A Study on the Potential of ML and DL Regression in Antenna Design: The Case Study of a Rectangular Microstrip Patch Antenna

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Received: 23 July 2025 | Revised: 6 September 2025 and 24 September 2025 | Accepted: 9 October 2025

 DOI: https://doi.org/10.48084/etasr.13605

ABSTRACT

This article presents an in-depth, comprehensive overview of Machine Learning (ML) regression and Deep Learning (DL) regression for the design and optimization of Microstrip Antennas (MSAs) in developing modern communication technologies. The study introduces a novel approach that leverages DL and neural network architectures to enhance the efficiency and accuracy of theoretical Rectangular MSA (RMSA) analysis within the 1–4 GHz frequency range. By employing ML and DL regression techniques, the method enables precise prediction of critical RMSA parameters, thereby streamlining the design process and enhancing overall design efficiency. The proposed approach offers significant advantages by reducing the reliance on domain-specific expertise throughout the RMSA design cycle. This study constructs a custom data generator that produces 1,920 samples. The results demonstrate that ML techniques yield strong predictive performance, whereas DL models exhibit architectural flexibility and high representational capacity, enabling consistently accurate predictions of parameters, such as S_{11}, bandwidth, and Voltage Standing Wave Ratio (VSWR), even for nonlinear antenna geometries. The Tabular Network (TabNet), which integrates interpretability with efficient data processing, emerges as a competitive and reliable tool, particularly for Multi-Input Multi-Output (MIMO) cases.

Keywords-modern communication; Deep Learning (DL) regression; geometry prediction; Machine Learning (ML) regression; Tabular Network (TabNet)

I. INTRODUCTION

Microstrip Antennas (MSAs) have gained increasing popularity with the rapid advancement of modern communication technologies. They represent one of the fundamental components in modern communication systems, offering several advantages in applications, such as 5G and beyond, the Internet of Things (IoT), satellite, and radar communication antennas [1]. MSAs can operate across a wide range of frequencies, such as the S-band, and are particularly valued for their wide bandwidth capability, reconfigurability, compact and low cost design, and high gain [2, 3]. Despite these benefits, the design and optimization processes of MSAs within this frequency range pose significant challenges due to the nonlinear and multimodal correlations between geometric parameters and the resulting complex Electromagnetic (EM) responses [4].

Traditional theoretical methods provide analytical formulas for calculating the patch and ground plane dimensions, specifically length (L) and width (W), based on the operating frequency, dielectric constant, and substrate thickness [5]. However, these methods have several limitations. One of them relies on simplifying assumptions, such as the assumption that EM fields are confined primarily around the patch edges, thereby neglecting the significant impact of fringing fields [6]. Moreover, their accuracy deteriorates due to the nonlinear behavior of wave propagation at frequencies below the S-band [7].

Various approaches have been proposed to overcome the limitations of traditional methods, with the most recent and widely adopted being the implementation of Machine Learning (ML) as in [2-8] and Deep Learning (DL) as in [9, 10]. While several studies have explored the use of ML and DL in the design of MSAs, several critical research gaps persist. First, many ML-based design and optimization approaches generally lack grounding in the empirical formulas, as in [11]. Second, most existing studies predominantly focus on predicting isolated antenna components, such as slot dimensions [12] or feeding parameters [13], rather than modeling the complete antenna geometry based on widely accepted empirical equations. Moreover, most implementations rely only on Multi-Input Single-Output (MISO) ML or DL models, such as bandwidth improvement [14], with limited exploration of multi-parameter approaches as in [15]. To date, no study has thoroughly investigated the EM characteristics of MSAs in the S-band using a design derived from empirical models. Third, comprehensive comparative analyses evaluating DL performance versus traditional ML algorithms in predicting MSA geometries, particularly Rectangular MSAs (RMSAs) within the 1–4 GHz operating range, are lacking.

This study proposes a novel approach that leverages DL and neural network architectures to enhance the efficiency and accuracy of theoretical RMSA analysis within the 1–4 GHz frequency range. The proposed model is a DL-based regression framework incorporating adaptive feature selection mechanisms and sequential processing structures, capabilities not available in traditional models such as Multilayer Perceptron (MLP), Random Forest (RF), XGBoost, and others. Furthermore, DL regression techniques predict key RMSA parameters, such as return loss (S_{11}), bandwidth, and Voltage Standing Wave Ratio (VSWR). Unlike previous studies, this approach integrates theoretical calculations and simulation results to improve the validity of the resulting predictive model. Table I shows the differences between this study and previous studies.

