Design and Comparative Analysis of THz Antenna through Machine Learning for 6G Connectivity

Rachit Jain, Vandana Vikas Thakare, and P.K. Singhal

***Abstract*—The rise of sixth-generation (6G) technology has become increasingly necessary to meet the growing demand for high-speed internet and the continuous advancements in technology. The development of an optimal antenna design is crucial to attain the required performance and capabilities. Traditional electromagnetic modeling approaches for antenna design are, however, time-consuming and computationally intensive requiring long simulation time and high-end computing systems. Therefore, Machine Learning (ML) technology can be utilized to deal with these limitations in the context of Terahertz (THz) antenna design, which has not been done before. The main objective of this work is to develop an antenna that operates in the THz Band, which is the essential 6G band for the future infrastructure revolution, and to predict and optimize the antenna's return loss using ML models like K-Nearest Neighbour (KNN), Extreme Gradient Boosting (XG-Boost), Decision Tree, and Random Forest and Mean Squared Error (MSE) of 3.816. The findings show that all of these models perform accurately, particularly Random Forest having the highest accuracy of 82% in predicting the return loss. ML offers novel possibilities for the development of optimized and efficient 6G antennas for high-speed communication.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/8517

***Index Terms*—6G, Decision Tree, KNN, Machine Learning, Random Forest, Return Loss, THz Antenna, XG-Boost.**

I. INTRODUCTION

Terahertz (THz) antennas are unique antennas developed for the transmission and reception of terahertz electromagnetic waves [1]. This band of the electromagnetic spectrum falls between the microwave and infrared regions and has huge possibilities for a variety of applications such as communication, sensing, imaging, and spectroscopy [2]. THz antennas play an important role in these systems because they allow for optimal energy and information transfer between the source and the target [3]. THz antenna design and fabrication, on the other hand, can be challenging, which requires significant research towards novel antenna structures, materials, and development techniques. THz antennas offer exciting possibilities to revolutionize diverse fields, from medical imaging and wireless communication to environmental monitoring and security screening [3], [4]. THz antennas are gaining interest in the development of sixth-generation (6G) communication systems due to their potential for high-speed data transfer and large bandwidths [4]. The 1 THz - 3 THz frequency band is used for various applications such as high-speed wireless communication, imaging, sensing, and spectroscopy. In high-speed wireless communication, this frequency band is utilized for achieving high data transfer rates and low latency in future 6G networks [5], [6]. THz imaging is useful for non-destructive testing and imaging applications, such as detecting defects in materials, monitoring food quality, and medical imaging. THz sensing involves the detection of chemicals and gases, and it is useful in security and environmental monitoring applications. THz spectroscopy is used for the analysis of the molecular structure and composition of materials, and it has applications in chemistry, biology, and materials science [3], [7].

Surface roughness at THz frequencies significantly impacts the performance of THz antennas, contributing to increased ohmic and surface losses. Advanced manufacturing techniques like 3D printing [8] and Focused Ion Beam (FIB) [9] technology offer potential solutions to minimize losses and optimize antenna efficiency. 3D printing allows for rapid prototyping of waveguides, horn antennas, and THz lenses, offering cost-effective and precise miniaturization benefits. In contrast, FIB technology enables the manufacturing of complex antennas like spiral antennas, overcoming challenges associated with traditional lithography, and enabling the creation of smoother antenna surfaces. The new THz process technology encompasses conventional micro-mechanical methods, including lithography and laser milling, along with innovative approaches like electroforming, discharge, and thick photoresist applications [2]. Notably, electroforming involves depositing conductive materials onto antenna structures, reducing the impact of surface roughness on antenna performance. Harnessing these manufacturing techniques and process technologies holds promise for minimizing ohmic, surface losses and optimizing THz antenna performance, fostering the development of efficient and high-performance THz communication systems for various applications [2], [7]-[8].

THz antenna for 6G connectivity must have high efficiency and low loss via optimized design and materials. Wide bandwidth to support higher frequencies. Compact size for device integration and flexible deployment. Effective thermal management for sustained performance. Directional radiation with high gain enhances signal strength and

Rachit Jain, Vandana Vikas Thakare, and Pramod Kumar Singhal are with Madhav Institute of Technology and Science, Gwalior, India. (e-mail: rachitjain2709@gmail.com, vandana@mitsgwalior.in and pks_65@mitsgwalior.in).

minimizes interference. Cost-effective manufacturing for mass production and commercial viability [2]-[6]. Overall, meeting these technical requirements as mentioned in Fig. 1 is crucial in developing THz antennas that can support the high-speed and high-capacity communication necessary for 6G systems.

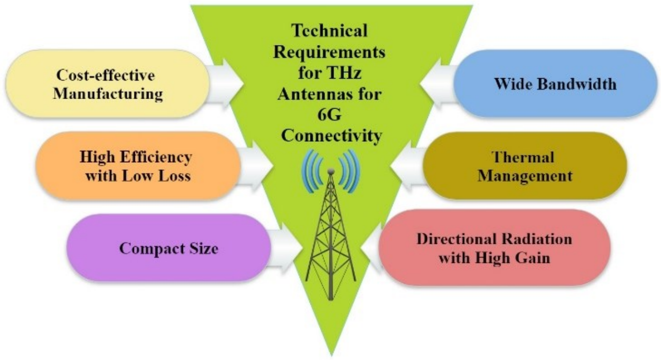


Fig. 1. Technical requirements for THz antennas.

The iterative process of refining antenna designs based on testing and simulations, especially in the domain of THz antennas, poses significant challenges for antenna engineers [2], [4]. This challenge arises from the necessity to frequently conduct computational electromagnetic simulations to attain the desired performance. THz antennas typically function at high frequencies characterized by short wavelengths. Simulating these frequencies demands substantial computational resources, including precise spatial and temporal resolutions to accurately capture THz behaviors. The optimization procedure often entails making incremental adjustments to antenna parameters, conducting simulations, and assessing outcomes. This iterative sequence may need to be reiterated multiple times to achieve the desired performance, thereby extending the overall timeline for design refinement. Machine learning (ML) can indeed offer a valuable solution to the time-consuming and computationally intensive process of optimizing THz antennas. By integrating ML into the THz antenna design process, engineers can streamline optimization efforts, reduce the number of resource-intensive simulations, and expedite the development of efficient THz antennas [10]. ML-based optimization algorithms streamline the search for optimal antenna configurations, reducing iterative cycles. Predictive ML models offer real-time guidance to designers, expediting decision-making [11]. This not only saves time and computational resources but also enhances the overall design efficiency and performance, to develop cutting-edge THz communication systems for 6G and beyond.

