Machine Learning Driven Design and Optimisation of a Dual-Band SRR Metamaterial Antenna for Emerging IoT Platforms

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***Abstract*—This research introduces a machine learning (ML) technique derived from the dual-band split-ring resonator (SRR) metamaterial antenna development and optimisation. The patch antenna with an SRR design is intended for use in 5G and 6G IoT applications. The method utilizes data driven prediction models to speed up design and optimisation instead of a normal trial and error process. The antenna responses were anticipated using different regression methods, including artificial neural network (ANN), K nearest neighbour (KNN), gradient boosting (GB), and eXtreme gradient boosting (XGBoost). When it comes to the techniques utilized, the eXtreme gradient boosting model was the one that reached the highest accuracy of 87.4 % in estimating return loss and thus it was the one that stood out the most. To support the claim of the effectiveness of the method, a dual-band split-ring resonator loaded microstrip antenna was designed and produced to operate in the ranges of 2.3 GHz to 2.55 GHz and 3.95 GHz to 4.15 GHz, respectively. The close agreement between predictions, simulations, and measurements further confirms the reliability of the machine learning-based design strategy. The proposed approach not only enables fast prototyping of compact antennas suitable for IoT devices, but also for industrial automation, smart home, and smart city applications.**

***Index Terms*—Antenna optimisation; IoT applications; Machine learning; Metamaterial; Smart city; XGBoost.**

I. INTRODUCTION

The development of antennas is still the main focus of modern wireless communication along with the increasingly widespread IoT. A lot of time is spent in coming up with compact, energy efficient designs that would give a stable transmission and reception for a variety of devices [1]. The introduction of metamaterials is one of the major breakthroughs in this field, which are man-made structured materials that can show behaviours with respect to electromagnetic waves such as negative permittivity, negative permeability, or even negative refractive index, properties that are not available in natural materials [2]. The response of these materials is, in fact, related to their internal structure and shape, rather than their chemical nature [3]. Due to the fact that their properties are controllable by changing the dimensions, the outline, or the arrangement of the constituents, metamaterials have been a great asset in enhancing the performance of microwave antennas, particularly those designed for IoT and next generation wireless technologies.

Numerous studies highlight the different kinds of antenna structures that have been developed for IoT devices. For instance, U-shaped antennas that are made for wearable devices work very well in the 2.4 GHz ISM band and take into account the human body-related effects [4]. Multiband antennas not only increase the range of devices, but also allow different communication technologies to operate at the same time [5]. Designs employing Minkowski fractal geometries provide miniaturisation and, at the same time, cover the bands for GPS, radar, and the up-and-coming 5G standard [6]. Moreover, dual-band multiple-input multiple-output (MIMO) configurations have been subsequently proposed to drive high-speed data rate IoT links [7], while some 5G and Wi-Fi dedicated antennas come with features for omnidirectional radiation so as to provide reliable coverage [8]. Moreover, triple-band IoT antennas have also been researched for utilisation in security systems and satellite-based communication [9].

Basic characteristics of antennas such as resonant frequency, bandwidth, gain, efficiency, directivity, and return loss can be evaluated with the help of electromagnetic simulation tools. Furthermore, the simulation tools allow the study of specific parameters of metamaterials, such as negative permeability and refractive index. Historically, antenna design has proceeded by first selecting the geometry, followed by calculating the dimensions, performing simulations, and finally refining the design through iterative improvements [10]. Even though the trial and error approach is effective, it is always associated with the downside of taking a long time, especially when dealing with more complicated structures and stricter performance

Manuscript received 16 August, 2025; accepted 28 September, 2025.

requirements [11]–[16]. These difficulties have led to the search for new and more systematic approaches, and machine learning (ML) has been identified as a very promising one.

