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ORIGINAL ARTICLE

AI-Powered S_{11} Prediction for a Compact 2.4 GHz Patch Antenna

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Abstract

Objectives: Designing and optimizing a compact 2.4 GHz patch antenna through AI-based models in predicting return loss (S_{11}) for facilitating effective performance estimation in IoT applications. **Methods:** Parametric analysis was performed to evaluate the effects of slot/feed dimensions on antenna performance. A bespoke dataset of 55,053 samples was created via CST simulations. Various regression models (e.g., XGBoost, KNN, MLP) were trained and compared for S_{11} prediction. Data preprocessing, train/test splitting, and statistical metrics (MAE, RMSE, R^2) were utilized to determine the most accurate model for performance prediction and inverse optimization. **Findings:** The suggested AI-enhanced method greatly curtailed design time and enhanced prediction accuracy as compared to conventional parametric sweeps. KNN and MLP models performed better than XGBoost with RMSE of 0.42 and 0.51, and R^2 of 0.9866 and 0.9803 respectively, for maintaining high correlation between predicted and simulated S_{11} values. Final antenna design was achieved for resonance at 2.45 GHz with a return loss of less than - 40 dB, showing perfect impedance matching. Sensitivity analysis revealed patch width and feed length as most dominant features. The correlation matrix pointed out that return loss relies on complicated non-linear relationships, validating the application of AI models. These findings vary from typical findings through the provision of an interpretable and efficient solution based on machine learning. In comparison to previous research, our methodology ensures quicker optimization and the capability to carry out inverse design, rendering it suitable for time-critical, miniaturized IoT devices. The amalgamation of AI hence presents a scalable and precise avenue to antenna engineering. **Novelty:** Unlike previous studies limited to small datasets or single algorithms, this work benchmarks six ML algorithms on over 55,000 simulated antenna samples. The results show that KNN and MLP achieved the highest prediction accuracy (R^2 > 0.98), outperforming traditional regression and advanced ensemble methods such as XGBoost, making it a highly scalable and efficient tool for inverse antenna design for IoT applications.

Keywords: Patch Antenna; Return Loss Prediction; Machine Learning; IA; IoT Applications

1 Introduction

The rapid expansion of Internet of Things (IoT) applications has created a demand for compact, efficient, and low-cost antennas for working reliantly on the 2.4 GHz ISM band [(1)], [(2)]. These should also comply with the parameters of return loss, bandwidth, miniaturization, and integration with wearable or embedded systems [(3)]. Conventional antenna design methods use full-wave electromagnetic simulation since these are usually very accurate; however, computational time becomes prohibitive when there are multiple geometric parameters simultaneous optimization are required [(4)], [(5)].

Several research articles on microstrip patch antennas have examined the performances of antennas through the variation of antenna parameters such as slot size, feed length, and substrate. The choice of substrate and its thickness play a significant role in deciding the overall functioning of the antenna. Rogers 5880 is known for its efficiency, directivity, and gain, usually at around 1.6 mm thickness, thus qualifying it as one of the best materials for high-frequency applications, such as 5G [(6)]. Comparisons have been drawn between substrates such as RT Duroid, Teflon, and FR4; RT Duroid and Teflon perform better in terms of return loss, while FR4 has the advantage with miniaturization [(7)]. Slot dimensions and patch design are essential factors influencing antenna characteristics. Introducing slots into the patch structure can significantly enhance bandwidth and improve radiation efficiency. Slotting the patches can enlarge bandwidth and efficiency. Adding slots to patch designs dramatically reduces return loss and enhances performance when the ground plane is adjusted [(8)]. Another work comparing the effects of different slot types such as E-shaped, U-shaped provides another set of practical insights into design optimization [(9)]. Feed length and method are also crucial in achieving proper impedance matching. Dimensioning and positioning of the feed line were critical to optimize coupling and impedance match. The aperture coupling method and microstrip line feeding were used to enhance bandwidth and return loss [(7)], [(10)].

Unfortunately, these approaches are still limited by non-generalization and inability to predict antenna behavior over a far greater design space.

Additionally, the capabilities of Artificial Intelligence (AI) aspects, especially machine learning (ML) and deep learning (DL) methods, are not fully exploited in antenna modeling, mainly for inverse design purposes. When effectively incorporated, AI not only enhances antenna performance and design efficiency but also introduces a new level of adaptability to meet increasingly rigorous and complex application requirements, signifying a major evolution in the field [(11)], [(12)]. This evolution is particularly relevant to new technologies like 5G, augmented reality, virtual reality, and the metaverse in which antennas must hold exacting demands with respect to size, return loss, gain, and multifunctionality [(13)]. Evolutionary algorithms have been found to explore very large design spaces and to deal well with conflicting objectives such as minimizing return loss versus maximizing gain, specifically with compact 5G antenna systems [(14)]. In a similar vein, machine learning is becoming an increasingly popular approach to automating the design process to minimize development time and do away with the need for vast domain knowledge [(15)], [(16)].

Previous studies [(17)], [(18)] have focused on the application of a single ML model (e.g., SVM or KNN) to specific antenna geometries using limited datasets. However, there is a lack of large-scale, comparative evaluations of ML algorithms for predicting antenna dimensions based on performance metrics. This study addresses that gap by performing a benchmark of six ML models on a large, diverse dataset to identify the most effective model for inverse design.

This study bridges these gaps by proposing a novel, data-driven approach to predict and optimize the return loss (S_{11}) of a compact 2.4 GHz patch antenna. By developing a custom dataset with over 55,000 simulation samples, we benchmark several regression models, including K-Nearest Neighbors (KNN), Multilayer Perceptron (MLP), and XGBoost, to identify the top performer in forecasting the antenna performance. Our work demonstrates that AI models can achieve high prediction accuracy ($R^2 > 0.98$) and significantly reduce design time compared to traditional methods. The main objectives of this study are to advance intelligent antenna design techniques using Machine Learning. First, an accurate prediction model is to be designed that can give the estimate of reflection coefficient (S_{11}) using the geometric and frequency-related features of the antenna. It also would serve as a platform to scrutinize and weigh the performance of different machine learning approaches, getting to know which one is best for the estimation of antenna performance. Further, this study aims at inverse design that would very quickly synthesize optimum antenna geometries conforming to a performance target. Ultimately, the search bridges the divide between traditional electromagnetic simulations and AI-guided design methodologies to create a better and intelligent antenna development workflow. To the best of our knowledge, this is one of the first studies to combine data-driven S_{11} prediction and inverse optimization using large-scale simulation data and to report the superiority of KNN and MLP models over classical approaches. Our findings contribute to the emerging field of AI-assisted antenna engineering and provide valuable insights for future IoT device development.