A. Machine Learning in Antenna Design

Artificial intelligence (AI) stands as a revolutionary technology, acknowledged for its transformative potential. AI, serving as the overarching domain, encompasses tasks that traditionally rely on human intelligence, such as recognizing objects or sounds, comprehending natural language, and solving complex probabilistic problems [12]. Within AI, ML emerges as a vital subset, enabling computers to autonomously acquire knowledge and insights from data and experience, all without explicit programming [11]. In recent years, the application of ML algorithms in the design and optimization of antennas has become increasingly popular. It can help automate the antenna design process, reduce design time and costs, and improve antenna performance [13]-[17]. It can be trained to analyze and interpret data collected from antenna measurements [18]-[20]. By training an ML model on a large dataset of measurements, it is possible to identify patterns and anomalies in the data that would be difficult to detect manually [10]-[11]. When ML is integrated with neural networks, it is known as Deep Learning [21]. The relationship between Artificial Intelligence, Machine learning, and Deep Learning is shown in Fig. 2. There are three categories of ML [3]: Supervised learning is a type of ML where the algorithm learns from labeled data, meaning that it is provided with inputs and corresponding desired outputs to learn the mapping between them [22]. Unsupervised learning, on the other hand, is a type of ML where the algorithm learns from unlabeled data, meaning that it must find hidden patterns or structures in the data on its own [23]. In reinforcement learning algorithms learn through interaction with an environment, receiving rewards or penalties for actions [22], [23].

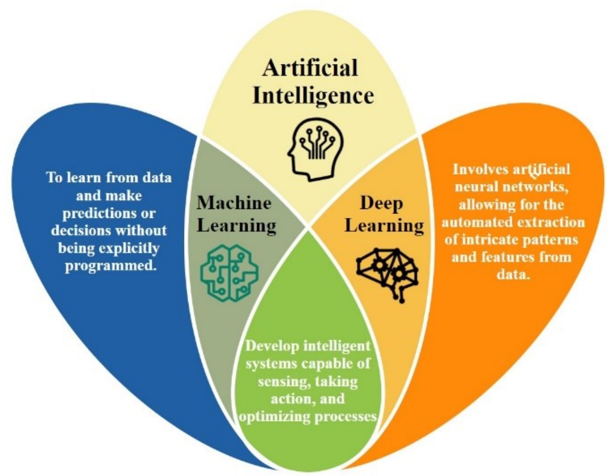


Fig. 2. Relationship between artificial intelligence, machine learning, and deep learning.

B. Summary of Related Work Employing Machine Learning in Antenna Design

Several researchers have explored the application of ML techniques to forecast antenna performance. In [13] authors proposed a multi-objective antenna design method that combines the use of Second-Order Gaussian Process Regression and Multi-Source Co-Training with Multi-Objective Learning methods that achieve improved prediction accuracies and convergence speed in antenna designing. The paper [14] introduces a surrogate model-assisted differential evolution algorithm, which utilizes a Gaussian process machine learning approach to predict the function value and uncertainty of new points making it suitable for practical antenna synthesis and complex antenna design optimization. Another article [16] compares three ML algorithms for optimizing double T-shaped monopole antennas, highlighting

ML's potential to transform electromagnetic modeling. A separate paper [17] explores AI applications in antenna design, reviewing various AI approaches and advocating for future research in the evolving field. The author [18] introduces an intelligent antenna synthesis system based on ML, showcasing superior classification and prediction accuracy compared to traditional models. In the paper [19] optimizes a Coplanar Waveguide (CPW) fed band-notched monopole antenna using ML, with KNN achieving 98% precision. Reference [20] provides a comprehensive review of ML and deep learning in antenna design for various applications, emphasizing efficiency and problem-solving potential. In [24] authors proposed a model that simplifies the design process and optimization of structures for the specified frequency of 5G antenna, resulting in reduced time and greater simplicity of implementation. In [25] authors proposed efficient resonant frequency predictions of microstrip antenna using Gaussian Process Regression, In [26] reliable return loss (S_{11}) predictions have been obtained using ML models for Dielectric Resonator Antenna. The author [27] introduced an intelligent ML model that combines a Fuzzy system and a Decision tree classifier, achieving a remarkable 99% accuracy in both antenna classification and geometric parameter prediction. In reference [28], the author introduced an ML-driven generative optimization technique employing masked auto-encoders to enhance multi-objective antenna decoupling structures, achieving a minimum 6 dB improvement in antenna isolation. In [29], the author presents an ML-based framework for computing resonance frequency in reconfigurable antennas and investigates beamwidth control using PIN diodes as a cost-effective alternative to simulations. In [30], the author introduces an ML-based method for predicting resonance and directivity in a quasi-Yagi antenna, showcasing remarkable accuracy in directivity predictions with minimal error.

These recent research papers demonstrate the potential of ML-based approaches for various antenna designs. As THz technology is still in its infancy and relatively unexplored, it is possible that ML techniques could offer new insights and solutions for optimizing antenna performance at these frequencies. THz antenna optimization with ML algorithms has not been explored as rigorously by previous researchers. The goal of this work is to explore the application of ML in optimizing THz antennas, with a focus on enhancing design efficiency and performance for advanced communication systems, as well as to conduct a comparative analysis of ML models for antenna design with return loss predictions.

The rest of the article is organized as follows: In Section 2, the research work methodology for antenna development, and the implementation of ML were presented. Section 3 provides a comprehensive presentation of the results and discussions. Finally, Section 4 concludes the article.

II. Research Work Methodology

The objective of this work is to design a THz antenna that operates in THz bands and applies ML to improve the process of optimization of a THz antenna return loss value, determining the most computationally efficient and accurate algorithm for predicting the behavior of THz antennas. By leveraging ML algorithms to analyze data and forecast parameters, the aim is to expedite design iteration cycles, enhance antenna performance, and minimize resource-intensive simulations.

A. Significance of Return Loss in the Antenna Domain

Return loss is the measure of how well an antenna or transmission line is matched to the impedance of the system to which it is attached. It ensures that the antenna efficiently transfers power from the source to free space, which is essential for effective wireless communication. It is defined as the ratio of the power that is reflected to the source due to impedance mismatch to the power that is incident on the antenna or transmission line. Return loss is usually expressed in decibels (dB) and is a measure of the amount of power that is lost due to impedance mismatch, mentioned in (1) [31].

$$S_{11} = 10\, log_{10}\left(\frac{P_{in}}{P_{ref}}\right) dB \tag{1}$$

A high return loss indicates that most of the power is being transmitted to the load, while a low return loss indicates that a significant amount of power is being reflected back to the source. In practical applications, return loss is crucial to ensure that the antenna performs optimally in terms of radiation efficiency, gain, directivity, and impedance matching. High return loss helps to minimize signal loss, increase the effective radiated power, and enhance the performance of the overall system. As a result, return loss is a critical parameter that must be considered during the design, testing, and optimization of antennas. Its significance concerning the antenna is shown in Fig. 3.