ML is definitely an artificial intelligence (AI) technique used for constructing predictive models based on example input data and for further applying them to new, yet to be observed cases. Its usefulness has already been shown in wireless, mobile, and vehicular communication systems for tasks such as traffic estimation, routing decisions, and congestion handling [17]–[19]. ML ability to learn nonlinear relationships has led to its adoption in several antenna related studies. In [20], ML techniques were used to refine the behaviour of a double T-shaped monopole antenna, resulting in minimal prediction error relative to electromagnetic simulations. The authors in [21] showed that random forest algorithms could outperform support vector regression (SVR) and kriging when modelling high-dimensional antenna responses. Data augmented ML methods in [22] improved the performance of circularly polarised base station antennas, while the authors in [23] demonstrated that ML can lower the computational demands of simulation driven optimisation. An efficient K nearest neighbour (KNN)-based approach that significantly speeds up optimisation was reported in [24]. The influence of dataset size on prediction performance was further examined in [25].

Additional studies in [26] showed that ML enabled the optimisation of dielectric resonator antennas in several frequency bands. Comprehensive reviews in [27]–[30] highlighted deep learning and ML as increasingly practical tools for antenna modelling and optimisation, reducing both design time and computational overhead. Further investigations covered travelling wave antennas [31] and rapid optimisation of ultra-wide band (UWB) fractal antennas [32]. A variety of models, including artificial neural networks (ANNs), Support Vector Machines (SVMs) [33], and Decision Trees (DTs) [34], have been applied. ANNs have been widely utilised to enhance bandwidth in dual ring antennas and to estimate the resonant frequency of patch structures [35], [36].

The rapid development of IoT devices has led to a demand for antennas that can withstand dense environments, operate on multiple frequencies, and be deployed in different ways (refer to Fig. 1).

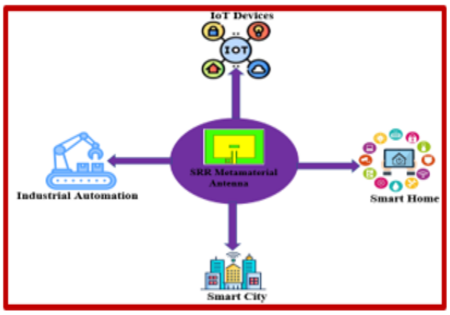


Fig. 1. SRR metamaterial antenna in IoT association of AI, machine learning, and deep learning.

ML methods have turned out to be very helpful in managing all these requirements through the use of IoT-specific constraints that are tailored for predictive modelling and performance tuning [37]–[46]. This work focuses on predicting the resonant frequency, bandwidth, and return loss characteristics of a split-ring resonator-based metamaterial antenna and uses four ML models: ANN, KNN, Gradient Boosting, and XGBoost.

This paper presents a review of the latest advancements in the use of ML in antenna engineering and examines the pros and cons of the different approaches currently available. In detailing the obstacles that remain to be overcome, the study suggests future research avenues that are rich in possibilities and intends to facilitate the widespread utilization of ML in the design of antennas for the growing IoT infrastructure.

II. Machine Learning Driven Framework for Antenna Design

The traditional methods of antenna designing are subject to a variety of limitations, such as the inability to cover wide design spaces efficiently, dependence on simplified models, the need for prolonged iterative processes, and problems have in dealing with the management of complex geometries and multi objective optimisation. To solve these issues, researchers and engineers are now more open to the adoption of data driven learning strategies and smart optimisation techniques. Among them is machine learning (ML), which is a specific area of artificial intelligence that empowers machines to learn from the input data without the explication of the programming, as depicted in Fig. 2. ML identify relationships by training on labeled datasets, enabling them to make predictions and adapt flexibly to new situations. The above-mentioned process of automation and analysis capability remarkably speeds up antenna development, giving rise to shorter design cycles and improved operational efficiency.

The incorporation of ML into traditional antenna design paradigms opens up the possibility of design transformation, thus increasing the adaptability and accuracy of designs. The very first step of the procedure consists of employing CST to come up with the idea, create a model, and run a simulation of a metamaterial microstrip antenna [30]. Subsequently, the antenna design undergoes extensive evaluation and iterative optimisation. A database containing various structural parameters and frequency ranges is created, and the data undergoes normalizing, feature extraction, and data augmentation. For data processing and ML deployment, core Python libraries such as NumPy, Pandas, and Matplotlib are used, and coding is performed in Google Colab [31]. The dataset gets divided into subsets for training (80 %) and testing (20 %), respectively, where the training subset is used for the development and fine-tuning of the chosen ML models [32], [33].