The main contributions of this work are summarized as follows:

1. Development of a large-scale, custom-built dataset of over 55,000 simulated patch antenna samples, each with 12 geometrical and electrical features, enabling comprehensive model training and evaluation.
2. Benchmarking and comparison of six machine learning algorithms (KNN, MLP, Random Forest, XGBoost, SVR, and Linear/Ridge Regression) for predicting the return loss (S_{11}) of a 2.4 GHz patch antenna.
3. Implementation of an inverse design framework that predicts optimal antenna dimensions based on target performance metrics.
4. Demonstration that KNN and MLP outperform all other tested models, achieving R^2 values above 0.98 and RMSE values below 0.52.
5. Comparative analysis with state-of-the-art works, showing the superiority of our proposed approach in terms of accuracy and dataset scale.

2 Methodology

2.1 Antenna modeling

2.1.1. Antenna layout Aspects

To meet the requirements of environmentally sustainable IoT systems, a compact and efficient UHF antenna has been designed and optimized. The antenna mentioned in Figure 1 consists of a rectangular patch having a double slot configuration at the feed. This structure is shaped for better impedance matching and surface current distribution at desired resonant frequency to realize better performance. The patch is fed using a microstrip line of 3 mm width, ensuring a robust and planar excitation mechanism compatible with printed circuit technology. The metal patch is placed over an FR4 substrate characterized by relative permittivity ϵ_r, of 4.3, the loss tangent being 0.02. The thickness of this substrate is 1.6 mm, whereas the patch metallization is of a height, h, of 0.035 mm. The ground plane, which is exceedingly necessary for carrying out the radiation mechanism, is placed on the bottom surface of the substrate and extends across the entire width and length of the dielectric. The dimensions of the patch are- width 42 mm, length 29.3 mm. Two narrow vertical slots which measure 2mm wide and 7mm long are placed symmetrically along the feed axis to help improve return loss and miniaturize the antenna. The feed line which is directly attached to a 50-ohm line is under the slots, measuring 11 mm long and 3 mm wide as mentioned in Figure 1.

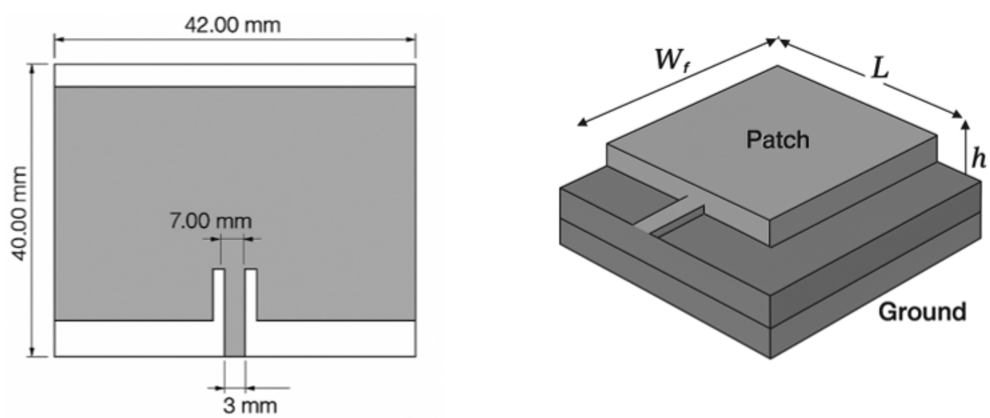

Fig 1. Antenna design

Table 1 provides an overview of the antenna geometry along with its parameters. These carefully optimized dimensions provide compact and mechanically feasible robust designs with superior electromagnetic characteristics for wireless multifunctional applications.

2.1.2. Effect of variation of Slot Width (SW), Slot Length Variation (SL) and Feed length (FL)

As shown in Figure 2 (a), varying the slot width of the antenna from 1 mm to 5 mm changes the S_{11} parameter significantly. All designs still resonate at approximately 2.4 GHz, but the return loss depth—indicating how well the energy is matched—demonstrates clear slot width dependence. The best result is attained with a slot width of 2 mm which corresponds to an S_{11}

Table 1. Antenna Dimensions

Parameters	Dimensions (mm)	Parameters	Dimensions (mm)
Substrate length	40	Patch length	29.3
Substrate width	42	Slot Width (SW)	2
feed width	3	Slot Length (SL)	7
High substrate	1.6	Patch width	42
High patch	0.035	feed length (FL)	11

value of –29.59dB. This illustrates a near perfect mismatch (in this case, low power reflection) and indicates minimal energy lost during the transmission at the targeted frequency. Other values like 1 mm yielding –22.09 dB, 2.5 mm –18.85 dB, and 3.5 mm –16.33 dB also provide reasonable power reflection—though not as favorable.

On the other hand, with exceeding slot widths of 4 mm, slow but steady return loss degradation occurs, hitting S_{11} values worse than –10 dB (for example 9.37 dB at 4.5 mm and –7.77 dB at 5 mm) meaning more power is reflected and the efficiency of the antenna is lower. All in all, these findings support that slot width is an extremely critical parameter for the antenna's input impedance. A width that is well picked enables resonant performance and significant return loss. The findings propose that widths within the range of 1.5 mm to 2.5 mm are suitable for applications in the 2.4 GHz ISM band since they offer good matching at 2.4 GHz.

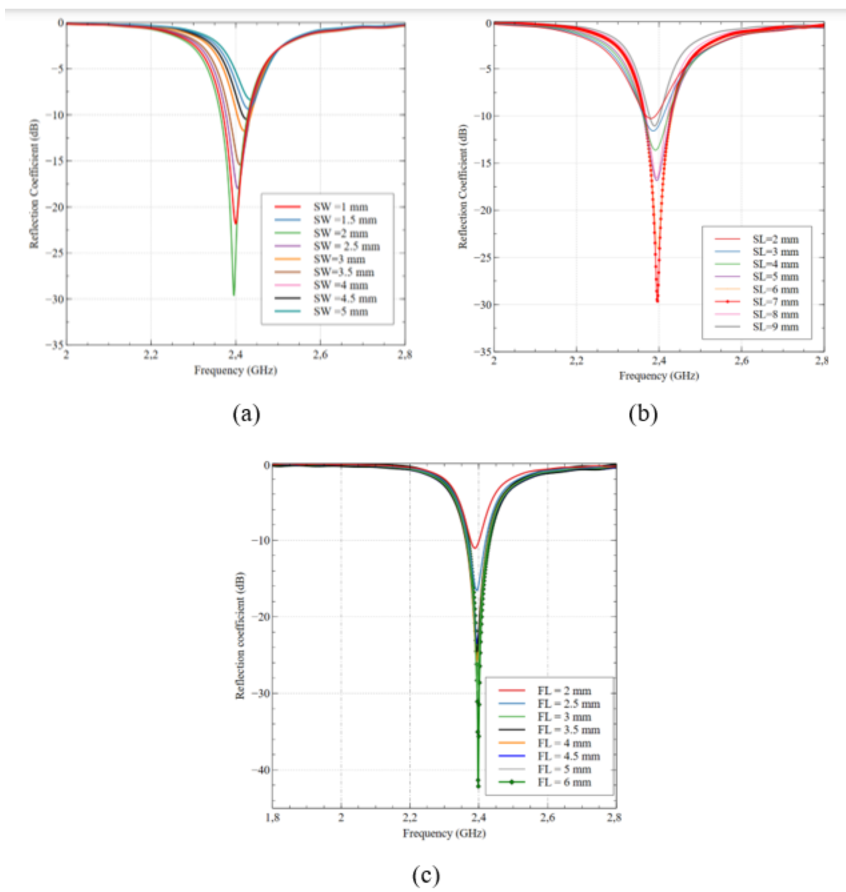

Fig 2. Impact of: (a) Slot Width, (b) Slot Length Variation (SL), and (c) Feed length on Antenna Return Loss Characteristics