In this study, the main contributions can be summarized as follows. First, unlike previous works that primarily employed MISO settings, this manuscript introduces a Multi-Input Multi-Output (MIMO) framework that allows the simultaneous prediction of multiple antenna performance parameters. Second, the proposed approach integrates ML, DL, and Tabular Network (TabNet) into a unified pipeline, enabling a systematic comparison and ensuring both predictive accuracy and robustness. Third, the framework is designed to generate fast predictions within seconds, thereby reducing computational overhead compared to traditional optimization-based methods. Finally, through global interpretability using TabNet, this work provides valuable insights into the role of each input parameter, strengthening the generalization capability for RMSA.

II. DATASET GENERATION

Various methods have been used to create antenna datasets for surrogate modeling; however, standard simulation tools typically produce only limited datasets. To overcome this limitation and ensure the development of an accurate model, this study constructed a custom dataset using the CST Microwave Studio. In total, 33 unique RMSA designs were modeled, and parameter sweeping was applied to each, generating 1,920 data points. Of these, 1,344 samples were designated for training, whereas 576 were reserved for testing.

TABLE I. COMPARISON OF ML AND DL APPLICATIONS IN ANTENNA DESIGN

Ref.	Approach / method	Input–output setting	Advantage	Scope of generalization
[2]	Only ML	Limited to MIMO	Better prediction results and fewer iterations	Applied to a circularly polarized base station antenna
[8]	Only ML	Limited to MISO	Provides acceleration factors lower than one order of magnitude	Applied to accelerate the cross-polar optimization of the same large reflect-array
[9]	Only DL	Limited to MISO	Efficiently predicts antenna performance parameters	Capable of predicting essential RMSA parameters
[10]	Only DL	Limited to MIMO	Reduces computational cost compared to classical methods	Optimized strategy for multi-resonant layered acoustic metamaterials
[12]	Only ML	Limited to MIMO	High efficiency in parameter estimation in only a few milliseconds	Estimation of the dielectric-filled slotted waveguide antenna design
[16]	Only ML	Limited to MISO	Eliminates the need to develop two separate models	Applied to UWB MIMO antennas
[17]	Only ML	Limited to MISO	Reduces computational complexity and shortens training time	Improved training efficiency but limited to MISO
[18]	Only ML	Limited to MISO	Decreases overall computational demand through multiphysics-driven learning	Generalized antenna design, but not specifically RMSA
[This work]	Comparison of ML, DL, and TabNet	Improved MISO and MIMO	Develops a unified framework capable of producing fast predictions and global interpretability	Comprehensive generalization of RMSA with full MIMO capability

Traditionally, RMSA performance has depended heavily on various design parameters. In [19], the authors reported that critical factors influencing RMSA performance include substrate width, ground plane length, patch length, and patch width. An increase in ground plane dimensions has been shown to impact radiation gain significantly. Authors in [20] used an inset-fed configuration, which can particularly affect impedance bandwidth and radiation efficiency. By adjusting the dimensional parameters associated with each antenna design, the S_{11} and VSWR of the RMSA were determined utilizing a time-domain solver that employed a hexahedral mesh configuration. This configuration was generally more efficient than the tetrahedral mesh in simulations utilizing the Finite Integration Technique (FIT), with numerical errors consistently maintained below −30 dB. The VSWR values represent S_{11} normalized to a 50 Ω impedance, thereby indicating impedance matching at the operating frequency.

This study employed a parameter sweep process to explore the impact of design parameter variations on the performance of the RMSA. A linear sweep method was employed, where specific parameter values were systematically varied within a predefined range using a fixed increment, commonly referred to as the step width. The investigated parameter values were systematically varied using a uniform step size approach, expressed as shown in (1):

$$P_i = P_{min} + i.\Delta P \quad (1)$$

where P_i denotes the parameter value at the i-th iteration, P_{min} is the lower bound, and ΔP is the incremental step size. The total number of sampling points N was determined as shown in (2):

$$N = \left\lfloor \frac{P_{max} - P_{min}}{\Delta P} \right\rfloor + 1 \quad (2)$$

This ensures complete coverage of the parameter range from P_{min} to P_{max} with evenly distributed values. This procedure was implemented across a range of design parameters, including the slot width of the antenna, which was varied within a specified range of 13 mm to 15 mm, utilizing a step width of 0.2 mm. Consequently, 11 distinct values were produced, facilitating a thorough analysis of the impact of each parameter variation on the antenna's response, as assessed through S_{11}. Furthermore, this step enabled the systematic evaluation of parameter configurations within the predetermined range to ascertain the optimal design that meets the performance criteria.