Proper algorithms, such as artificial neural network (ANN), K nearest neighbour (KNN), gradient boosting, and eXtreme gradient boosting (XGBoost), have been utilized to predict the return loss and resonant frequency features of the split-ring resonator (SRR)-based metamaterial antenna. The effectiveness of the model is evaluated through various metrics, including the R^2 score, mean squared error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and fitting and prediction times [34], [35]. The proposed workflow of the framework is depicted in Fig. 3. Ultimately, the simulation and experimental validation of the prototype support the accuracy and reliability of the ML-aided design process.

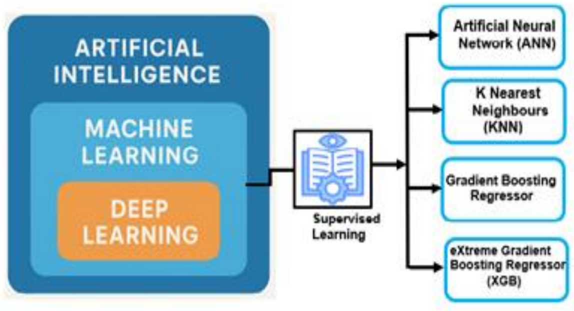


Fig. 2. Association of AI, machine learning, and deep learning.

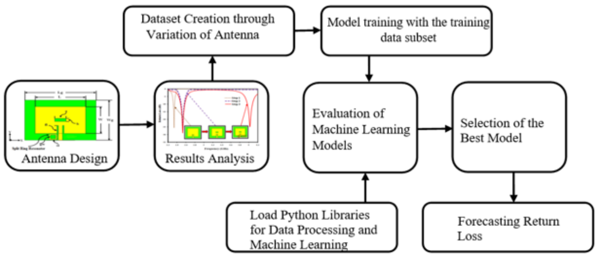


Fig. 3. Flowchart of the SRR-based dual-band metamaterial antenna research methodology.

Impact of Return Loss and Resonant Frequency on Antenna Behaviour. Return loss is an essential parameter that indicates how well the antenna is matched to the characteristic impedance of the system, which consequently governs the quantity of power that is radiated from the source to the free space effectively [24]. This parameter is commonly presented in decibels, and its corresponding formula can be found in (1), which accounts for the incident power and reflected power as P_i and P_r, respectively [36]

$$S_{11} = 10\log_{10}\left(\frac{P_i}{P_r}\right)\text{dB}. \quad (1)$$

The greater the return loss value, the better the power transfer, because only a small part of the signal is reflected, while a lower value indicates poor matching and a larger part of the signal returning to the source [25]. The reduction of return loss is associated with limitation of signal deterioration, increase in radiated power, and thus the overall performance of the antenna system. Therefore, it is one of the important parameters considered in antenna design, testing, and performance optimisation processes.

ML enables one to uncover the nonlinear relationship between return loss and design parameters such as the antenna physical structure and its frequency range. The ability to accurately predict return loss greatly enhances the optimisation process by facilitating impedance matching and reflection suppression, which is particularly crucial for antenna development targeted at IoT applications. To manage these design challenges, multiple ML techniques were incorporated into the study, and a brief overview of the selected models is given in Table I.

TABLE I. LIST OF ML MODELS APPLIED IN THE STUDY.

S. No.	Algorithm	Type	Mathematical Model	Advantages	Disadvantages
1	ANN	Supervised Learning	Neuron output: $y = \sigma(W\text{x} + b)$, where W is the weight matrix, x is the input vector, b is the bias, and σ is the activation function (e.g., ReLU, sigmoid).	Extremely adaptable, capable of modelling complex patterns, and suitable for multiple tasks.	Depends on large datasets, is computationally demanding, and exhibits black-box behaviour.
2	KNN	Nonparametric	Distance metric: $\text{d(x, y)} = \sqrt{\sum(Xi - yi)^2}$ Prediction: $\hat{y} = (1/k)\sum yi$ for regression.	Easy to implement and works well with small datasets.	Requires significant computation for large data, is influenced by outliers, and faces dimensionality challenges.
3	Gradient Boost	Ensemble Learning	Loss function: $L(y, F(x)) = \sum l(yi, F(xi))$ Gradient Boost update: $\text{Fm} + 1(\text{x}) = \text{Fm}(\text{x}) + \gamma\text{hm}(\text{x})$	Highly accurate and capable of solving complex challenges.	Resource-intensive, easily overfits, and lacks interpretability.
4	XG Boost	Gradient Boosting	Objective Function: $\text{Obj} = \text{L}(\text{y}, \hat{y}) + \sum \Omega(\text{fk})$ Regularisation term: $\Omega(\text{f}) = \gamma\text{T} + (1/2)\lambda\sum Wj^2$	Efficient and capable of achieving superior performance.	Has a high computational cost and requires extensive hyperparameter optimisation.

