predict multiple parameters with high accuracy. It also uses ANOVA to validate the model, making the prediction process more reliable and efficient. In [44], advanced ML methods including a Taguchi based Neural Network were used to predict reflection coefficients. The optimized model achieved an R-

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Squared of 0.848 with minimal MSE. Experimental results showed gain of 6.3dBi, bandwidth of 3GHz and excellent efficiency more than 98% with very low coupling in the MIMO setup making it ideal for future 5G/mmWave systems. CNNs and SVMs were used for modelling [6] and predicting antenna gain and return loss, showing that hybrid ML techniques improve prediction accuracy. The antenna design is evaluated using CST and ADS tools and ML models are used to predict gain and directivity. Among various regression models, Ridge regression shows the best accuracy 98% for gain, while Gaussian process regression performs best for directivity. These results highlight the effectiveness of ML in antenna parameter prediction. However, despite these advancements, integration of ML in the antenna design covering concept generation, parametric optimization and performance validation remains limited. Existing studies focus on enhancing one or two specific metrics gain or bandwidth rather than achieving a balanced, fully optimized design that simultaneously meets multiple performance targets.

In parallel, ML based antenna design has emerged as a promising methodology for accelerating the design process and reducing dependence on exhaustive full wave simulations. ML models such as regression trees, support vector regression (SVR), deep neural networks (DNN), and ensemble methods have achieved prediction accuracies with R-Squared values close to 1, while reducing computational time by up to 90% compared to traditional iterative design approaches. These ML based methods have been successfully applied in predicting key antenna performance parameters such as return loss, resonant frequency and gain, enabling fast optimization. Recent applications of ML in mmWave antenna research include optimization of array geometries for beam steering, prediction of mutual coupling in compact MIMO systems [42,44] and optimization for bandwidth, gain, and radiation efficiency [6,10,23]. However, despite these advancements, integration of ML in the antenna design covering concept generation, parametric optimization and performance validation remains limited.

This indicates about the end-to-end ML integration that not only offers performance prediction with high accuracy but also guides into an iterative refinement towards multicriteria optimization and addressing of the requirements for modern mmWave applications such as 5G FR2, V2X communications, high-throughput satellite links and so on.

It is seen from the literature review that, there is insufficient research done as to how to achieve high gain and broadband performance at 28GHz from compact practical designs by incorporating ML optimization techniques. Because, ML approach reduces simulation time by maintaining accuracy. This work aims to bridge the gaps by developing a compact microstrip patch antenna specifically optimized for 28GHz 5G applications from ML-based models.

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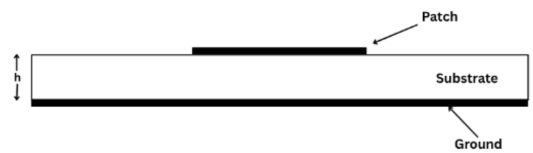
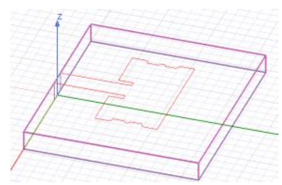
3. ANTENNA DESIGN AND SIMULATION SETUP

Initial Geometry

The proposed antenna consists of a radiating rectangular patch, a dielectric substrate, a conducting ground plane, and an inset feed line as shown in Fig. 1(a). The initial design (Design I) follows the transmission line model equations (1) through (7) to determine patch dimensions [43].



(a)



(b)

Fig. 1: (a) Microstrip Patch Antenna (b)

$$W = \frac{c}{2f_r\sqrt{\frac{\epsilon_r+1}{2}}} \qquad (1)$$

$$\epsilon_{reff} = \frac{\epsilon_r+1}{2} + \frac{\epsilon_r-1}{2}\left(1+12\frac{h}{W}\right)^{-0.5} \qquad (2)$$

$$L_{eff} = \frac{c}{2f_r\sqrt{\epsilon_{reff}}} \qquad (3)$$

$$\Delta L = 0.412h\frac{(\epsilon_{reff}+0.3)(\frac{W}{h}+0.264)}{(\epsilon_{reff}-0.258)(\frac{W}{h}+0.8)} \qquad (4)$$

$$L = L_{eff} - 2\Delta L \qquad (5)$$

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$$W_g = 6h + L \quad (6)$$

$$L_g = 6h + W \quad (7)$$

This resonates at 28GHz, with physical dimensions 9.615×8.347×0.917mm³ using Rogers RT5880 substrate with dielectric constant ϵ_r=2.2, loss tangent = 0.0009. The patch is made of copper with standard thickness 0.035mm.