III. PROPOSED APPROACH

A. Multi-Input Single-Output Machine Learning Regression

This approach employed several ML regression models, including RF, Linear Regression (LR), and Support Vector Machine (SVM) to perform a comparative analysis. The model demonstrating the highest average performance across multiple evaluation metrics was selected among these models. Subsequently, the selected model was trained multiple times using the same input set, producing a separate model for each output variable.

B. Multi-Input Single-Output Neural Network Regression

This approach followed a standard neural network architecture. The output layer was configured to produce only a single output value. Similar to traditional regression models, the neural network was trained multiple times, each instance yielding a distinct model for each output. The number of neurons in each hidden layer was systematically varied to optimize performance and improve accuracy, and the results were evaluated and compared accordingly.

C. Multi-Input Multi-Output Tabular Neural Network

This approach adapted the TabNet architecture to simultaneously address the MIMO regression task on RMSA parameter data. Two groups of input features were defined: structural features (x_1: f_r, W_{gp}, L_{gp}, L_f, W_f, T_c) and geometrical features (x_2: W_p, L_p, W_{sf}, L_{sf}, S_t). These feature sets were processed through parallel encoders, allowing for the independent extraction of deep latent representations from each group. The resulting representations were subsequently fused and passed into a global decision-making module designed to produce multi-output predictions, including key antenna performance parameters such as S_{11}, bandwidth, and VSWR.

To optimize the predictive performance, a multi-task regression strategy was implemented using a composite loss function based on the weighted Mean Squared Error (MSE), where the weights were assigned proportionally according to the complexity and scale of each output. Model evaluation was conducted using standard regression metrics, Root Mean Squared Error (RMSE), coefficient of determination (R^2), and Mean Absolute Error (MAE) to assess prediction accuracy, model robustness, and generalization performance across the range of target variables.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experiment 1: Comparison Analysis of Multi-Input Single-Output Machine Learning Regression

Table II presents a comprehensive performance evaluation of the four regression algorithms: LR, RF, Support Vector Regression (SVR), and Gradient Boosting (GB). Among them, ensemble learning-based approaches demonstrated superior predictive accuracy across all three target outputs: bandwidth, S_{11}, and VSWR.

TABLE II. PERFORMANCE EVALUATION OF DIFFERENT MODELS ON BANDWIDTH, S_{11}, AND VSWR PREDICTION

Output	MAE	MSE	RMSE	R^2 score
LR				
Bandwidth	0.2897	0.1613	0.4017	0.2435
S_{11}	3.5424	18.7306	4.3279	0.706
VSWR	1.2436	3.5873	1.894	0.6921
Average per unit	1.6919	7.4931	2.2079	0.5472
RF				
Bandwidth	0.0033	0.0002	0.014	0.9991
S_{11}	0.4378	0.8659	0.9305	0.9864
VSWR	0.1074	0.1078	0.3284	0.9907
Average per unit	0.1828	0.3246	0.4243	0.9921
SVR				
Bandwidth	0.1292	0.0717	0.2677	0.664
S_{11}	1.5114	7.4011	2.7205	0.8838
VSWR	0.7358	3.5022	1.8714	0.6995
Average per unit	0.7921	3.6583	1.6199	0.7491
GB				
Bandwidth	0.0064	0.0005	0.0231	0.9975
S_{11}	0.6338	1.2277	1.108	0.9807
VSWR	0.0928	0.0376	0.1941	0.9967
Average per unit	0.2443	0.4219	0.4417	0.9916

RF consistently achieved the best overall performance, resulting in the lowest MAE, MSE, and RMSE values, as well as R^2 scores approaching 1, particularly for bandwidth (R^2 = 0.9991) and S_{11} (R^2 = 0.9864). GB also delivered competitive results and outperformed all other models in predicting VSWR, achieving an R^2 score of 0.9967. However, one of the main challenges lies in the model's non-parametric, ensemble-based nature, which complicates the direct interpretation of causal correlations between design parameters and the resulting antenna characteristics [21]. In practical antenna engineering, a clear understanding of the contribution of each geometric variable is essential for exploration grounded in EM principles.