III. Optimising Metamaterial Antenna Design with Machine Learning Techniques

A. *Stage 1: Evolution and Optimisation of Metamaterial Antenna Design*

The proposed antenna design is developed in three progressive phases, integrating a rectangular patch and a square split-ring resonator (SSRR). It is fabricated on an FR-4 substrate with a thickness of 1.6 mm, a dielectric constant (ε_r) of 4.4, and a loss tangent of 0.002, resulting in a compact footprint of $0.31\lambda_0 \times 0.24\lambda_0$. As shown in Fig. 4, *Phase 1* represents a conventional rectangular patch antenna tuned at 2.4 GHz. *Phase 2* introduces a central slot to enhance the impedance bandwidth [41], [42]. *Phase 3* incorporates an SSRR adjacent to the inset feedline, where mutual coupling between the patch and the SSRR produces a magnetic resonance at 4.1 GHz [43], [44].

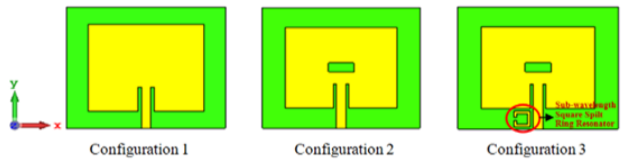


Fig. 4. Evolution of SRR-based metamaterial antenna.

The final configuration of the proposed antenna, illustrated in Fig. 5, presents the optimised dimensions corresponding to the fundamental frequency of 2.4 GHz.

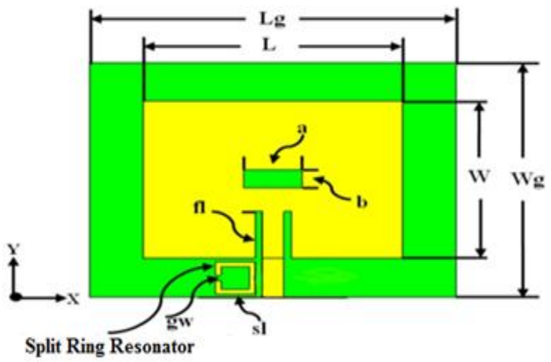


Fig. 5. Dimensions of the proposed antenna.

The design parameters of the SRR-based dual-band metamaterial antenna are presented in Table II. The reflection coefficient (S_{11}) characteristics of the proposed antenna are shown in Fig. 6 at different evolutionary stages. In Phase 1, the conventional rectangular patch resonates at 2.4 GHz with an S_{11} of -27.21 dB, covering the 2.3 GHz–2.55 GHz band. An inset feed is used to achieve better impedance matching, while Phase 2 introduces a slot in the patch to enhance the impedance bandwidth to 250 MHz. In Phase 3, the integration of the SSRR near the feedline enables dual-band operation, retaining the fundamental band (2.3 GHz–2.55 GHz, resonance at 2.4 GHz) and generating an additional band (3.95 GHz–4.15 GHz) with an S_{11} of -29.62 dB, attributed to magnetic resonance induced by the SSRR at 4.1 GHz. In Fig. 7, the proposed antenna induces surface current distribution at 2.4 GHz and 4.1 GHz.

TABLE II. DESIGN PARAMETERS OF THE SRR-BASED DUALBAND METAMATERIAL ANTENNA.