As shown in Figure 2 (b), the S_{11} parameters for slot lengths between 2 mm to 9 mm were simulated. These results demonstrate that while the resonance frequency tends to stay at 2.4 GHz, the return loss depth exhibits a strong dependence on the slot length due to changing impedance matching-efficiency. The best matching was seen with a slot length of 7 mm and achieved a minimum S_{11} of -29.59 dB, indicating remarkable energy transfer and minimal reflection. Conversely, longer slot lengths worsen the matching, increasing S_{11} above -10 dB, indicating lower efficiency with worse matching. The outcome proves that the slot length is a vital geometric parameter which directly determines the resonance behavior and return loss performance. For optimal performance, systems intended for the ISM band, like IoT and wearable wireless devices, require fine tuning the dimensions to ensure efficient operation at the targeted 2.4 GHz frequency.

Some parametric studies were conducted, with the feed length changing from 2 mm to 6 mm in steps of 0.5 mm, to observe feed-length induced changes in impedance matching the antenna.

The reflection coefficient (S_{11}) results, shown in Figure 2 (c) in the presented connection, clearly demonstrate that the resonant frequency and return loss of the antenna are highly sensitive to the FL fluctuations. As the feed length is increased, the resonance becomes deeper and moves slightly, with the best matching -40dB achieved around FL = 5mm at about 2.4 GHz. This shows that the tuning of the feed length is very important to achieve the best impedance matching and power reflection minimization, especially in ISM-band applications.

2.1.3. Limitations of Traditional Approaches

While parametric studies remain a standard and essential tool in antenna design, they present significant limitations in terms of time and computational efficiency. In the present work, extensive parameter sweeps were conducted to assess the impact of both the slot length and slot width on the return loss characteristics of the antenna. While these analyses provided critical knowledge on geometric parameters- centering the optimum slots around a 3 mm length and 2 mm width- the complete parametric sweep simulation took more than 15 hours.

This trial-and-error approach soon becomes prohibitive when such type of analysis must be carried out over large areas in a genuine multi-parameter optimization or broad-frequency range, especially considering the miniaturization and environmental considerations of wearable or compact IoT antennas. Another drawback of such traditional sweeps is that they do not generalize the knowledge gained for performance prediction across unexplored configurations; each time a new design is selected, one must still solve the equations again.

To overcome such limitations, AI techniques, especially machine learning methods, can be applied. Such an AI-based surrogate model learns the complicated nonlinear relationship between antenna geometry and electromagnetic performance, predicting key parameters such as S_{11}, bandwidth, gain, or resonance frequency immediately. Moreover, using inverse design approaches aided by AI, even the best antenna geometry for any target specification can be generated automatically, thereby greatly speeding up the design cycle and cutting down time in repeated simulations.

In the forthcoming sections, we shall see how performance prediction of the antenna can be done using data-driven models trained over our simulation dataset, and even how inverse mappings can be generated for efficient synthesis of antennas. This hybrid approach combining physics-based simulation with AI-guided optimization opens new avenues for smart antenna design frameworks, particularly suitable for next-generation wireless and wearable applications.

2.2 Optimizing using a machine learning algorithm (50000 Line & 12 features "costum DataSet)

To overcome the time-consuming limitations of traditional parametric sweeps, we developed a data-driven framework to predict the antenna's return loss (S_{11}) using Artificial Intelligence (AI) models trained on a custom dataset comprising 55,053 simulated samples[19]. The dataset includes key geometric parameters (e.g., substrate and patch dimensions, slot width and length, etc.) and operating frequency, with the S_{11} value as the target output. Six regression models were implemented and benchmarked: Linear Regression, Ridge Regression, Support Vector Regression (SVR), Random Forest, XGBoost, and a Deep Learning model based on Multilayer Perceptron (MLP). Each model was trained using a standardized pipeline involving data normalization, train-test split (80/20), and performance evaluation based on Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). Among all models, KNN achieved the highest prediction accuracy, closely followed by MLP, both surpassing XGBoost in RMSE and R^2. While XGBoost offered competitive performance, it did not outperform KNN and MLP in our dataset. This AI-based modeling approach not only reduced the design time from hours to seconds but also enabled inverse design possibilities, allowing for rapid synthesis of antenna geometries tailored to specific electromagnetic responses. These results validate the integration of AI as a transformative tool in antenna engineering, particularly for rapid prototyping and optimization in next-generation IoT and wearable applications.

To predict perfectly the S_{11} or reflection coefficient of the proposed antenna system, we had compared several machine learning models, such as Linear Regression, Ridge Regression, SVR, Random Forest, XGBoost, KNN, and MLP. The performance criteria based on which these models were compared include MAE, RMSE, and R^2. It can be observed in Figure 3 that these algorithms, based on trees and neural networks, outperform linear and kernel-based algorithms in prediction.