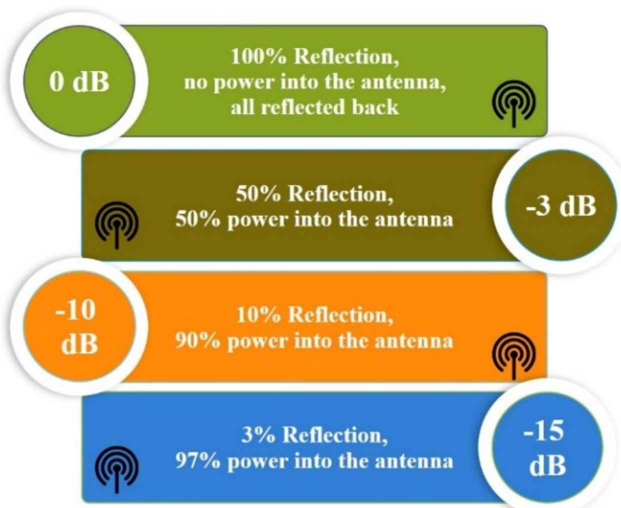


Fig. 3. Significance of Return Loss in Antenna.

B. Proposed Methodology

Return loss is a critical parameter in antenna design and analysis because it directly relates to antenna performance, signal quality, and efficiency. It's important to note that, in this specific case, the Joule's Effect losses are not taken into account in the design process and are assumed negligible. This recognition highlights the unique considerations involved in optimizing antenna performance for this specific application. Moreover, including Joule's Effect losses in the design process might demand significant computational resources, and incorporating them could introduce complexity to the analysis. For specific applications or scenarios, simplifying the model by omitting negligible factors can streamline the design process and facilitate easier analysis and optimization [32]. To predict return loss using ML, a dataset is created by varying dimensions with all these design parameters variation in the design and simulation of each antenna is done in Ansys High-Frequency Structure Simulator (HFSS) [33], to train the ML model, the dataset is split into training and testing subset, in which the first 80% is used for training the model, and the remaining 20% is used for testing the model [34]. After that accuracy is checked, how well the model is performing through performance metrics like R square & mean square error, and a new design variation is given to the best model to see the prediction of return loss. Python programming [35] is chosen to execute these models due to its versatility, rich libraries, ease of use, and user-friendly nature. The flowchart of the proposed methodology is shown in Fig. 4.

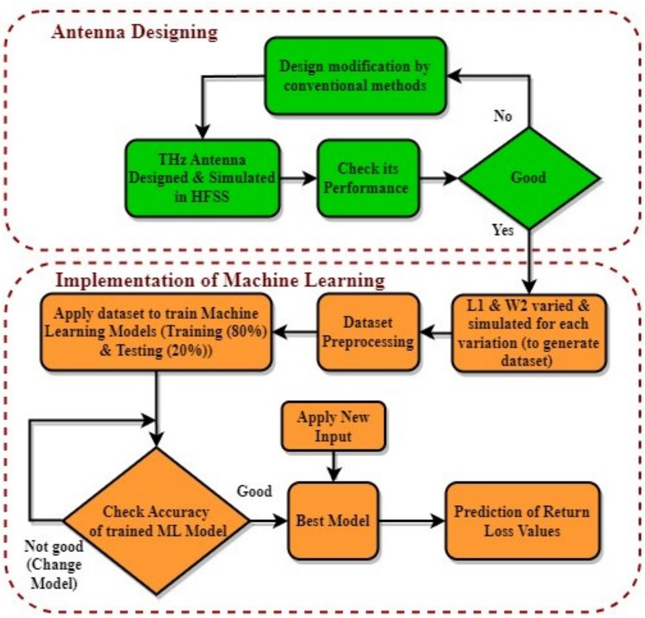
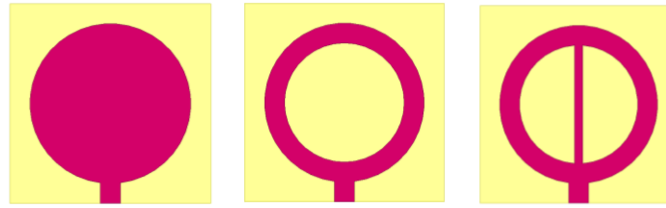


Fig. 4. Proposed methodology flowchart.

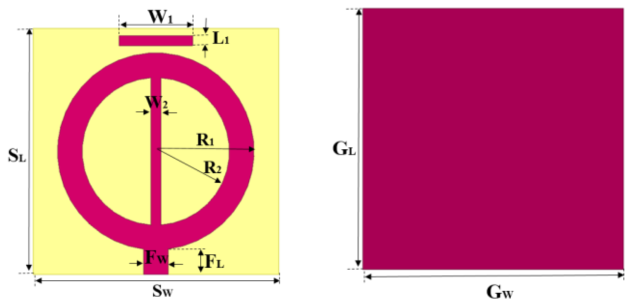
C. Antenna Dimensions & Development

Fig. 5 and 6, show the proposed antenna structure along with its' design iterations, which is planned to emit radiations at the THz frequency band of 1 THz - 3 THz, whose dimensions are mentioned in Table I. The length of the substrate is 100 µm, the width is 100 µm and the thickness is 10 µm. The substrate used for the proposed antenna is RT/Duriod6010 (εr=10.2) with a height of 10 µm. The radius of the concentric circular patch is 40µm which is 10 µm wide and divided into two halves as shown in Fig. 5. The microstrip feed line has a length of 10 µm and a width is 10 µm. Parasitic element of length 30 µm & width 4 µm. Ansys HFSS software has been used for the simulation and analysis of the antenna.



(a) Design 1 (b) Design 2 (c) Design 3

Fig. 5. Antenna Design iterations.



(a) Front View (b) Back View

Fig. 6. Dimensions of Design 4 (Proposed Antenna).