Parameter	Value (λ_0)	Parameter	Value (λ_0)
Lg	0.43	fl	0.07
Wg	0.35	a	0.07
L	0.31	b	0.03
W	0.24	sl	0.035
		gw	0.01

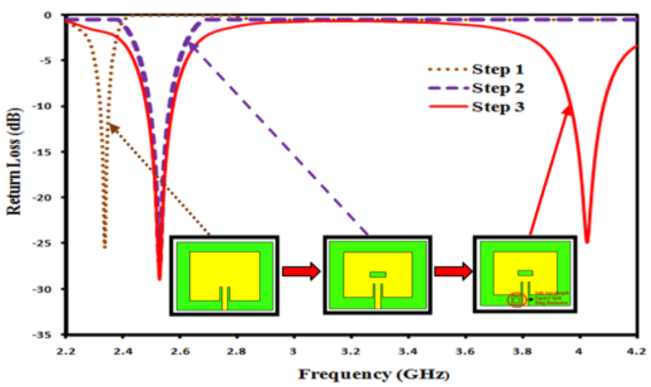
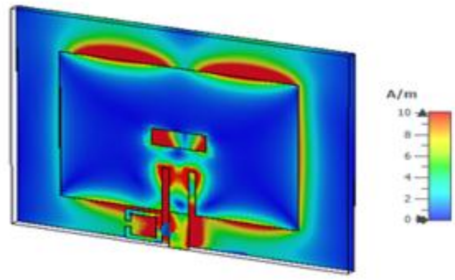
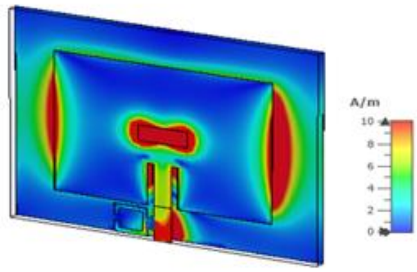


Fig. 6. Return loss comparison for step 1, step 2, and step 3.



(a)



(b)

Fig. 7. Current distributions at (a) 2.4 GHz and (b) 4.1 GHz.

B. Stage 2: Problem Definition and Data Acquisition in Machine Learning

Prediction of antenna return loss characteristics is performed using an ML method, which is further enhanced, with particular emphasis on dual-band operation suitable for Internet of Things (IoT)applications. The primary SRR parameters, which are side length (sl) and split gap (gw), are systematically varied to create a dataset for model training. The operating frequency is also included as an input feature for the learning algorithm along with these parameters. The side length (sl) starts at $0.0035\lambda_0$ and goes up to $0.035\lambda_0$ in steps of $0.0035\lambda_0$, while the split gap (gw) is set between $0.002\lambda_0$ and $0.01\lambda_0$ with an increment of $0.002\lambda_0$. CST simulations check each different setup to get return loss curves from 2.2 GHz to 4.2 GHz frequency range, which is sampled at 450 frequency points. Thus, the total number of data samples from the simulation results is 36,080.

The mean absolute percentage error (MAPE) is defined as the absolute percentage difference between the actual and predicted values, providing a relative measure of prediction accuracy. The time taken to train the model on the dataset is called the "fitting time", and the time taken to make a prediction by the trained model is called the "prediction time" [34], [35]:

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

$$MSE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}, \quad (3)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|, \quad (4)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|. \quad (5)$$

In this case, n represents the number of data points, y_i represents the actual value, $\hat{y}_i$ represents the predicted value, and $\bar{y}_i$ represents the mean of the actual values.

C. Model Testing and Optimisation

The different ML algorithms gave rise to the values of R squared, MSE, MAE, MAPE, fitting time, and prediction time, which are summarised in Table III. The XGBoost model is eventually the one with the best overall performance, even though all models have high accuracy and very low error rates [45], [46]. In the case of return loss values, the actual ones and the predicted ones for each algorithm were illustrated in a manner that Fig. 8 clearly indicates the proper training of the models and the very close resemblance of the predicted and actual responses. The plots created in Python with the help of the Matplotlib library [31] in Google Colab showcase the strength of these tools for visualization and analysis that are not only easy, but also effective.

TABLE III. COMPARISON OF PERFORMANCE METRICS FOR VARIOUS ML MODELS.