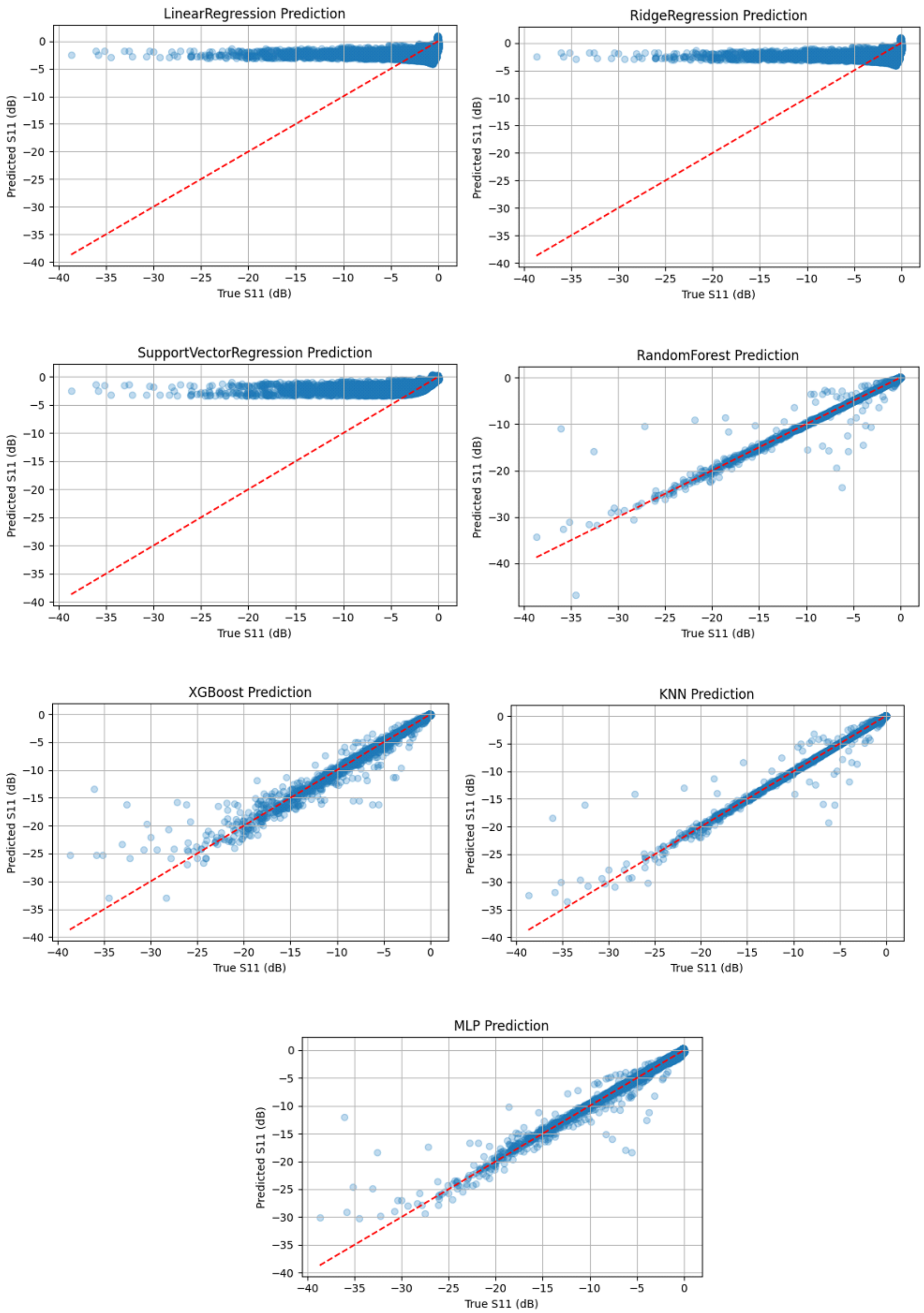

Fig 3. Model Performance Evaluation for S_{11} Prediction.

Table 2. Performance Comparison of Regression Models for S_{11} Prediction

Model	MAE	RMSE	R^2 Score
K-Nearest Neighbors	0.0495	0.4216	0.9866
Multi-Layer Perceptron	0.1795	0.5110	0.9803
Random Forest	0.0600	0.5380	0.9782
XGBoost	0.1329	0.5855	0.9742
Support Vector Regression	1.2276	3.3202	0.1690
Linear Regression	1.9968	3.5244	0.0637
Ridge Regression	1.9968	3.5244	0.0637

Table 2 describes how the KNN model had the lowest RMSE (0.4216) and thus the highest R^2 (0.9866), whereas the second best was the MLP model, having RMSE at 0.5109 and R^2 at 0.9803. The linear regression models, such as L.R. and Ridge, showed errors almost 10 times higher (RMSE $\approx$ 3.52) and R^2 values very near to zero ($\approx$ 0.06), which may imply limited fitting and poor generalization. If SVR exhibited lower results, this might be credited to the careful tuning of its parameters and the non-linearity of the data. Despite remaining a previously concluded shining-star, XGBoost remained highly susceptible to being trumped here by KNN and MLP, indicating that sometimes simpler models such as instance-based and neural ones would do better in modeling the distribution underlying the data. This indicates the importance that empirical evaluation carries in terms of being included across dissimilar model families for S_{11} prediction tasks in antenna-based smart systems.

Despite being saved as 'Best_S_{11}_Model_XGBoost.pkl', XGBoost remained second or third behind KNN and MLP in terms of RMSE and R^2. This result highlights the necessity of a thorough model benchmarking procedure.