Additionally, RF tends to perform poorly in extrapolating beyond the known design space, thus limiting its relevance for innovative design studies or extreme scenarios.

B. Experiment 2: Deep Learning Regression with Multi-Input Single-Output Architecture

In Experiment 2, which built upon the initial investigation into utilizing DL for antenna parameter prediction, a DL model was developed using a feedforward neural network architecture. The model comprised two hidden layers employing ReLU activation functions and a 20% dropout rate for regularization to mitigate overfitting. This study evaluated four configurations of neuron counts in the first hidden layer: 500, 750, 1000, and 1200, with each model trained using the Adam optimizer over 100 epochs and a batch size of 16. Figure 1 presents the comparison results between predicted and actual values for each antenna parameter. The DL model with 500 neurons demonstrated excellent predictive performance on the test data, exhibiting low errors and a strong correlation between predicted and actual values, as detailed in Table III.

TABLE III. SUMMARY OF THE EVALUATION RESULTS BY THE DL MODEL FOR EACH ANTENNA PERFORMANCE PARAMETER

Output	MAE	MSE	RMSE	R^2 score
DL (500)				
Bandwidth	0.0217	0.0019	0.0434	0.9912
S_{11}	0.7238	1.7554	1.3249	0.9725
VSWR	0.2307	0.1871	0.4326	0.9839
Average per unit	0.3254	0.6481	0.6003	0.9825
DL (750)				
Bandwidth	0.0228	0.0028	0.0525	0.9871
S_{11}	0.8683	2.2319	1.4940	0.9650
VSWR	0.2621	0.2257	0.4751	0.9806
Average per unit	0.3844	0.82013	0.6738	0.9775
DL (1000)				
Bandwidth	0.0255	0.003	0.0543	0.9862
S_{11}	0.7666	1.7901	1.338	0.9719
VSWR	0.261	0.237	0.4868	0.9797
Average per unit	0.3510	0.6767	0.6264	0.9793
DL (1200)				
Bandwidth	0.0317	0.004	0.0636	0.981
S_{11}	0.882	2.0299	1.4247	0.9681
VSWR	0.28	0.2368	0.4866	0.9797
Average per unit	0.3979	0.7569	0.6583	0.9763

To evaluate the predictive accuracy of the models on RMSA performance parameters, Table III presents the prediction results of four DL configurations with varying numbers of neurons (500, 750, 1000, and 1200), along with the RF model, applied to five test samples for S_{11}, bandwidth, and VSWR. The results demonstrate that the RF model consistently yields the lowest deviations across all parameters, particularly at extreme values that characterize RMSA antennas, such as sharp reflections (S_{11} < –10 dB), very narrow bandwidths (< 0.1 GHz), and low VSWR values (< 2). Conversely, DL models with more neurons (1000 and 1200) tend to exhibit greater error fluctuations, indicating potential overfitting and reduced generalization ability, especially in the narrow bandwidth regime, where prediction errors exceeded 80%. The DL (500) model showed more stable performance than other DL variants, but still underperformed relative to RF, particularly in predicting extreme S_{11} and bandwidth values.