TABLE I
ANTENNA DIMENSIONS

Parameters	Dimensions in µm
W_1	30
W_2	4
L_1	4
R_1	40
R_2	30
F_L	10
S_L	100
$S_W = G_L = G_W$	100

D. Implementation of Machine Learning Models

The initial step in using ML to predict the return loss (S_{11}) is to train a model. To do this, a dataset is created by varying the lengths of L_1 and W_2, which serve as input features to the ML algorithms, along with frequency (F) as an additional input feature. The resulting value will be a single parameter, return loss, which is referred to as a label, represented in (2).

$$f(L_1, W_2, F) = S_{11}\ (values) \tag{2}$$

L_1 is varied from 1 µm to 9 µm with a step size of 1 µm, while W_2 is varied from 1 µm to 9 µm with a step size of 1 µm, For each antenna design generated through these parameter variations, simulations are run in HFSS to obtain the corresponding return loss values over a frequency range of 1 THz - 7 THz, divided into 451 points. This process results in the generation of a dataset having 113,649 values, which are used to train and test the ML models. The next step is data preprocessing which is a crucial step in ML that involves cleaning, transforming according to relevant features, and organizing raw data to make it suitable for training ML models. The training set consists of 80% of the data, while the remaining 20% is used for testing the model [34], [36]. To extract patterns hidden in the training data, the next step is to obtain a relation between the input and output parameters that can be set up for prediction. Regression is a fundamental tool in supervised ML, particularly when dealing with problems that involve predicting continuous relationships between input features and the target variable [36]. It offers a clear and interpretable way to model relationships between variables and make predictions based on those relationships.

The ML models that can do regression analysis employed in this work are addressed as follows: Decision Tree [37] is an ML model that indicates decisions and their potential outcomes in the form of a tree. In a decision tree, the complete data set is partitioned into subsets, and the output will belong to the subset where the input features fit. They are powerful as they are capable of handling non-linearity, feature relationships, and missing information. The random forest algorithm [38] is based on a decision tree algorithm. The decision tree algorithm employs only one tree, but the random forest technique uses a large number of trees to create a forest. The final prediction is made by combining predictions from all trees. The gradient boosting technique Extreme Gradient Boosting (XG-Boost) [39] is an intelligent ML algorithm. It is intended to improve predictive performance by adding weak learners (typically decision trees) to the model in a sequential manner while minimizing errors. XG-Boost is well-known for its effectiveness, adaptability, and excellent predicted accuracy. K-Nearest Neighbours (KNN) [40] is a relatively easy ML technique that may be utilized for both classification and regression tasks. It is a non-parametric learning method that produces predictions based on similarities between the new data point and its neighbours in the training dataset. Building an ML model typically begins with loading the dataset. Once the dataset is loaded, various ML models can be applied to it. Python programming is implemented through Google Colab [41] for ML model development and experimentation because it gives access to free cloud-based Graphical & Tensor Processing Unit (GPU/TPU) resources, which simplifies the setup process and enables developers to focus on modeling and experimentation rather than managing infrastructure.

III. Results and Discussions

This section commences with a comprehensive analysis of the proposed THz antenna. Following this, an evaluation of various ML models utilized in the research is carried out, accompanied by a comparison using performance metrics. The section concludes with the presentation of comparative analyses featuring informative graphs, with a particular emphasis on return loss analysis. These analyses encompass a meticulous investigation into both simulated and predicted return loss for randomly generated variations in antenna design. This approach provides valuable insights into the effectiveness of ML revolutionizing THz antenna design.

A. Analysis of Proposed THz Antenna

From Fig. 5, Design 1 is a simple circular patch antenna having a THz band from 1.6 THz to 2.68 THz, resonating at 2.1 THz with -15 dB return loss, and some small bands resonating at 3.5 THz, 4 THz, 4.4 THz, 4.8 THz, 5.2 THz with -16 dB, -17 dB, -19 dB,-17 dB, -17 dB return loss respectively. Further the n next modification i.e. Design 2, circular slot of radius 30 µm in which THz band occurs between 2.1 THz to 3.2 THz resonating at 2.7 THz & 3 THz with a return loss of -17.3 dB & -17.7 dB respectively along with some small THz bands resonating at 3.5 THz, 4 THz, 4.4 THz with a return loss of -28 dB, -20.8 dB & -20.3 dB respectively. Further modified by inserting a vertical stub at the center of the concentric circular patch which gives the result two bands from 1.8 THz to 2.7 THz & 2.8 THz to 3.1 THz resonating at 2.4 THz & 3 THz with a return loss of -20.4 dB & -16 dB respectively also some small bands resonating at 3.5 THz & 4.2 THz with a return loss of -33 dB & -22 dB respectively. In the final Design 4 as shown in Fig. 6, which is the proposed antenna that gives THz wideband from 1.8 THz to 3.3 THz resonating at 2.8 THz with a return loss of -24 dB along some small THz bands resonating at 3.7 THz, 4.1 THz, 4.6 THz with return loss of -24 dB, -23 dB & -20 dB respectively, which can be seen in the comparison of return loss for Design 1 to Design 4 in Fig. 7.

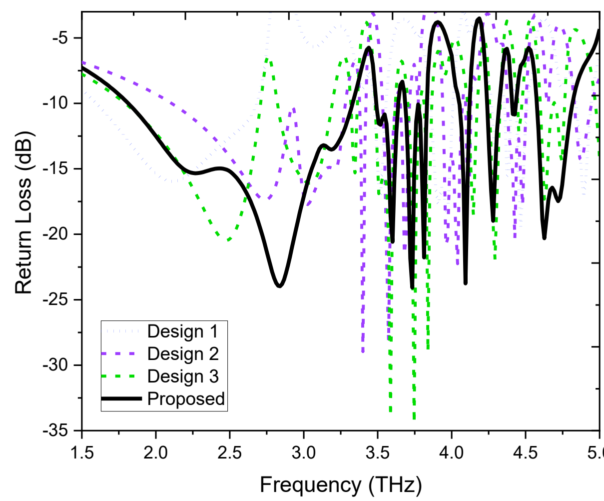
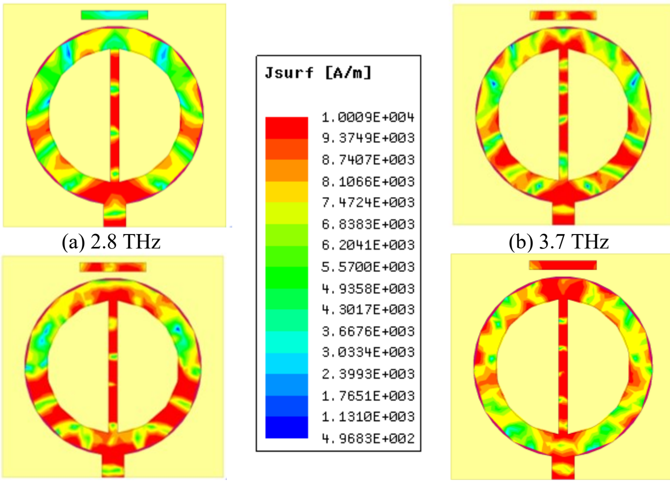


Fig. 7. Comparison of Return Loss for Design 1, Design 2, Design 3 & Design 4 (Proposed antenna).