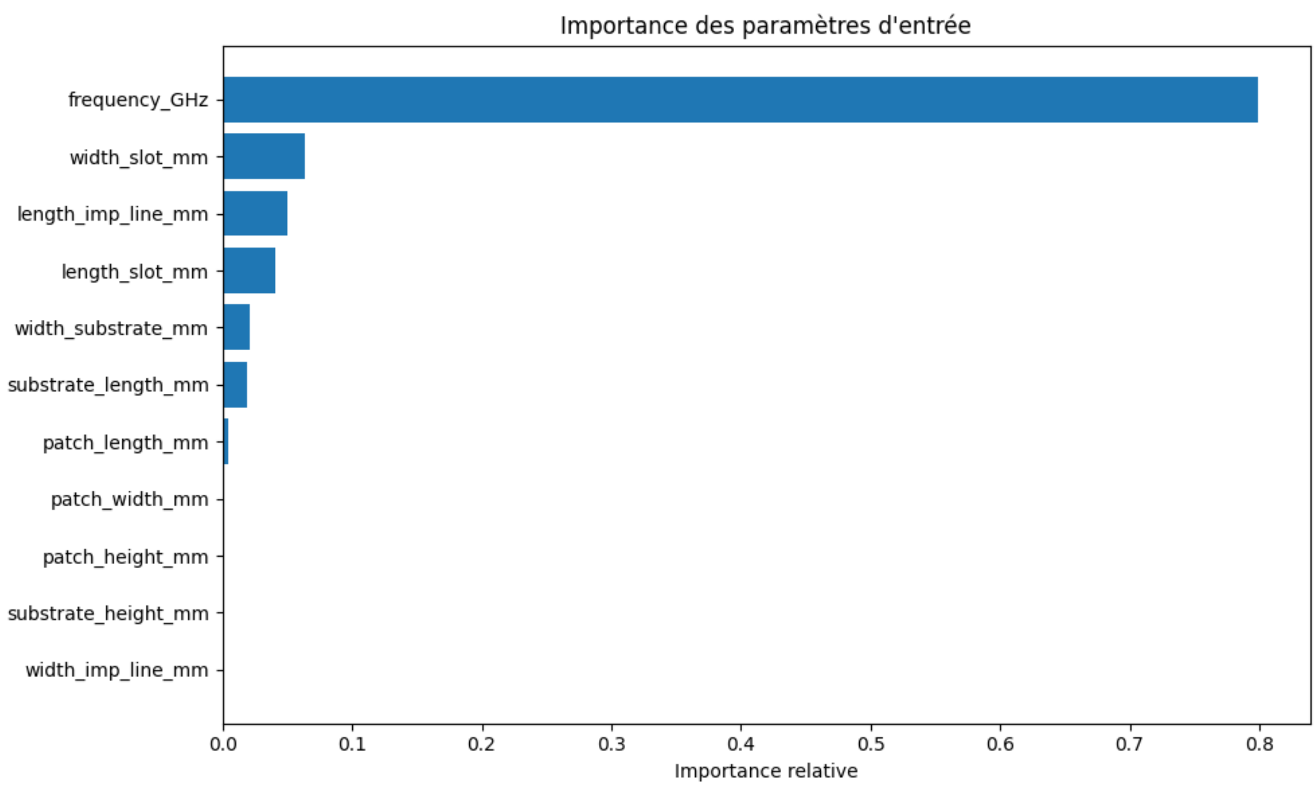

Fig 4. Importance of Parameters

Figure 4 shows the relative importance of each geometric parameter of the antenna in predicting the S_{11} value. It can be observed that the patch width and the length of the feed line are the most influential factors. This analysis confirms well-known physical results while providing a useful prioritization for AI-based optimization. Figure 5 shows how the predictions correlate with the real values for the S_{11} parameter (in dB) from a Multi-Layer Perceptron (MLP) model application. The blue dots denote the respective predicted values plotted against the true ones, with the red dashed line giving the ideal reference line along which the predicted values are exactly equal to the real ones (i.e., y = x).

The scattering of points around the diagonal indicates an excellent agreement between the predicted and real S_{11} values, in the interval from moderate to high reflection (−25 dB to 0 dB). Some slight deviations occur at the extreme ends (for example, $S_{11} < -30$ dB), possibly due to sparse data being recorded at those levels and the difficulty in modeling sharp resonances.

In general, the plot indicates the MLP model achieves a degree of prediction accuracy that reliably demonstrates its ability to learn the nonlinear relationship behind an antenna's design parameters and electromagnetic performance.

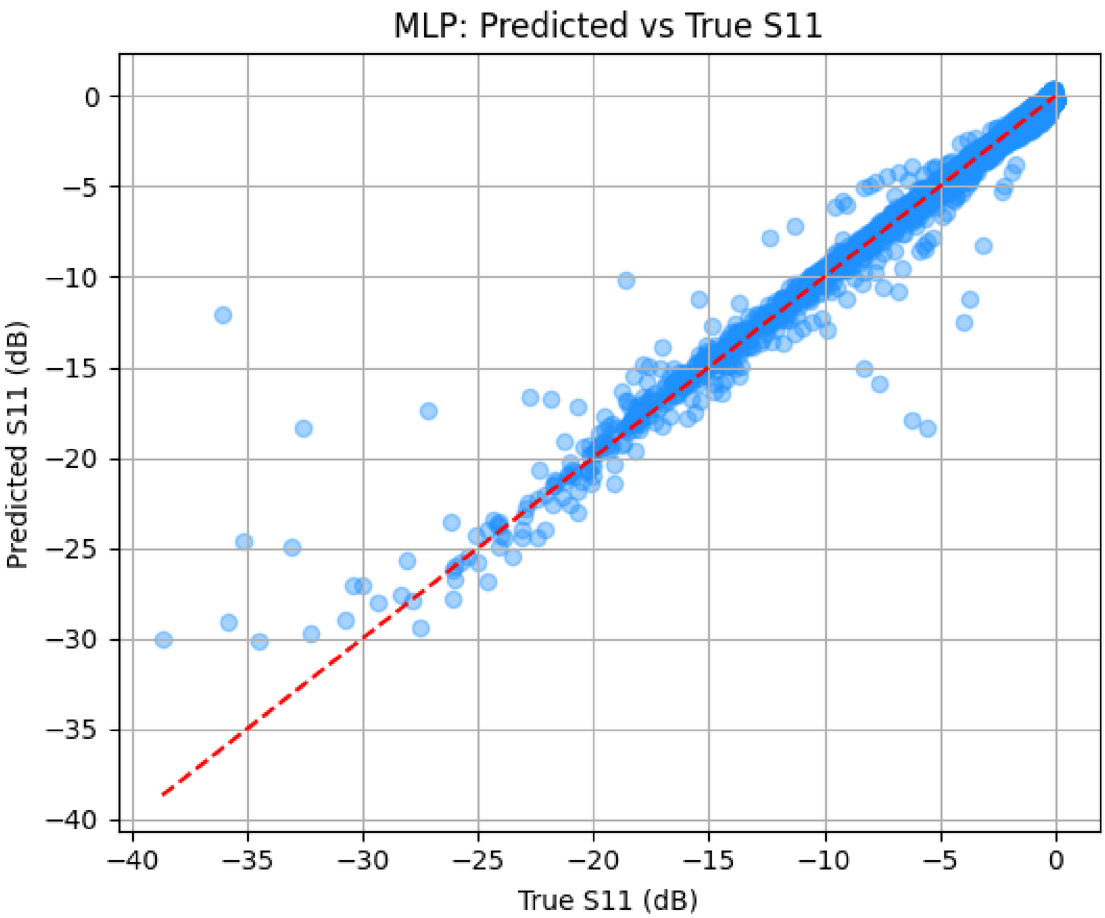

Fig 5. Model prediction performance for S_{11} values. The scatter plot includes 55,000 data points representing predicted vs. actual values, with the solid line indicating the ideal y = x reference

2.3 Pearson correlation matrix between antenna design parameters and performance metrics

Pearson-correlation matrix constructed between all design parameters and performance metrics is represented in Figure 6. Strengths of linear relationships are based on color coding, with red showing strong positive correlation and blue showing either negative or no correlation.

The S_{11} parameter (bottom row) exhibits very weak correlations with all input features (maximum $|r| \approx 0.13$), indicating that no single geometric feature dominates the return loss behavior. Instead, S_{11} is influenced by complex non-linear interactions, reinforcing the need for advanced machine learning models to accurately predict it. And, the operating frequency also shows a low correlation with the physical dimensions, again suggesting a multi-parameter dependency rather than a single driving variable.