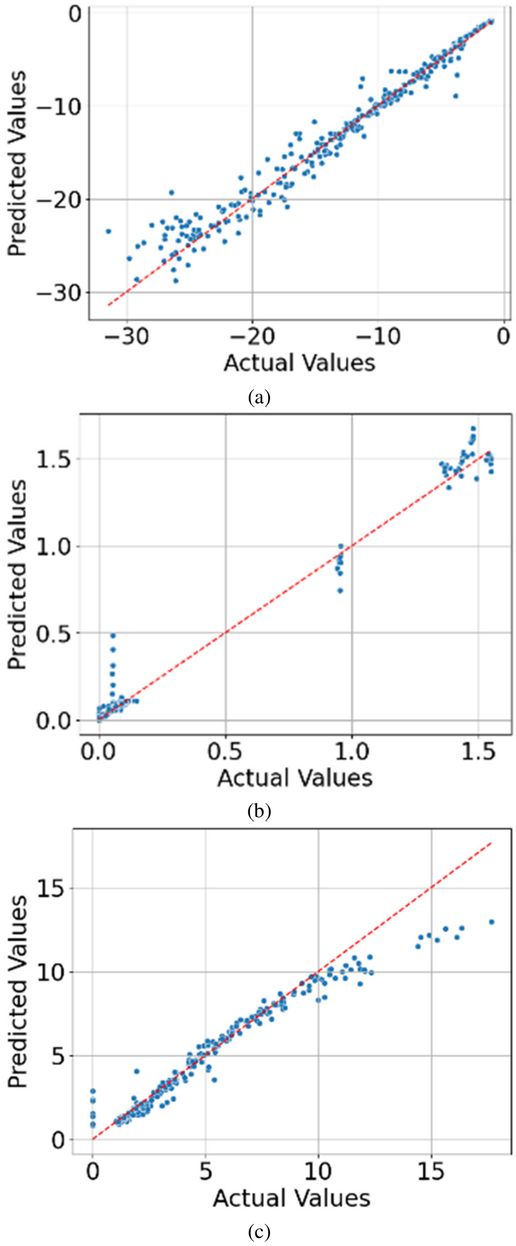

Fig. 1. Comparison between actual and predicted values for: (a) S11, (b) bandwidth, and (c) VSWR.

Although the predictive performance for S_{11} was notably high, as shown in Figure 1(a), slight deviations were observed in regions of very low (around –30 dB) and moderately high (close to 0 dB) actual values, indicating a minor lack of precision at the extreme ranges. This issue commonly arises due to the non-uniform distribution of the dataset and the potential influence of outliers in the actual S_{11} measurements. Such deviations can be attributed to the inherent sensitivity of RMSA antennas to variations in patch and slot dimensions, particularly under design conditions that yield either exceptionally good or poor impedance matching. Figure 1(b) shows that the predicted bandwidth points are highly concentrated at two extremes: values near 0–0.2 GHz and around 1.4–1.6 GHz. This pattern may indicate that the actual data are predominantly distributed around these two clusters, or it may reflect the strong nonlinear influence of input features, such as patch dimensions, slot geometry, and substrate thickness on the resulting bandwidth. In the context of RMSA antenna design, this finding aligns with its intrinsic characteristic of exhibiting a naturally narrow bandwidth due to its sharp resonance behaviors. Figure 1(c) reveals a slight deviation, particularly in two extreme regions, very low actual VSWR values (< 2) and very high values (> 15). This indicates that although the model was well-trained, its predictive accuracy slightly deteriorates under extreme conditions. This decline is most likely attributed to the uneven distribution of VSWR data and the presence of outliers associated with specific geometric configurations. These findings reaffirm that ensemble-based models, such as RF, address the inherent nonlinear complexity of RMSA antenna characteristics more effectively, demonstrating consistent predictive accuracy even under uneven data distributions and extreme value ranges. This result corroborates previous research in [22]. However, it is important to note that RF has inherent limitations in handling multi-output regression tasks directly. As a result, simultaneous modeling of multiple antenna performance parameters requires either a wrapper-based strategy or independent modeling for each output. The subsequent experiment investigates a DL approach tailored for multi-output prediction.

C. Experiment 3: Multi-Input Multi-Output Tabular Network

The TabNet regressor is a DL architecture that integrates the strengths of decision trees and neural networks for modeling tabular data. In this context, the implementation of TabNet provides both automatic feature selection capabilities and enhanced interpretability compared to traditional models, particularly making it suitable for handling normalized numerical data derived from the physical parameters of antenna designs. The trained model configurations were subsequently compared and evaluated regarding their relative performance in predicting key antenna performance parameters, including S_{11}, bandwidth, and VSWR.