Design Methodology:

Figure 2 illustrates the proposed design methodology for the ML assisted inverse design of a 28GHz patch antenna. The process begins with the initial antenna design and dataset generation through full wave electromagnetic simulations in HFSS by varying key geometrical parameters. The dataset is then used to train multiple machine learning models, which are evaluated using performance metrics to select the most accurate model. An interpolation model is built using the best performing ML model and an inverse design objective function is defined to target desired antenna characteristics return loss S_{11}, gain, resonance frequency. Global optimization techniques are applied to determine the optimized antenna parameters, which are then validated through HFSS simulations to confirm performance against the target specifications.

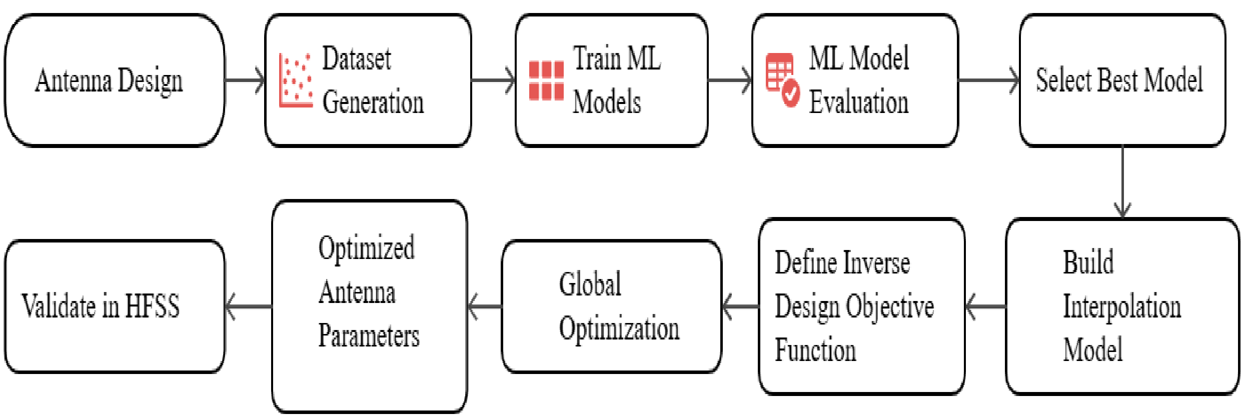

Fig.2: Design Methodology

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Design Procedure:

The proposed antenna is designed in three successive configurations namely, Design-I, Design II and Design-III. The Design I represents a basic rectangular patch with inset-feed for impedance matching. Design II comprises of two symmetrical side notches introduced on patch to shift the resonant frequency and improve impedance matching further. The symmetrical semi-circles on notch edges of patch are added in Design III to further enhance the bandwidth and return loss, its top view is shown in Fig.1(b). The design parameters for all configurations have been shown in Table 1. Fig. 3 depicts the top view and physical dimensions of all antenna configurations as mentioned above. The physical dimensions shown in Fig. 4 refer to Design-III.

(a) (b) (c)

Fig.3: Top view of the proposed antenna (a) Design – I (b) Design – II (c) Design - III

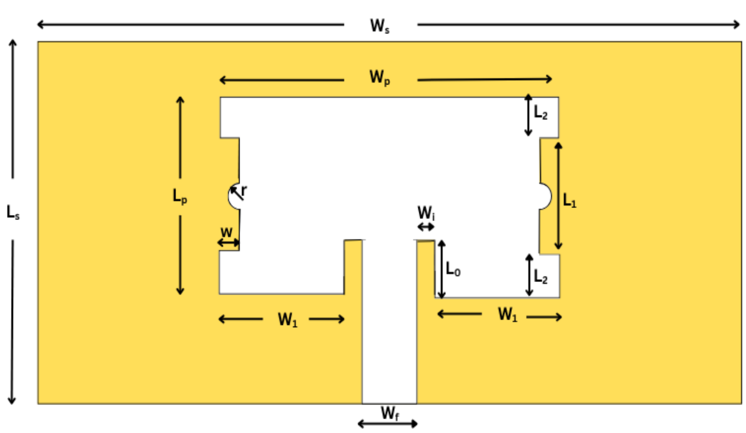

Fig.4: Dimensions of Design-III.