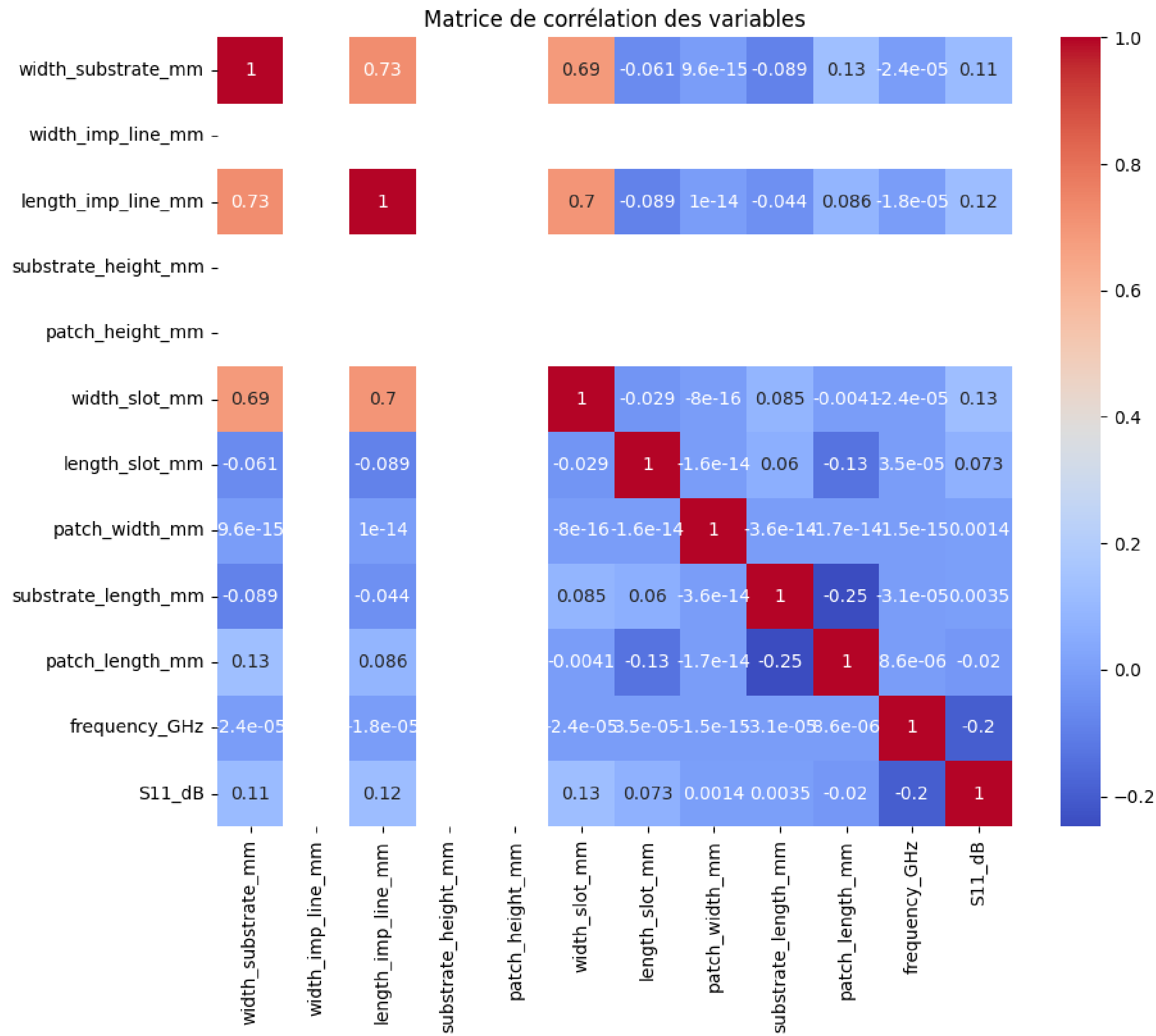

Fig 6. Correlation Matrix Interpretation

These chosen algorithms represent machine-learning paradigms that are applicable for nonlinear regression tasks. KNN serves as an instance-based learner, probably to catch some local patterns within the data. MLP represents a neural network architecture that can teach complex nonlinear relationships. Random Forest and XGBoost are tree-based ensemble methods, both robust, and perform well with heterogeneous feature sets. SVR, meanwhile, offers kernel regression, well suited to high-dimensional spaces. Linear and Ridge Regression work out as baseline linear models for benchmarking. With this diversity in place, one can look at the overall performance capabilities of the models on the proposed antenna dataset.

3 Results and Discussion

3.1 Return Loss (*S11*)

After an exhaustive parametric evaluation of the key geometric parameters like feed length and width, slot length, and width, it was possible to identify the best configuration that would ensure resonance within the intended frequency band.

Figure 7 shows the reflection coefficient (S_{11}) of the final antenna design deployed based upon the optimization parameter values from inverse optimization as well as parametric analysis. The antenna exhibits a deep resonance at 2.45 GHz and a return loss of less than −40 dB with an excellent impedance matching. This final configuration validates the robustness of the design methodology and validates the importance of fine-tuning structural parameters to achieve an optimized performance of ISM-band operations.