(a)

(b)

(c)

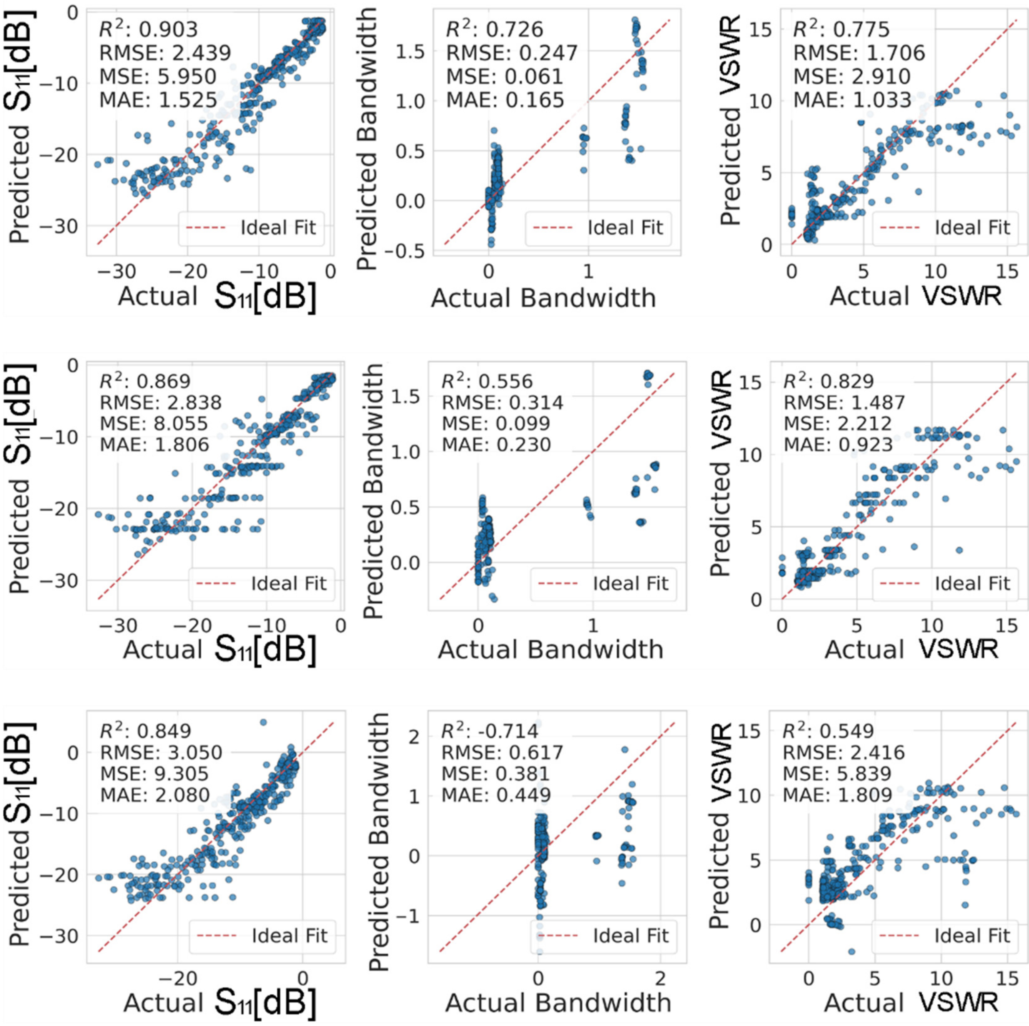

Fig. 2. Comparison between predicted and actual values for different TabNet configurations across three antenna parameters: (a) default, (b) base TabNet, and (c) effect of depth.

As illustrated in Figure 2(a), the default configuration consistently demonstrated the best performance compared to both the base TabNet (Figure 2(b)) and the effect of depth configuration (Figure 2(c)), particularly in modeling the S_{11} and VSWR parameters, which are key indicators of impedance matching and power reflection efficiency in RMSA. For the S_{11} parameter, the default achieved the highest coefficient of determination ($R^2 = 0.903$), accompanied by the lowest RMSE and MAE values, 2.439 and 1.525, respectively, indicating a highly accurate prediction capability for the complex physical characteristics underlying the power reflection behavior of RMSA antennas.

As illustrated in Figure 3, regarding the importance of global features, a critical aspect for identifying the most influential parameters in antenna design, the feature L_f (feed length) emerged as the most significant contributor to the model's predictions (global interpretability), followed by L_p (resonant frequency) and W_p (patch width). TabNet possesses highly desirable characteristics for antenna design, particularly for RMSA, as it enables the identification of the most influential parameters in predicting specific performance metrics, such as S_{11}, bandwidth, and VSWR. These findings are consistent with previous studies, which report that DL models exhibit strong robustness in modeling antenna parameters, enable the rapid generation of innovative antenna structures, offer greater structural reliability, and provide cost efficiency compared to traditional methods for designing complex antennas.