Model	R Squared	MSE	MAE	MAPE	Fitting time	Predictive time
ANN	0.7112	9.8641	2.0302	51.0382	155.36	0.0151
KNN	0.7134	9.8126	1.9241	20.432	0.088	0.1434
Gradient Boosting Regressor	0.758	7.6912	1.7468	19.0652	2.5856	0.036
XGB Regressor	0.8737	6.7326	1.4987	12.3699	4.146	0.0218

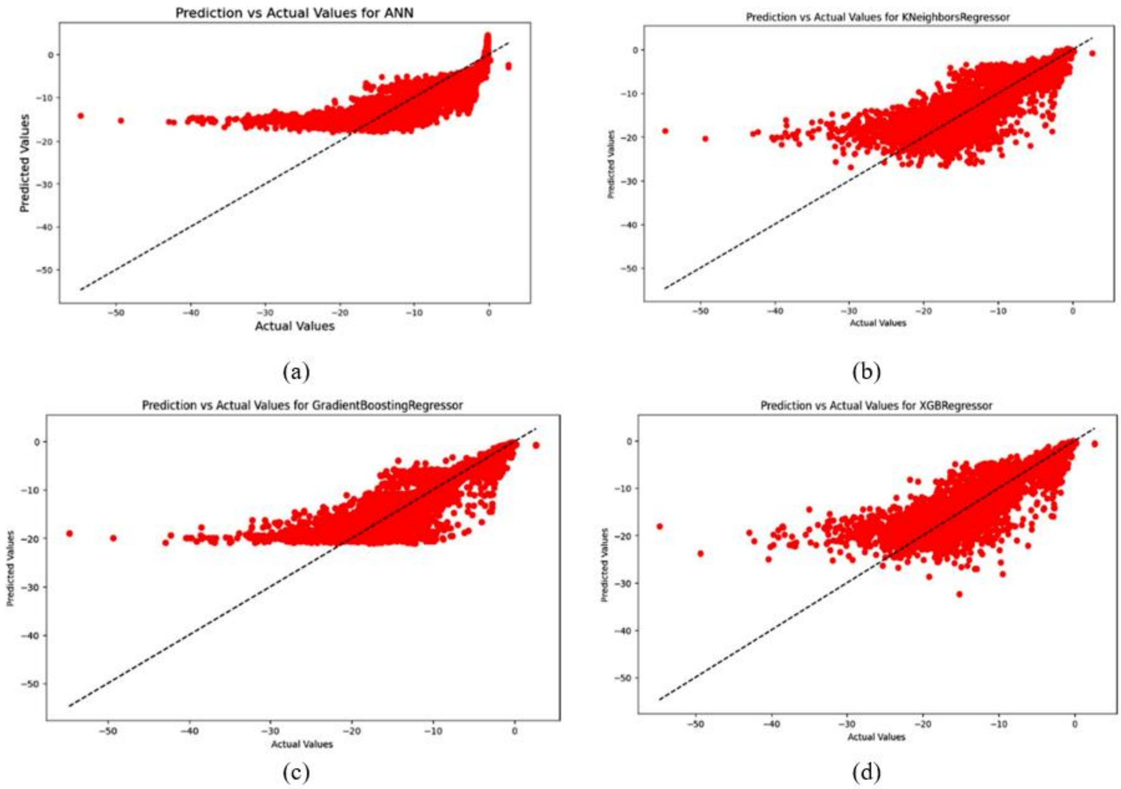


Fig. 8. Actual values vs. predicted values for: (a) Artificial neural network (ANN); (b) K nearest neighbours (KNNs); (c) Gradient boosting; (d) XG boost.

The results indicate that the measured, simulated, and model predicted results are very consistent, which supports the reliability of the ML-based design method. This approach is very fast in terms of antenna development, because it reduces the repetition of the sudden simulations and minimizes the computations needed. The method is as well applicable in a broad spectrum of IoT sectors home automation, IoT devices, industrial automation and smart city networks. Indicatively, in home automation systems, the antenna is used to maintain consistent communication between the smart devices that have been interconnected in order to enable effective remote monitoring and control. However, in industrial IoT automation, it is useful in gathering and transmitting data efficiently in predictive maintenance and asset tracking.