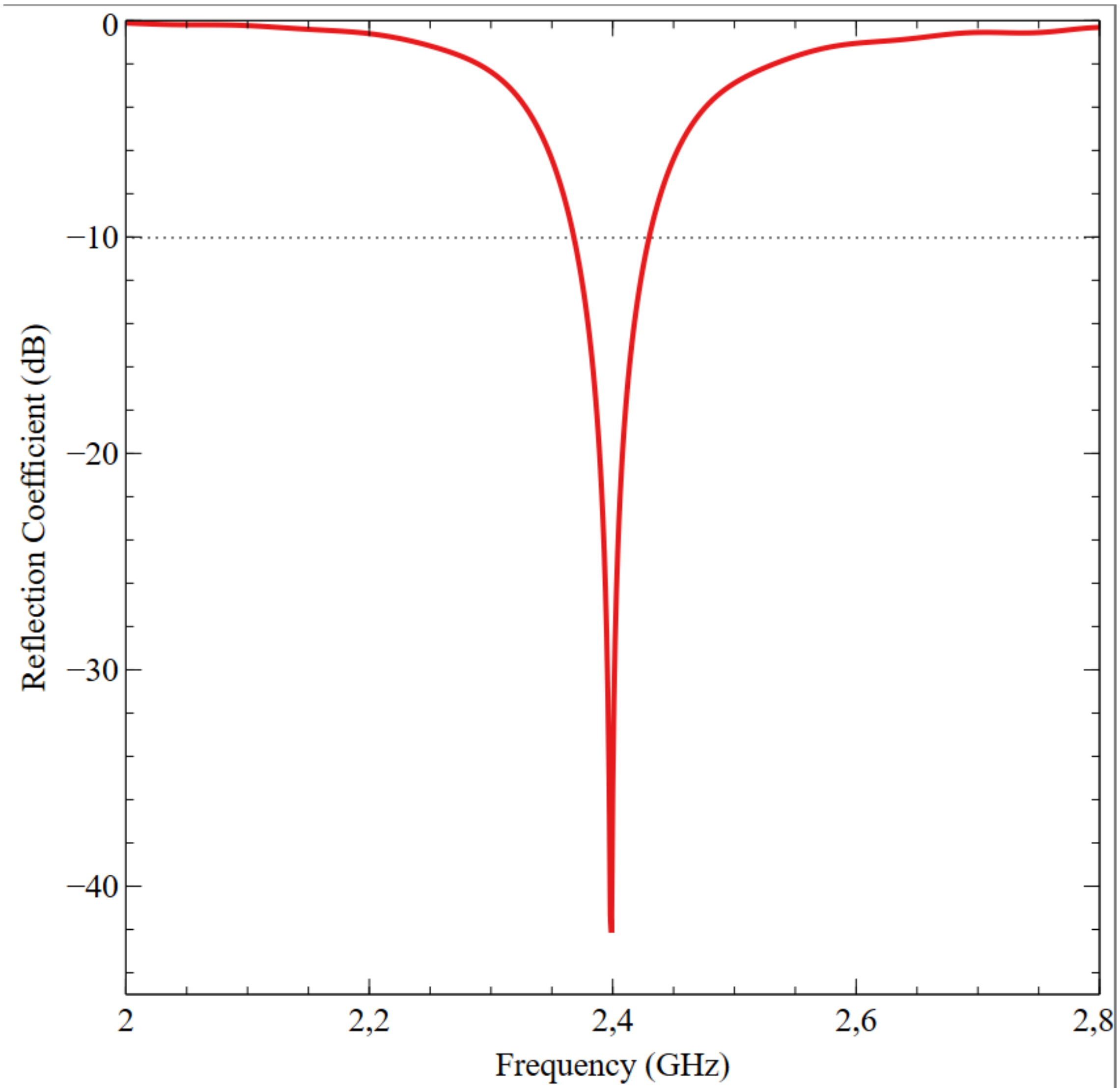

Fig 7. Final structure

3.2 Surface current

Figure 8 illustrates the simulated surface current distribution of the proposed 2.4 GHz microstrip patch antenna. The arrows represent the direction and relative magnitude of the current density on the metallic patch surface. A high current concentration is observed near the feed point and the inset region, shown in red and orange, indicating strong electromagnetic excitation at the feed interface. The current then propagates symmetrically across the patch, diminishing in intensity toward the outer edges. This behavior confirms effective coupling and energy transfer from the feed line into the radiating structure. The distribution pattern is characteristic of the fundamental TM_{10} mode, where the current flows primarily along the patch's length. In this mode, it is guaranteed that the radiation performance is optimal in the target frequency and that the antenna works near its design resonance. The antenna was perfectly excited, and it radiated as expected, thus supporting the theoretical design considerations and showing the effectiveness of the geometric configuration.

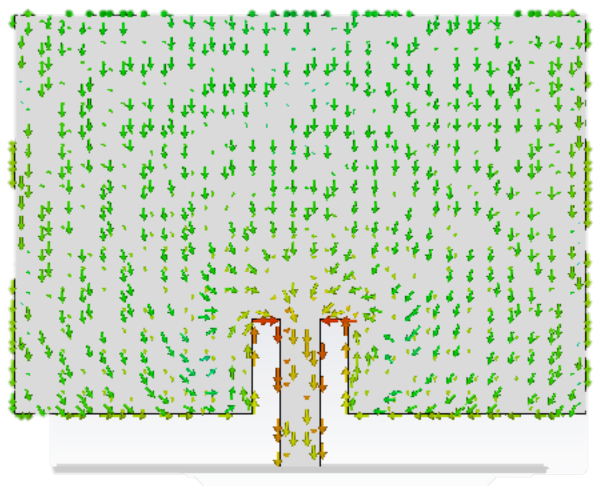

Fig 8. Surface current

3.3 Analysis of Efficiency

The proposed patch antenna with two symmetrical slots shows a measured efficiency of around 82% at the target frequency of 2.45 GHz, which rules within the Industrial, Scientific and Medical (ISM) band and is widely being used in wireless communication techniques such as Wi-Fi, Bluetooth, and RFID as mentioned in Figure 9. Because of this high radiation efficiency, it shows that there are almost losses due to reflection inside the antenna; this means that there is perfect impedance matching and there are also lesser losses due to the conduction of the material. These dual slots seemingly have their application in improving the distribution of surface current that further improves the radiation characteristics and possibly the bandwidth performance.

Compared to traditional single-layer microstrip antennas, such a slot-loaded design provides a more efficient radiation mechanism without sacrificing compactness or manufacturability. Hence, these results validate the slot integration approach and certify the antenna for each high-performance low-area wireless system working in the 2.4 GHz ISM band.

3.4 Radiation Pattern

The radiation performances of the proposed antenna were assessed for its gain and directivity at the operating frequency of 2.4 GHz, and the results are illustrated in Figure 10 below. Referring to the gain pattern in Figure 10, the antenna exhibits a main lobe gain of 4.23 dB at 1.0° thus confirming nearly broadside radiation for typical 2.4–2.5 GHz wireless communication systems. For directivity, the antenna setup has a peak directivity of 5.21 dBi at around 1.0° with 3 dB angular widths of 96.0° for both gain, and directivity. Side lobe levels of −7.5 dB indicate efficient suppression of unwanted radiation, which minimizes electromagnetic interference and enhances radiation efficiency.

Hence, the antenna gives a trade-off between somewhat directional performances and a somewhat wide coverage: hence, it is suitable for IoT, WLAN, Bluetooth, and smart-wearable-based applications in the 2.4 GHz ISM band.

3.5 Comparative study

The proposed method is compared with previous work to demonstrate its effectiveness and originality in Table 3, depicting main points of difference such as the dataset size, number of features, machine learning algorithms used, and the performance metrics (R^2 and RMSE).