The surface current distribution represents the primary electric current within the radiating patch induced by the electromagnetic field. This analysis helps examine the energy flow across the antenna structure, providing insights into the distribution of electromagnetic waves over the patch surface. By identifying potential losses and inefficiencies, it aids in optimizing the antenna system's performance. Fig. 8 presents the surface current distribution of the proposed design at 2.8 THz, 3.7 THz, 4.1 THz, and 4.6 THz frequencies, highlighting the specific region of the radiating patch crucial for resonating the antenna at the desired frequency.



(a) 2.8 THz (b) 3.7 THz (c) 4.1 THz (d) 4.6 THz

Fig. 8. Surface Current Distribution at (a) 2.8 THz, (b) 3.7 THz, (c) 4.1 THz, (d) 4.6 THz.

B. Performance Metrics to Evaluate Machine Learning Models

To evaluate the performance of these ML models, metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), R-square, Mean Absolute Percentage Error (MAPE), Fit Time (in seconds), and Prediction Time (in seconds) score were used [33]. The accuracy of the model based on the predictions made on the entire training dataset was determined using MSE as represented in (3).

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

The determination of how effectively an ML model predicts observed outcomes can be achieved through the R-square value, as represented in (4).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (4)$$

On the other hand, the MAE, as shown in (5), corresponds to the mean of the absolute difference between the model prediction and the true value.

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

The MAPE serves as a relative indicator of prediction accuracy, calculated as the average percentage difference between predicted and true values, as represented in (6).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(y_i - \hat{y}_i)}{y_i}\right| X\ 100 \quad (6)$$

where n is the number of data points, y_i is the true value, $\hat{y}_i$ is the predicted value, and $\bar{y}_i$ is the mean of true values.

Fit time “T_fit” is the amount of time required to train an ML model on a given dataset. Prediction time “T_predict” is the amount of time it takes for a trained ML model to make predictions.

The performance metrics, including R-Square, MSE, MAE scores, Fit time, and Prediction time predicted by various ML algorithms are presented in Table II. It is noteworthy that all the models exhibit an accuracy level above 71%, indicating their potential usefulness, with minimal error. Random Forest attains the best predictive accuracy with the lowest MSE value of 3.816, although it requires the most time for predictions, with a Prediction Time of 0.8913 seconds. On the other hand, KNN stands out as the fastest to train, with a Fit Time of 0.0165 seconds. Overall, Random Forest outperforms with the highest R-Square and lowest MSE, making it the top-performing model, while KNN is the fastest model to train, but its performance is not as good as Random Forest, which can be seen in Fig. 9.

TABLE II
COMPARISON OF PERFORMANCE METRICS FOR DIFFERENT ML MODELS

Model	R-Square	MSE	MAE	MAPE	T_fit (sec)	T_predict (sec)
Decision Tree	0.715	6.257	0.987	0.104	0.353	0.009
Random Forest	0.826	3.816	0.861	0.094	0.891	0.058
XG-Boost	0.807	4.262	1.110	0.122	4.181	0.016
KNN	0.787	4.672	0.877	0.108	0.016	0.027

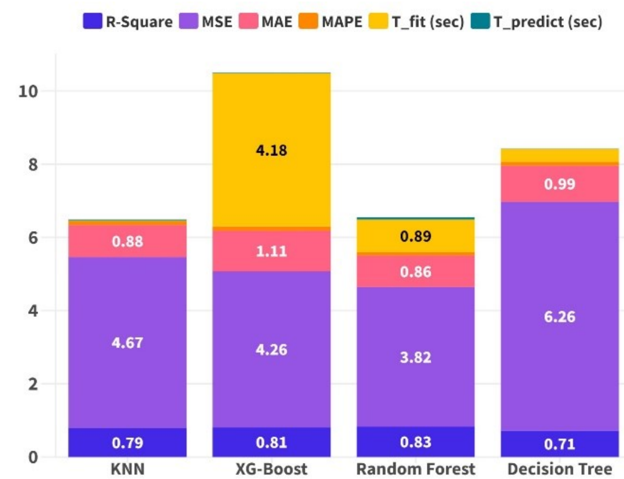
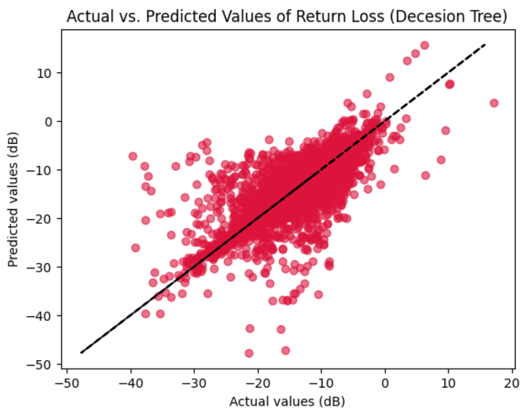


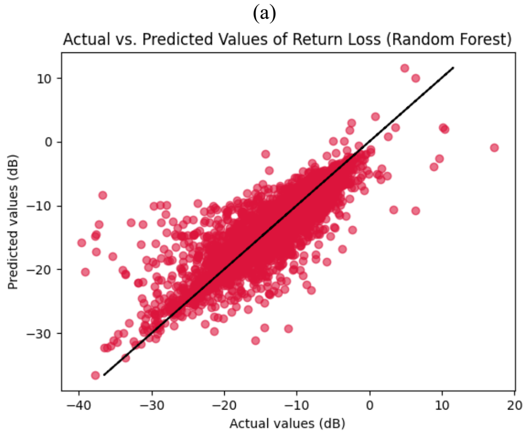
Fig. 9 Comparison graph of performance metrics.

C. Graphical Representation in Terms of Return Loss Analysis

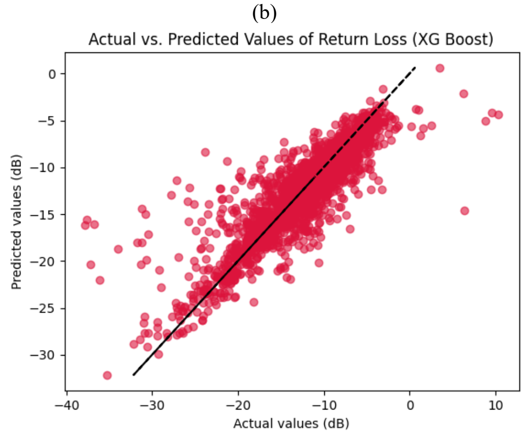
In Fig. 10, the graphical representation showcases the alignment between forecasted and factual return loss values for Decision Tree, Random Forest, XG-Boost, and KNN within the 1 to 7 THz frequency span. This visual evidence substantiates the models' precise training, affirming the remarkable congruence between predicted and real values. Notably, these graphs were generated using Python programming in Google Colab with the Matplotlib library, demonstrating the versatility and utility of these tools in data visualization and analysis.