IV. Results and Discussions

Following the XGBoost-based optimisation in Stage 3, a new antenna design was generated to verify the model prediction accuracy. Parameters were randomly selected, with sl = $0.035\lambda_0$ and gw = $0.01\lambda_0$.

The fabricated prototype, shown in Fig. 9, was realised on an FR-4 substrate with a dielectric constant of 4.4, a loss tangent of 0.002, and a thickness of 1.6 mm. The antenna operates in two frequency bands: 2.3 GHz to 2.55 GHz, resonating at 2.4 GHz with a return loss of -27.21 dB, and 3.95 GHz to 4.15 GHz, resonating at 4.1 GHz with a return loss of -29.62 dB. Return loss measurements were performed using a Keysight N9918A Vector Network Analyzer. Figure 10 compares the measured, simulated (CST) and XGBoost predicted return loss values, showing excellent agreement among them and validating the accuracy and reliability of the proposed machine learning-based antenna design method. Minor variations between measured and simulated outcomes are primarily due to fabrication tolerances, substrate property variations, and measurement uncertainties, but these remain within acceptable limits and do not significantly affect performance [45], [46]. The Conet Technologies anechoic chamber measurement setup is shown in Fig. 11, and the radiation patterns at 2.4 GHz and 4.1 GHz are presented in Figs. 12(a) and 12(b), respectively.

Table IV provides a comparative summary of the present work with existing studies, demonstrating the superior performance and validation of the proposed approach.

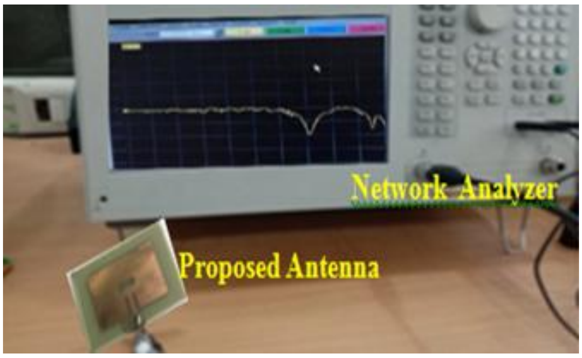


Fig. 9. Fabricated antenna with network analyzer for return loss measurement setup.

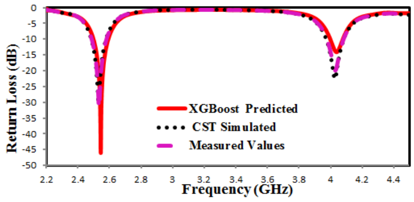


Fig. 10. Comparison of return loss between XGBoost predicted, CST simulated, and experimentally measured values.

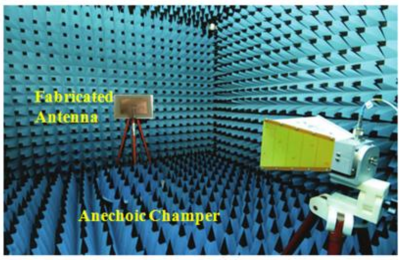


Fig. 11. Comparison of return loss between XGBoost predicted, CST simulated, and experimentally measured values.

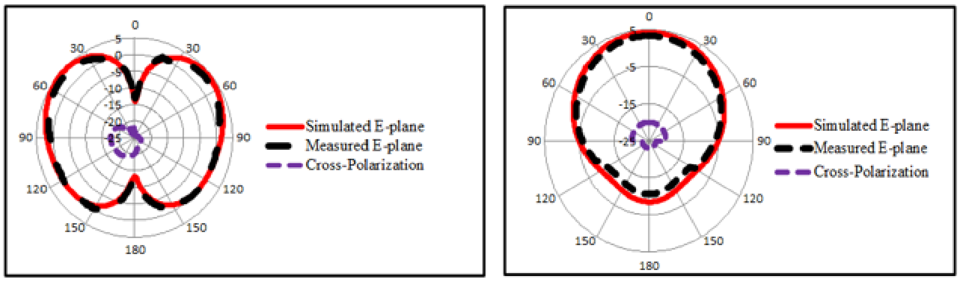


Fig. 12. Anechoic champer measurement setup.