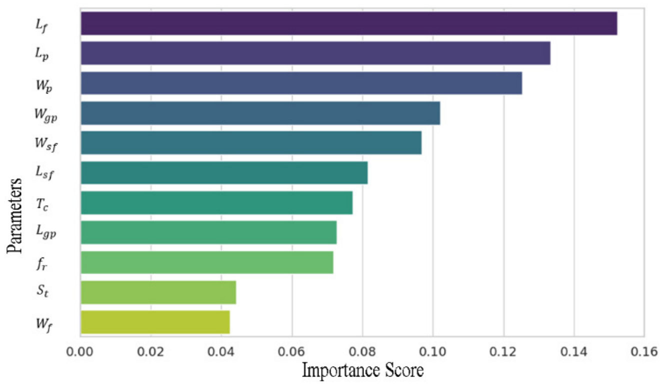

Fig. 3. Global feature importance for RMSA performance prediction using TabNet.

V. CONCLUSION

The overall findings of this study successfully addressed the core research problem of accurately and efficiently predicting the performance parameters of Rectangular Microstrip Antenna (RMSA)-type antennas based on geometric design variables. Both Machine Learning (ML) and Deep Learning (DL) regression approaches effectively captured the complex nonlinear relationships between the physical dimensions of the antenna and its Electromagnetic (EM) response. In particular, DL models exhibited architectural flexibility and high representational capacity, enabling consistently accurate predictions of parameters such as S_{11}, bandwidth, and Voltage Standing Wave Ratio (VSWR), even for complex, nonlinear antenna geometries.

The Tabular Network (TabNet), which integrates interpretability with efficient data processing, emerged as a competitive alternative to traditional models. Its success in predicting five test samples with low error rates and high correlation reinforces the conclusion that these models are practically applicable to data-driven RMSA antenna design and optimization processes. Moreover, TabNet was able to identify critical features that align with established EM principles, making its model interpretation not only statistically robust but also physically meaningful.

Therefore, this approach is not only relevant for laboratory-scale studies but also holds strong potential for real-world implementation, where speed and accuracy are critical in Microstrip Antenna (MSA) development. Even a gain of just a few seconds is highly significant in the implementation of data-driven intelligent systems, as such systems demand instant responsiveness, computational efficiency, and high adaptability to the dynamic processes of design and optimization.

ACKNOWLEDGMENT

This study was funded by the Indonesian Education Scholarship (BPI) from the Centre for Financing and Assessment of Higher Education (PPAPT) of the Ministry of Higher Education, Science, and Technology, and the Education Fund Management Institute (LPDP).

REFERENCES

[1] A. Y. Al-Zahrani and M. Najim, "Design and Implementation of a High Gain Hexagon Loop Antenna for 5G and WLAN Application," *Engineering, Technology & Applied Science Research*, vol. 14, no. 4, pp. 15620–15624, Aug. 2024, https://doi.org/10.48084/etasr.7323.

[2] J. Zhang, J. Xu, Q. Chen, and H. Li, "Machine-Learning-Assisted Antenna Optimization With Data Augmentation," *IEEE Antennas and Wireless Propagation Letters*, vol. 22, no. 8, pp. 1932–1936, Aug. 2023, https://doi.org/10.1109/LAWP.2023.3269811.

[3] J. S. Alkasassbeh, A. Y. Hindi, I. Trrad, M. O. Dwairi, E. A. Dwairi, and M. Alja'fari, "Design and Optimization of a Compact Inset Feed Microstrip Antenna for 5G Applications with Enhanced MIMO Performance," *Engineering, Technology & Applied Science Research*, vol. 15, no. 2, pp. 21373–21382, Apr. 2025, https://doi.org/10.48084/etasr.10094.

[4] A. Tiwari, A. A. Khurshid, and K. Sharma, "Compact wearable microstrip antenna design using hybrid quasi-Newton and Taguchi optimization," *Scientific Reports*, vol. 15, no. 1, Jan. 2025, Art. no. 116, https://doi.org/10.1038/s41598-024-83864-9.

[5] D. Mathur, S. K. Bhatnagar, and V. Sahula, "Quick Estimation of Rectangular Patch Antenna Dimensions Based on Equivalent Design Concept," *IEEE Antennas and Wireless Propagation Letters*, vol. 13, pp. 1469–1472, 2014, https://doi.org/10.1109/LAWP.2014.2334362.