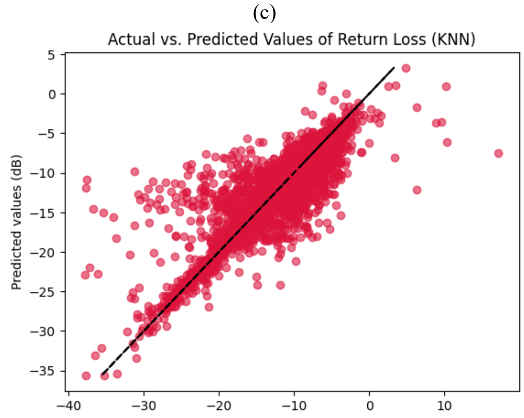
(a)



(b)



(c)

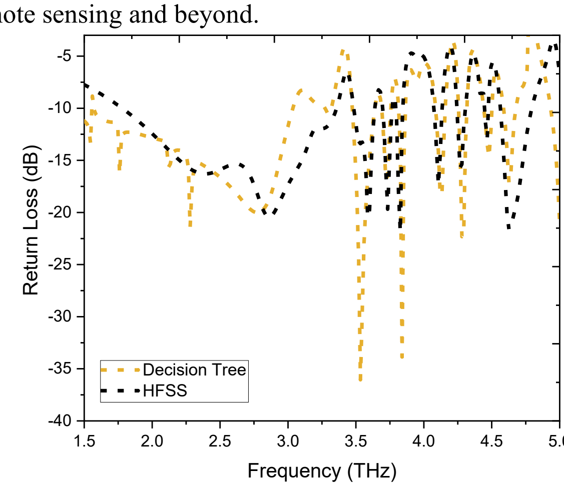


(d)

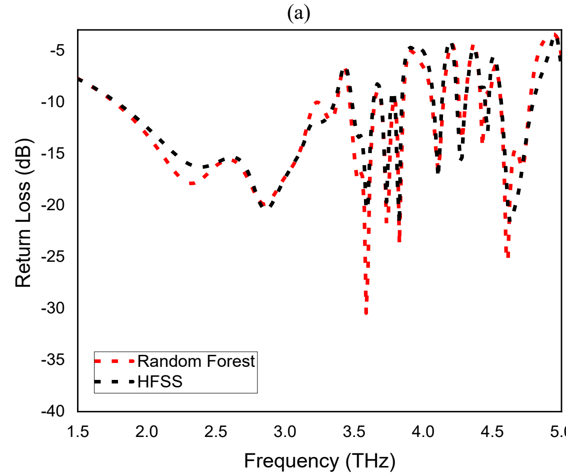
Fig. 10. Actual values versus predicted values of Return Loss (a) Decision Tree, (b) Random Forest, (c) XG-Boost, (d) KNN.

D. Simulated and Predicted Return Loss for Random New Variation in Antenna Design

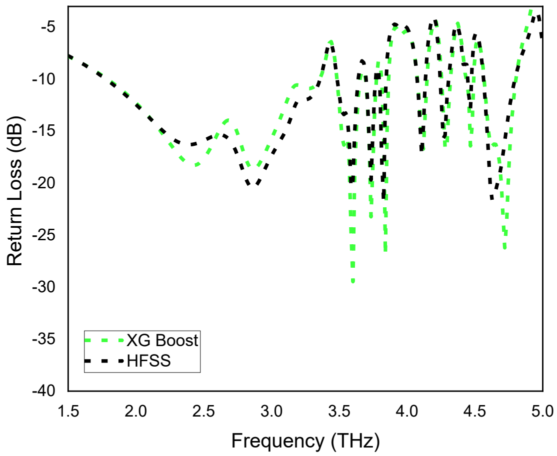
Innovative antenna design often requires extensive electromagnetic simulations to fine-tune performance, a process that can be resource-intensive and time-consuming. This study introduces a paradigm shift by leveraging ML to optimize antenna performance swiftly. After training ML models, to test prediction capability a new antenna configuration with a random variation (L_1= 3.5 µm & W_2=5.5 µm) is used as input to the models, these values are not included in the training and testing of the model. Fig. 11 illustrates a compelling outcome: the return loss values predicted by various ML models (a) Decision Tree, (b) Random Forest, (c) XG-Boost, and (d) KNN) closely align with those obtained from rigorous electromagnetic simulations. This impressive convergence signifies a breakthrough in antenna design efficiency. It means that antenna engineers can harness the predictive power of ML to rapidly optimize antenna parameters without the need for protracted electromagnetic simulations. By significantly reducing the iterative cycles required for optimization, ML not only expedites the design process but also conserves computational resources. This transformative approach facilitates the development of cutting-edge antennas with reduced time and effort, ultimately advancing the capabilities of various applications, from wireless communication to remote sensing and beyond.



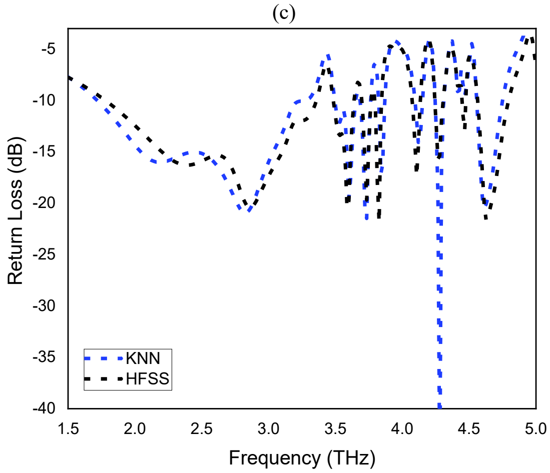
(a)



(b)



(c)



(d)

Fig. 11. Simulated & Predicted Return loss for random new variation in antenna design (a) Decision Tree, (b) Random Forest, (c) XG-Boost, (d) KNN.

IV. Conclusion

In conclusion, designing an optimal THz antenna that meets the requirements of 6G communication is a challenging task due to the numerous design factors involved. In this work, ML models such as KNN, XG-Boost, Decision Tree, and Random Forest were used to predict the return loss of an antenna operating at the THz band, which is an essential 6G band for future infrastructure. With an accuracy exceeding 71%, the results demonstrate strong performance across all models, with the Random Forest model leading the pack at 82% accuracy. Additionally, the Random Forest model exhibits a minimal MSE of 3.816, indicating exceptional accuracy in minimizing the squared error between predicted and actual values. However, this advantage is associated with a slightly longer prediction time, approximately 0.8913 seconds. In contrast, KNN demonstrates the quickest fit time at 0.0165 seconds but lags in performance compared to the Random Forest, which excels in R-Square and MSE values, making it the preferred choice. The work is distinctive as it is the initial effort to forecast the return loss of THz antennas using ML methodologies. This method differs from conventional ones that use simulation and analytical approaches for predicting antenna performance. It is a promising option for researchers and engineers working in the field of THz technology since it can significantly reduce the time and processing power needed for antenna design.