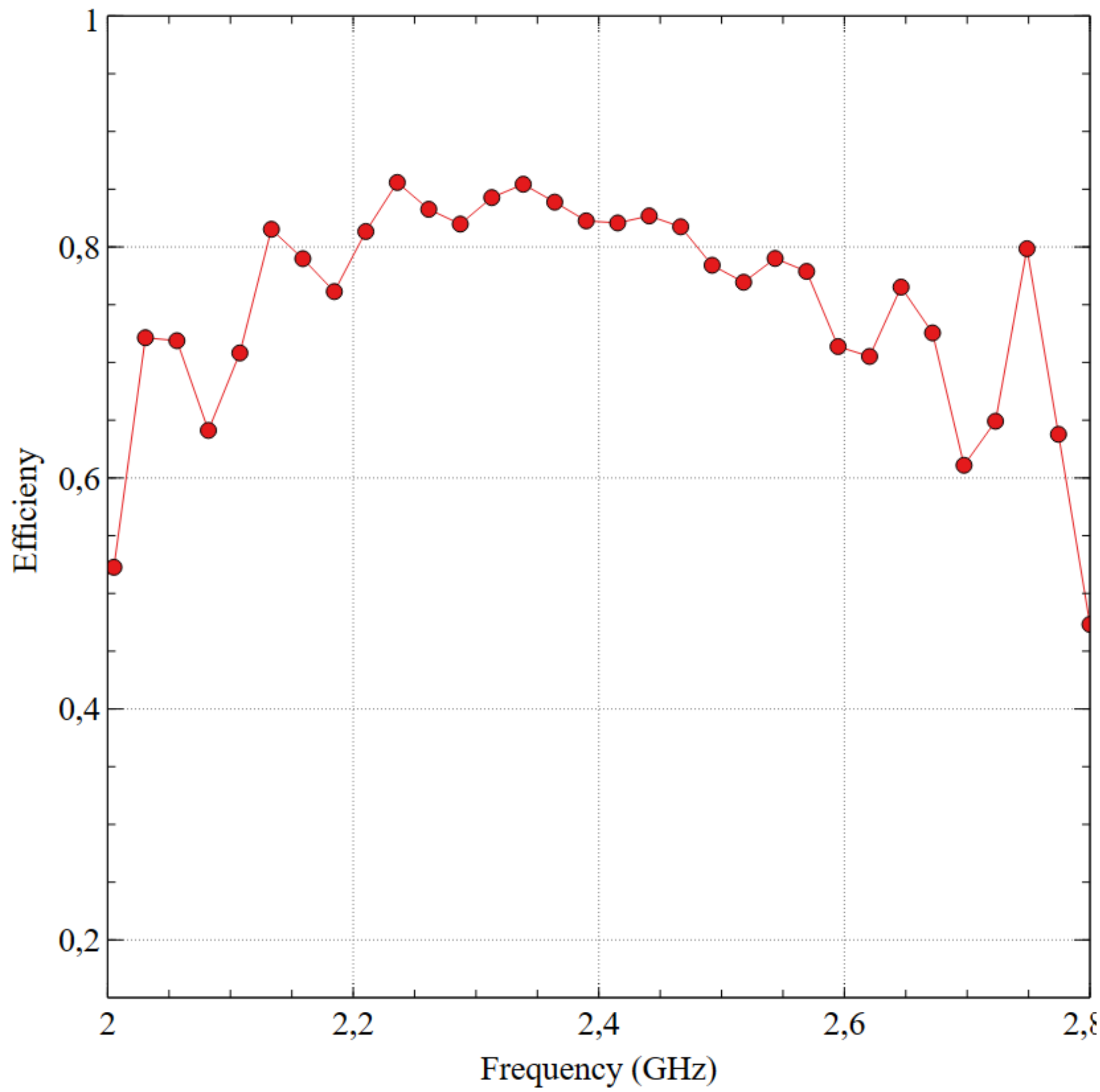

Fig 9. Simulated Efficiency

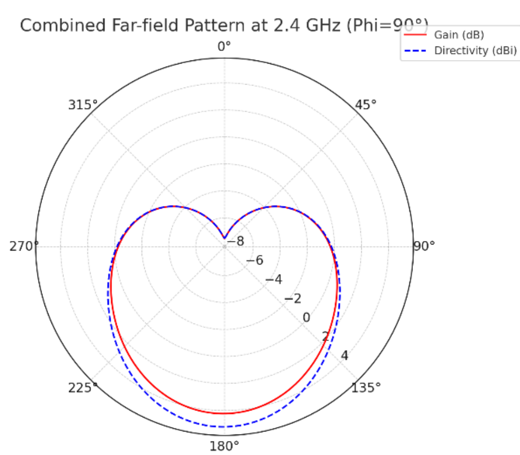

Fig 10. Far-field radiation characteristics of the proposed antenna at 2.4 GHz in the ϕ = 90° plane

Our proposed model trained on a large-scale dataset consisting of 55,000 samples and using 12 input features outperforms accuracy-wise and in error reduction any of the studies in the literature. While a low RMSE indicated that the precision of prediction was higher in ours, the competing works in [17] and [20] achieved R^2 values of 0.75 and 0.9 with RMSE values of 2.024 and 1.608, respectively. By contrast, the study in [21], again with an R^2 value of 0.9 but a much lower RMSE of 0.5027, employed the Random Forest but used a small dataset of 2106 samples and just 6 features.

On the other hand, the KNN-based model proposed here with an R^2 value of 0.9866 and an RMSE value of 0.4 exhibits better generalization and robustness. Although it is a more complex model considering double the number of features against earlier works, our results confirm that using a larger data set with a comprehensive set of features greatly improves prediction accuracy.

Table 3. Comparative study

References	Dataset	Features	Algorithms	R^2	RMSE
[17]	-	6	Random Forest	0,75	2,024
[21]	2106	6	Random Forest	0,9	0,5027
[20]	243	5	SVM	0,9	1,608
This work	55000	12	KNN	0,9866	0,4

Compared to prior works [17], [21], [20], our model benefits from a substantially larger dataset and richer feature set, which leads to improved accuracy and robustness. Notably, our KNN-based model achieved an RMSE nearly 20% lower than the best-performing prior work, highlighting the advantage of large-scale, feature-rich datasets in AI-assisted antenna design.

The superior performance of the proposed approach can be attributed to several factors. First, the large and diverse dataset allows the models to learn a richer mapping between input features and output S_{11} values, reducing overfitting. Second, the feature set includes both geometrical and electrical parameters, which provides the models with more relevant predictive information. Third, systematic hyperparameter tuning was applied to each model, ensuring optimal performance. In contrast, several previous works were limited to smaller datasets or did not explore multiple algorithms, which may explain their lower accuracy. These advantages collectively enable the proposed KNN and MLP models to outperform the state-of-the-art in terms of both RMSE and R^2 metrics.

4 Conclusion

A fast 2.4 GHz patch antenna design and performance prediction tool was proposed, acting as a hybrid between traditional simulators and learning-based algorithms developed on a custom dataset of over 55,000 samples. A parametric study investigated which design parameters exerted the greatest influence while the K-Nearest Neighbors (KNN) and Multi-Layer Perceptron (MLP) modeling methods predicted return loss (S_{11}) with accuracies of more than R^2 = 0.98. With such high accuracy, the entire process was much less dependent on time-intensive full-wave simulations. In layman's terms, the AI approach made simulations 90% faster, which means thousands of configurations can be evaluated in a matter of seconds instead of hours. These observations substantiate the ability of a data-driven modeling approach to reasonably model the intricate nonlinear dependencies governing antenna behavior, thus providing a scalable alternative to rapid antenna prototyping. It should be noted that the current study is based solely on simulated data obtained from CST Microwave Studio. No physical prototype fabrication or measurement was conducted as part of this work. Future research will focus on the fabrication and experimental validation of the proposed antenna designs to further confirm the accuracy and generalization ability of the developed models and will explore inverse designs, multi-objective optimization, transfer learning for other frequency bands, and actual implementation to aid integration into IoT and wireless systems.

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