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Table 1: Antenna parameters

Parameter	Dimensions (mm)
Substrate Width (W_s)	9.615
Substrate Length (L_s)	8.347
Substrate Height (h)	0.917
Patch Width (W_p)	5.389
Patch Length (L_p)	2.976
Feedline Width (W_f)	0.903
Inset Feed Notch Width (W_i)	1.410
Inset Feed Notch Depth (L_0)	0.705
Notch Width (g)	0.2116
Notch Length (L_1)	1.809
Semicircle Radius (r)	0.141
W_1	1.285
L_2	0.584

4. RESULTS AND ANALYSIS

The performance metrics with respect to the antennas pertaining to Design-I through Design-III are evaluated for return loss, S_{11} (dB), gain (dBi) and resonant frequency (Hz) using HFSS and the results are shown in Fig. 5. It is observed that the value of return loss progressively improves from Design-I to Design-III. Table 2 shows comparison of performance parameters. The antenna corresponding to Design-III provides a return loss of −49.97dB at 28GHz. The current distribution shown in figure 10 (a) represents the best impedance matching for Design-III. Figure 11 (a) represents radiation pattern.

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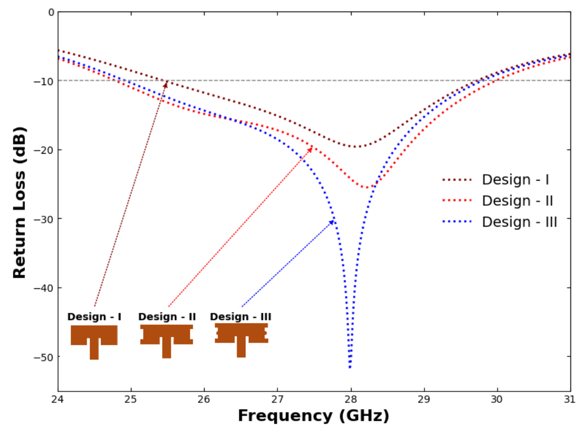

Fig. 5: Return loss for Design -I, II and III.

Table 2. Comparison of performance parameters.

Parameter	Design-I	Design-II	Design-III
Return loss (dB)	-19.63	-25.53	-51.93
Gain (dBi)	7.35	7.19	7.15
Frequency (GHz)	28.08	28.22	27.99

It is evident that, Design III demonstrates the best return loss indicating optimal impedance matching and minimal reflection at the target frequency leading it to be the most suitable candidate for subsequent machine learning (ML) based inverse design analysis.

Dataset Generation & Machine Learning Approach: The optimization is carried out focussing on four key design parameters patch width, substrate height, semicircle radius and inset feed notch depth. The proposed antenna patch width variation is over 5.2-5.4 mm with an increment of 0.05 mm, substrate height is over 0.7-1.1mm with an increment of 0.1mm, semicircle radius is over 0.1-0.2 mm with an increment of 0.05mm, inset feed notch depth variation over 0.6-0.8 mm with increment of 0.1mm. Each parameter variation is simulated in HFSS to generate return loss over frequencies from 24GHz to 31GHz, dividing into 401 points. This process generates a dataset of 90225 values. The dataset is prepared for ML training by preprocessing. The dataset is then split into 80% used for training the ML model and 20% for testing it [45, 46]. Various regression algorithms Linear Regression, Random Forest, Extra Tree and ANN are applied to predict antenna return loss, gain and frequency. The performance metrics such as R-squared, MAE, MSE and prediction time are used for evaluation [25].

The design parameters such as Wp, h, r, L_0 serve as the primary input features. Return loss (S_{11}), resonant frequency (f_r) and gain are taken as target variables.