Acknowledgment

The author expresses deep gratitude to P.K. Singhal, V.V. Thakare, and P. Ranjan for their invaluable contributions, guidance, and resources, which were instrumental in the successful completion of this project.

References

[1] S. Koenig, D. Lopez-Diaz, J. Antes, F. Boes, R. Henneberger, A. Leuther, A. Tessmann, R. Schmogrow, D. Hillerkuss, R. Palmer, T. Zwick, C. Koos, W. Freude, O. Ambacher, J. Leuthold, and I. Kallfass, "Wireless sub-THz communication system with high data rate," Nature Photonics, vol. 7, no. 12, pp. 977–981, 2013.

[2] Y. He, Y. Chen, L. Zhang, S. Wong, and Z. N. Chen, "An overview of terahertz antennas," China Communications, vol. 17, no. 7, pp. 124–165, 2020, doi: https://doi.org/10.23919/J.CC.2020.07.011

[3] V. Petrov, A. Pyattaev, D. Moltchanov, and Y. Koucheryavy, "Terahertz band communications: Applications, research challenges, and standardization activities," IEEE Xplore, Oct. 01, 2016.

[4] Z. R. M. Hajiyat, A. Ismail, A. Sali, and Mohd. N. Hamidon, "Antenna in 6G wireless communication system: Specifications, challenges, and research directions," Optik, vol. 231, p. 166415, Apr. 2021, doi: https://doi.org/10.1016/j.ijleo.2021.166415.

[5] M. H. Rahaman, A. Bandyopadhyay, S. Pal, and K. P. Ray, "Reviewing the Scope of THz Communication and a Technology Roadmap for Implementation," IETE Technical Review, pp. 1–14, Jun. 2020, doi: https://doi.org/10.1080/02564602.2020.1771221.

[6] R. Jain, K. Aole, S. Mittal, and P. Ranjan, "An Analysis on Wireless Communication in 6G THz Network and Their Challenges," Terahertz Devices, Circuits and Systems, pp. 167–181, 2022, doi: https://doi.org/10.1007/978-981-19-4105-4_10.

[7] A. Bandyopadhyay and A. Sengupta, "A Review of the Concept, Applications, and Implementation Issues of Terahertz Spectral Imaging Technique," IETE Technical Review, vol. 39, no. 2, pp. 471–489, Jan. 2021, doi: https://doi.org/10.1080/02564602.2020.1865844.

[8] B. Zhang, Y.-X. Guo, H. Zirath, and Y. P. Zhang, "Investigation on 3-D-Printing Technologies for Millimeter-Wave and Terahertz Applications," Proceedings of the IEEE, vol. 105, no. 4, pp. 723–736, Apr. 2017, doi: https://doi.org/10.1109/jproc.2016.2639520.

[9] V. Lubecke, K. Mizuno, and G. M. Rebeiz, "Micromachining for terahertz applications," IEEE Transactions on Microwave Theory and Techniques, vol. 46, no. 11, pp. 1821–1831, Nov. 1998, doi: https://doi.org/10.1109/22.734493

[10] H. M. E. Misilmani, T. Naous, and S. K. Al Khatib, "A review on the design and optimization of antennas using machine learning algorithms and techniques," International Journal of RF and Microwave Computer-Aided Engineering, vol. 30, no. 10, Jul. 2020, doi: https://doi.org/10.1002/mmce.22356.

[11] Sadiq, M., bin Sulaiman, N., Isa, M.M. and Hamidon, M.N., 2022. A Review on Machine Learning in Smart Antenna: Methods and Techniques. TEM Journal, 11(2), p.695. Available: https://www.ceeol.com/search/article-detail?id=1045967.

[12] Russell, Stuart J. Artificial intelligence a modern approach. Pearson Education, Inc., 2010

[13] Q. Wu, H. Wang, and W. Hong, “Multistage Collaborative Machine Learning and its Application to Antenna Modeling and Optimization,” IEEE Transactions on Antennas and Propagation, vol. 68, no. 5, pp. 3397–3409, May 2020, doi: https://doi.org/10.1109/tap.2019.2963570

[14] B. Liu, H. Aliakbarian, Z. Ma, G. A. E. Vandenbosch, G. Gielen, and P. Excell, “An Efficient Method for Antenna Design Optimization Based on Evolutionary Computation and Machine Learning Techniques,” IEEE Transactions on Antennas and Propagation, vol. 62, no. 1, pp. 7–18, Jan. 2014, doi: https://doi.org/10.1109/tap.2013.2283605

[15] J. P. Jacobs, “Efficient Resonant Frequency Modeling for Dual-Band Microstrip Antennas by Gaussian Process Regression,” IEEE Antennas and Wireless Propagation Letters, vol. 14, pp. 337–341, 2015, doi: https://doi.org/10.1109/lawp.2014.2362937.

[16] Y. Sharma, H. H. Zhang, and H. Xin, “Machine Learning Techniques for Optimizing Design of Double T-Shaped Monopole Antenna,” IEEE Transactions on Antennas and Propagation, vol. 68, no. 7, pp. 5658–5663, Jul. 2020, doi: 10.1109/tap.2020.2966051.

[17] S. K. Goudos, P. D. Diamantoulakis, M. A. Matin, P. Sarigiannidis, S. Wan, and G. K. Karagiannidis, “Design of Antennas through Artificial Intelligence: State of the Art and Challenges,” IEEE Communications Magazine, vol. 60, no. 12, pp. 96–102, Dec. 2022, doi: https://doi.org/10.1109/MCOM.006.2200124.

[18] D. Shi, C. Lian, K. Cui, Y. Chen, and X. Liu, “An Antenna Synthesis Method Based on Machine Learning,” IEEE Transactions on Antennas and Propagation, vol. 70, no. 7, pp. 4965–4976, Jul. 2022, doi: https://doi.org/10.1109/tap.2022.3182693

[19] P. Ranjan, A. Maurya, H. Gupta, S. Yadav, and A. Sharma, "Ultra-Wideband CPW Fed Band-Notched Monopole Antenna Optimization Using Machine Learning," Progress In Electromagnetics Research M, Vol. 108, 27-38, 2022.

[20] Mohammad Monirujjaman Khan, Md. Sazzad Hossain, P. Majumder, S. Akter, and Z. Salam, “A review on machine learning and deep learning for various antenna design 110 applications,” vol. 8, no. 4, pp. e09317–e09317, Apr. 2022, doi: https://doi.org/10.1016/j.heliyon.2022.e09317.