TABLE IV. COMPARISON OF PERFORMANCE METRICS FOR VARIOUS ML MODELS.

Ref.	Antenna Type	Patch Size (λ^2)	Frequency Band	ML Approach used	Key findings
[3]	Dual-band metamaterial inspired monopole antenna	0.3×0.2	2.40 GHz–2.48 GHz, 5.15 GHz–5.80 GHz	-	Achieves effective miniaturisation while providing resonances for both lower and upper Wi-Fi bands.
[10]	Miniaturised Patch Antenna	0.38×0.38	2.42 GHz–2.48 GHz	-	Complementary split-ring resonators were positioned between the patch and the ground plane to achieve a four-fold miniaturisation.
[11]	Frequency reconfigurable coplanar stripline (CPS)-like meta-material antenna	0.4×0.4	2.2 GHz–2.6 GHz	-	This work introduces a compact CPS type metamaterial antenna with a simple geometry that supports frequency reconfigurability at 1.8 GHz (GSM) and 2.4 GHz (WLAN).
[12]	Frequency reconfigurable microstrip patch array	0.43×0.10	1.95 GHz–1.97 GHz, 2.35 GHz–2.37 GHz	-	A compact series fed microstrip patch array employing CRLH transmission lines and PIN diodes to enable frequency reconfigurability and broadside radiation.
[13]	Metamaterial-inspired dual-band frequency reconfigurable antenna	0.67×0.67	2.36 GHz–2.60 GHz, 3.34 GHz–3.73 GHz	-	The proposed antenna provides omnidirectional and broadside radiation patterns.
[20]	Double T-shape monopole	0.6×0.6	2.4 GHz–3.0 GHz, 5.15 GHz–5.6 GHz	Lasso, KNN, ANN	A 2.90 % deviation from the HFSS simulation was observed for the KNN model.
[22]	Circularly polarised base station antenna	2.3×0.11	3.13 GHz–3.48 GHz	Random forest with data augmentation	DA-RF enhances the AR bandwidth by 41 % and boosts optimisation accuracy.
[24]	Dipole antenna and new dumb-bell-shaped slot antenna	0.37×0.25 (dipole) 0.4×0.4 (dumbbell)	1.6 GHz–2.8 GHz (dipole), 4 GHz–5 GHz (dumbbell)	ANN, GPR, KNN, Modified KNN	The modified KNN method operates 5 to 30 times faster than conventional ML techniques.
[42]	MIMO antenna	0.30×0.30	2.4 GHz	ANN and Random forest	Flexible solution for next gen communication and smart infrastructure.
Proposed Antenna	**Split-ring resonator-based dual-band metamaterial antenna for IoT**	**0.31×0.24**	**2.3 GHz–2.55 GHz, 3.95 GHz–4.15 GHz**	**ANN, KNN, gradient boost, XG boost**	**ML offers high prediction accuracy, rapid processing, and low error rates, making it a reliable solution for antenna design in IoT, Industrial IoT, Smart city, and emerging IoT applications.**

V. CONCLUSIONS

The research demonstrates a machine learning (ML)-based approach for designing and optimising a dual-band SRR metamaterial antenna suited for emerging IoT communication systems. Four ML models were carefully explored, and the XGBoost model performed best, achieving a prediction accuracy of 87.4 % on return loss. The model was also very stable and precise, with a mean squared error (MSE) of 6.73, a mean absolute error (MAE) of 1.49, and a mean absolute percentage error (MAPE) of 12.36. The training time was 4.146 seconds and the prediction time was 0.0218 seconds. The prototype antenna was then manufactured and experimented with, and the experimental data were in good agreement with the simulated ones. The antenna is most effective at a frequency of 3.95 GHz–4.15 GHz, resonating with a return loss of -29.62 dB and a frequency of 2.3 GHz–2.55 GHz, resonating with a return loss of -27.2 dB. The findings suggest that ML can be applied effectively to antenna engineering, providing a stable and valid solution to enhance the performance of future IoT and wireless communication systems.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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