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ML Performance Metrics

The proposed model Design-III is evaluated using R-squared, MAE and MSE and prediction time [25] shown in Eq. (8) to (10). R-Square is a statistical measure that indicates the proportion of predictable dependent value from independent value.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \qquad (8)$$

MAE finds the average of the absolute difference between predicted and actual values, which indicates the average magnitude of errors.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (9)$$

MSE finds the average of the squares of the errors and measures the average squared difference predicated and actual values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (10)$$

Each model was assessed for the metrics such as, the coefficient of determination (R^2), mean absolute error (MAE), mean squared error (MSE), and prediction time (s), and the analysis of return loss, gain and frequency are mentioned in Table 3 through Table 5.

Table 3. Analysis of return loss for various ML models.

Name of the Model	R^2	MAE	MSE	Prediction Time (s)
Linear Regression	0.128	4.503	34.140	0.0007
Random Forest	0.998	0.122	0.065	0.9467
Extra Trees	0.999	0.067	0.018	0.0570
ANN	0.989	0.410	0.447	0.0929

Table 4. Analysis of frequency for various ML models.

Model	R^2	MAE	MSE	Prediction Time (s)
Linear Regression	0.787	0.151	0.047	0.0002
Random Forest	0.953	0.087	0.010	0.0142
Extra Tree	0.952	0.087	0.011	0.0192
ANN	0.928	0.103	0.016	0.0007

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Table 5. Analysis of gain for various ML models.

Model	R^2	MAE	MSE	Prediction Time (s)
Linear Regression	0.766	0.150	0.095	0.0003
Random Forest	0.983	0.051	0.007	0.0139
Extra Tree	0.982	0.051	0.007	0.0228
ANN	0.884	0.114	0.048	0.0007

The comparisons of actual values of return loss, frequencies and gain with their values predicted by (a) Linear Regression (b) Random Forest (c) Extra Trees and (d) ANN are shown in Fig. 6 through Fig. 8, respectively.

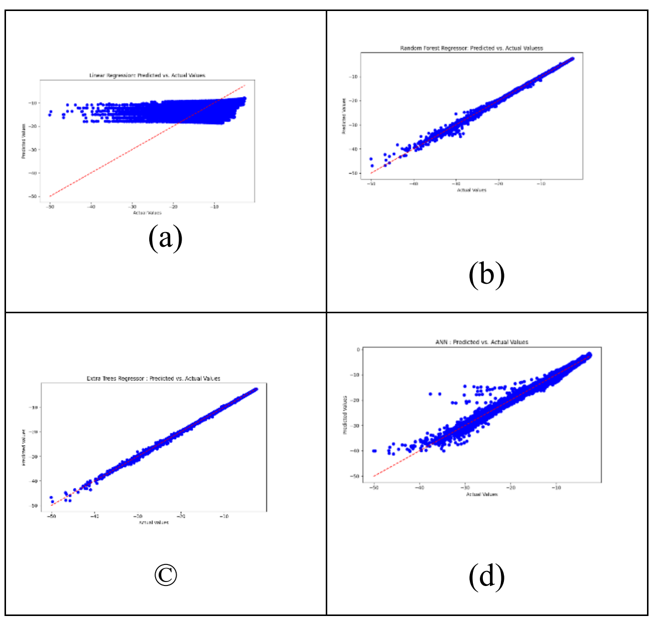

Fig. 6. S_{11} actual values vs predicted values for (a) Linear Regression (b) Random Forest (c) Extra Trees (d) ANN

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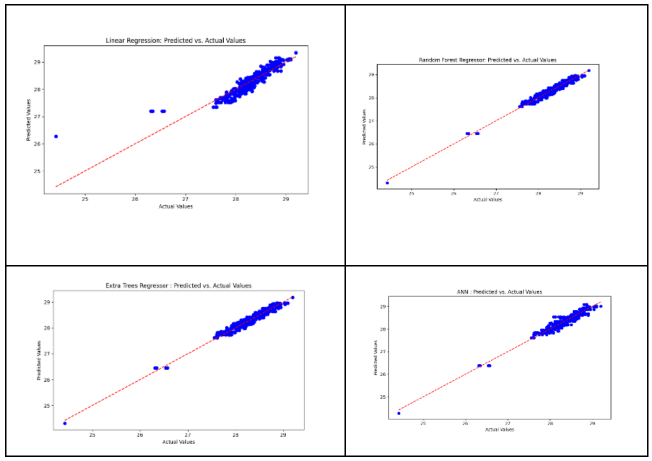