[21] Ragedhaksha, Darshini, Shahil, and A. Nehru, “Deep learning-based real-world object detection and improved anomaly detection for surveillance videos,” Materials Today: Proceedings, Jul. 2021, doi: https://doi.org/10.1016/j.matpr.2021.07.064

[22] Mohri, M., Rostamizadeh, A., & Talwalkar, A. Foundations of machine learning. MIT press. 2018.

[23] Shalev-Shwartz, Shai, and Shai Ben-David. Understanding machine learning: From theory to algorithms. Cambridge University Press, 2014.

[24] S. Pavithran, S. Viswasom, S. K. S, and A. J, “Designing of a 5G Multiband Antenna Using Decision Tree and Random Forest Regression Models,” IEEE Xplore, Aug. 01, 2021. https://ieeexplore.ieee.org/document/9566117.

[25] K. Sharma and G. P. Pandey, “Efficient modelling of compact microstrip antenna using machine learning,” AEU - International Journal of Electronics and Communications, vol. 135, p. 153739, Jun. 2021.

[26] S, V. Kumar, A. Pandey, A. Sharma, P. Ranjan, and R. Tripathi, “Machine Learning Assisted Optimization of Dielectric Resonator based mm-Wave MIMO Antenna for 5G Communication System,” Europe PMC, 2022.

[27] R. Ramasamy, and M. A. Bennet, "An Efficient Antenna Parameters Estimation Using Machine Learning Algorithms," Progress In Electromagnetics Research C, Vol. 130, 169-181, 2023

[28] H. Huang, X. Yang, and B. Wang, “Machine-Learning-Based Generative Optimization Method and Its Application to an Antenna Decoupling Design,” IEEE Transactions on Antennas and Propagation, vol. 71, no. 7, pp. 6243–6248, Jul. 2023, doi: https://doi.org/10.1109/tap.2023.3270716.

[29] A. M. Montaser, “Machine Learning Based Design of Pattern Reconfigurable Antenna,” IEEE Access, vol. 11, pp. 33121–33133, Jan. 2023, doi:https://doi.org/10.1109/access.2023.3263581.

[30] Md. Ashraful Haque et al., “Machine Learning-Based Technique for Resonance and Directivity Prediction of UMTS LTE Band Quasi Yagi Antenna,” Heliyon, vol. 9, no. 9, pp. e19548–e19548, Sep. 2023, doi: https://doi.org/10.1016/j.heliyon.2023.e19548.

[31] T. S. Bird, “Definition and Misuse of Return Loss [Report of the Transactions Editor-in-Chief],” IEEE Antennas and Propagation Magazine, vol. 51, no. 2, pp. 166–167, Apr. 2009, doi: 10.1109/map.2009.5162049.

[32] A. Abohmra, “Terahertz antenna design for future wireless communication,” theses.gla.ac.uk, 2022. Available: https://theses.gla.ac.uk/83007/.

[33] “Ansys HFSS | 3D High Frequency Simulation Software,” www.ansys.com. https://www.ansys.com/en-in/products/electronics/ansys-hfss

[34] “Training and Test Sets: Splitting Data | Machine Learning Crash Course,” Google Developers, 2019. https://developers.google.com/machine-learning/crash-course/training-and-test-sets/splitting-data

[35] Python, “Python,” Python.org, 2019. https://www.python.org/

[36] “Regression and Classification | Supervised Machine Learning - GeeksforGeeks,” GeeksforGeeks, Dec. 01, 2017. https://www.geeksforgeeks.org/regression-classification-supervised-machine-learning/

[37] S. Wiyono, D. S. Wibowo, M. F. Hidayatullah, and D. Dairoh, “Comparative Study of KNN, SVM, and Decision Tree Algorithm for Student’s Performance Prediction,” International Journal of Computing Science and Applied Mathematics, vol. 6, no. 2, p. 50, Aug. 2020.

[38] M. R. Khan, C. L. Zekios, S. Bhardwaj, and S. V. Georgakopoulos, “Performance of Random Forest Algorithm in High-Dimensional Surrogate Modeling of Antennas,” 2021 IEEE International Symposium on Antennas and Propagation and USNC-URSI Radio Science Meeting (APS/URSI), Dec. 2021, doi: https://doi.org/10.1109/aps/ursi47566.2021.9703847.

[39] W. T. Li, H. S. Tang, C. Cui, Y. Q. Hei, and X. W. Shi, “Efficient Online Data-Driven Enhanced-XGBoost Method for Antenna Optimization,” IEEE Transactions on Antennas and Propagation, vol. 70, no. 7, pp. 4953–4964, Jul. 2022, doi: 10.1109/TAP.2022.3157895.

[40] L. Cui, Y. Zhang, R. Zhang, and Q. H. Liu, “A Modified Efficient KNN Method for Antenna Optimization and Design,” IEEE Transactions on Antennas and Propagation, vol. 68, no. 10, pp. 6858–6866, Oct. 2020, doi: https://doi.org/10.1109/tap.2020.3001743.

[41] “Google Colaboratory,” colab.research.google.com. https://research.google.com/colaboratory.

Rachit Jain is a Ph.D. scholar at MITS, Gwalior. He received his M.E. from MITS, Gwalior. He is a member of the Institutes of Electronics and Telecommunications Engineers (IETE) and the Institute of Electrical and Electronics Engineers (IEEE). Some of his research has been published in Web of Science, Emerging Sources Citation Index (Clarivate Analytics), Scopus and reputed peer-reviewed journals and he presented research papers at various international and national conferences. His research interests include antenna design, antenna design for 5G and 6G communications, and machine learning in antenna design. (e-mail: rachitjain2709@gmail.com).

Vandana Vikas Thakare received PhD from MITS Gwalior M.P., India in 2011. She is an associate professor at MITS Gwalior, M.P., India in the Department of Electronics Engineering. She is a member of The Institutions of Engineering and Technology (IET), a fellow of The Institutions of Electronics and Telecommunications Engineers (IETE), fellow of The Institutions of Engineers (India). Published more than hundreds of papers in reputed journals. Her research area includes antenna designing, antenna for biomedical applications, artificial intelligence in antenna designing, etc. (e-mail: vandana@mitsgwalior.in).

P.K. Singhal received a Ph.D. from Jiwaji University Gwalior M.P., India in 1997. He is a professor at MITS Gwalior, M.P., India in the Department of Electronics Engineering. Experience of more than 28 years of teaching, research, and development in diversified areas of electronics engineering and computer science. Published 150 research papers, which include papers in IEEE Transaction, international and national journals, and international and national conferences. His interest includes research and teaching in microwave engineering, communication systems, microwave antennas, computer-aided design of microwave integrated circuits, and software development. (e-mail: pks_65@mitsgwalior.in).