Fig. 7. Frequency actual values vs predicted values for (a) Linear Regression (b) Random Forest (c) Extra Trees (d) ANN

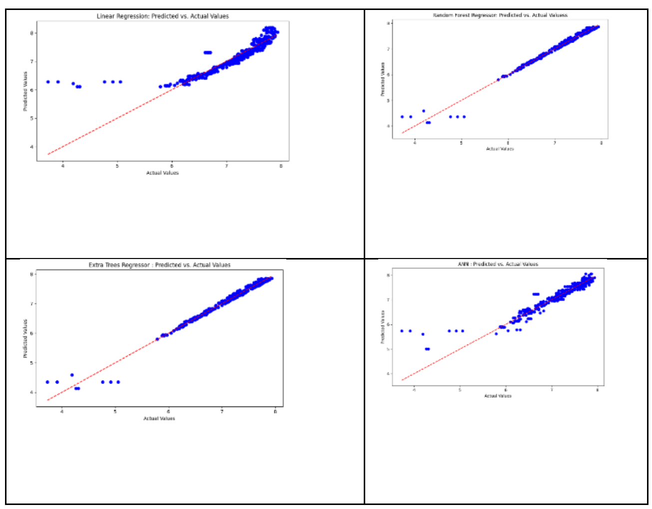

Fig. 8. Gain actual values vs predicted values for (a) Linear Regression (b) Random Forest (c) Extra Trees (d) ANN

Based on the performance metrics, the Extra Trees is identified as the best performing model for predicting S_{11}, achieving near perfect accuracy. For both resonant frequency and gain, the Random Forest is selected as the optimal model due to its consistently high R^2 values, low errors, and reasonable prediction time. These models can be effectively integrated into the antenna design workflow, enabling accurate parameter estimation with minimal computational cost. The Extra Tree model selected in the dataset evaluation stage as the most accurate for S_{11} prediction is used

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to construct an interpolation based surrogate model capable of predicting antenna performance across the multidimensional design space. Radial Basis Function (RBF) interpolator [47] is applied for the surrogate model

The inverse design is aimed at identifying the optimal antenna parameters that achieve a desired return loss, resonant frequency, and gain while minimizing deviations from target values. In this work, the inverse design objective is defined to achieve a resonant frequency of 28 GHz, a return loss below –30 dB and a gain more than 7dBi. To achieve inverse antenna design targeting a fixed resonant frequency, an objective function shown in eq. (11) is defined to minimize the difference between the predicted return loss (S_{11}) from the ML based surrogate model and the desired target S_{11}. Equation (11) shows the objective function.

$$f(x) = \left(\hat{S}_{11}(x, f_{fixed}) - S_{11}^{target}\right)^2 \quad (11)$$

Where $\mathbf{x} = [r, h, W_p, L_0]$ represents the antenna design variables, $\hat{S}_{11}(\mathbf{x}, f_{\text{fixed}})$ is the predicted return loss at the fixed frequency f_{fixed}, obtained from the trained RBF interpolator, S_{11}^{target} is the desired return loss at the target frequency. The objective function $f(\mathbf{x})$ finds the squared error between predicted and target S_{11}. Minimizing this gives the optimized design variables, achieves the required EM performance. A global search algorithm based on the Genetic Algorithm (GA) [48] is used for optimization. The GA improved the design iteratively by applying selection, crossover and mutation operations to the design variables patch width W_p, substrate height h, semicircle radius r and inset feed notch depth L_0. The global optimization has given the optimized parameters W_p = 5.350mm, h = 0.9050mm, r = 0.1464mm, L_0 = 0.7179mm, were validated in HFSS. Design-III and optimized design parameters are shown in table 6. Figure 9 presents the comparison of S_{11} responses between the HFSS of Design-III and the HFSS validation of the ML based inverse design. The Design-III was specified to resonate at 27.99GHz with an S_{11} of −51.93dB. Using the ML based inverse design approach, the optimized design parameters predicted by the ML model is simulated in HFSS and validated. The validation result shows a resonance at 27.97GHz with S_{11} = −49.08dB, representing good agreement with the Design-III. The frequency deviation is only 0.02 GHz, gain deviation of 0.01dBi, and the return loss difference is 2.85 dB, indicating the high accuracy and reliability of the ML based inverse design method for predicting antenna parameters corresponding to desired EM performance.

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Table 6: Table comparison of proposed antenna Design – III and its inverse design by ML

	Wp (mm)	h (mm)	r (mm)	L_0 (mm)	Frequency (GHz)	S11(dB)	Gain (dBi)	Bandwidth (GHz)
Design – III	5.3890	0.9170	0.1410	0.7050	27.99	-51.93	7.15	4.9
ML Inverse	5.3500	0.9050	0.1464	0.7179	27.97	-49.08	7.16	4.7

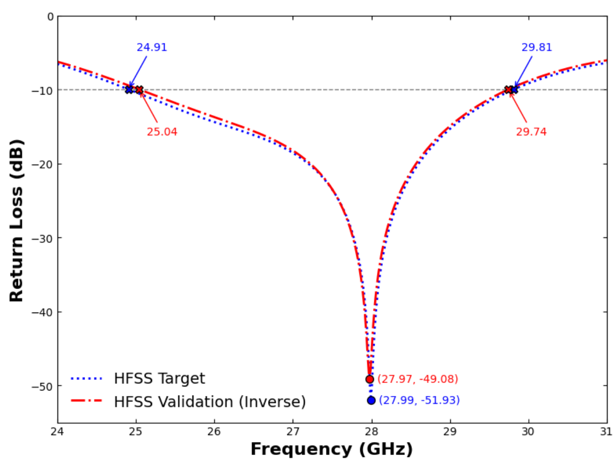

Fig.9. Return loss Design – III (HFSS target) and ML inverse (HFSS Validation)

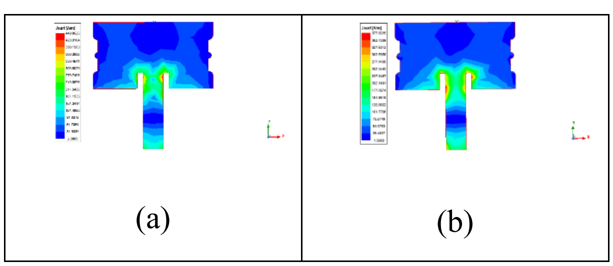

Fig.10. Current distributions (a) Design – III (b) ML – inverse design

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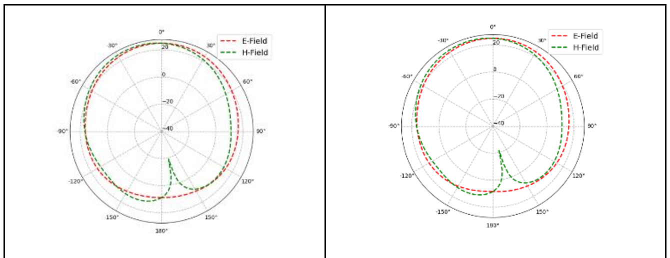

(a) (b)

Fig.11. Radiation Pattern of Design – III and ML Inverse Design

Table 6 summarizes the geometry parameters, resonance frequency, return loss, gain, and bandwidth for the selected HFSS design and the ML optimized inverse design. Figure 11 shows radiation patterns of Design-III and ML Inverse and it is observed that both resulting close match.

5. CONCLUSION

This work presents a microstrip patch antenna design at 28 GHz using both conventional HFSS simulations and ML based inverse design approach. Among the three designs, Design III exhibited the best return loss fof−51.93 dB at 28.00 GHz and a gain of 7.15 dBi, indicating superior impedance matching. The ML based inverse design method successfully predicted an optimized antenna parameter, simulated these optimized parameters in HFSS for validation, observed resonance at 27.97 GHz, return loss of −49.08 dB, and gain of 7.16 dBi, closely matching to the Design-III. These results indicate that the proposed ML based inverse design method provides highly accurate predictions of antenna performance. The slight deviations are negligible for practical applications and shows the potential of ML techniques in reducing design iterations, enabling rapid retrieval of antenna parameters for desired EM performance

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