[6] J. Dinkic, M. N. Stevanovic, and A. Djordjevic, "Physical Models for Influence of Substrate Permittivity on the Gain of Microstrip Antennas," *IEEE Transactions on Antennas and Propagation*, vol. 71, no. 11, pp. 9078–9083, Nov. 2023, https://doi.org/10.1109/TAP.2023.3310165.

[7] A. Esmaeilkhah, C. Ghobadi, J. Nourinia, and M. Majidzadeh, "Effect of Substrate Scaling on Microstrip Patch Antenna Performance," *Advanced Electromagnetics*, vol. 7, no. 5, pp. 82–86, Nov. 2018, https://doi.org/10.7716/aem.v7i5.840.

[8] D. R. Prado, J. A. López-Fernández, M. Arrebola, and G. Goussetis, "Support Vector Regression to Accelerate Design and Crosspolar Optimization of Shaped-Beam Reflectarray Antennas for Space Applications," *IEEE Transactions on Antennas and Propagation*, vol.

67, no. 3, pp. 1659–1668, Mar. 2019, https://doi.org/10.1109/TAP.2018.2889029.

[9] M. R. Khan, C. L. Zekios, S. Bhardwaj, and S. V. Georgakopoulos, "A Deep Learning Convolutional Neural Network for Antenna Near-Field Prediction and Surrogate Modeling," *IEEE Access*, vol. 12, pp. 39737–39747, 2024, https://doi.org/10.1109/ACCESS.2024.3377219.

[10] D. Yago, G. Sal-Anglada, D. Roca, J. Cante, and J. Oliver, "Machine learning in solid mechanics: Application to acoustic metamaterial design," *International Journal for Numerical Methods in Engineering*, vol. 125, no. 14, July 2024, Art. no. e7476, https://doi.org/10.1002/nme.7476.

[11] Q. Wu, W. Chen, C. Yu, H. Wang, and W. Hong, "Multilayer Machine Learning-Assisted Optimization-Based Robust Design and Its Applications to Antennas and Array," *IEEE Transactions on Antennas and Propagation*, vol. 69, no. 9, pp. 6052–6057, Sept. 2021, https://doi.org/10.1109/TAP.2021.3069491.

[12] T. Naous, A. A. Merie, S. K. A. Khatib, M. Al-Husseini, R. M. Shubair, and H. M. El Misilmani, "Machine Learning-Aided Design of Dielectric-Filled Slotted Waveguide Antennas With Specified Sidelobe Levels," *IEEE Access*, vol. 10, pp. 30583–30595, 2022, https://doi.org/10.1109/ACCESS.2022.3158976.

[13] Y.-F. Liu, L. Peng, and W. Shao, "An Efficient Knowledge-Based Artificial Neural Network for the Design of Circularly Polarized 3-D-Printed Lens Antenna," *IEEE Transactions on Antennas and Propagation*, vol. 70, no. 7, pp. 5007–5014, July 2022, https://doi.org/10.1109/TAP.2022.3140313.

[14] Y. Su, Y. Yin, S. Li, H. Zhao, and X. Yin, "Bandwidth Improvement for Patch Antenna via Knowledge-Based Deep Reinforcement Learning," *IEEE Antennas and Wireless Propagation Letters*, vol. 23, no. 12, pp. 4094–4098, Dec. 2024, https://doi.org/10.1109/LAWP.2024.3432182.

[15] L.-Y. Xiao, W. Shao, F.-L. Jin, and B.-Z. Wang, "Multiparameter Modeling With ANN for Antenna Design," *IEEE Transactions on Antennas and Propagation*, vol. 66, no. 7, pp. 3718–3723, July 2018, https://doi.org/10.1109/TAP.2018.2823775.

[16] D. Sarkar, T. Khan, Jayadeva, and A. A. Kishk, "Machine Learning Assisted Hybrid Electromagnetic Modeling Framework and Its Applications to UWB MIMO Antennas," *IEEE Access*, vol. 11, pp. 19645–19656, 2023, https://doi.org/10.1109/ACCESS.2023.3248961.

[17] W. Chen, Q. Wu, B. Han, C. Yu, H. Wang, and W. Hong, "Efficient Incremental Variable-Fidelity Machine-Learning-Assisted Hybrid Optimization and Its Application to Multiobjective Antenna Design," *IEEE Transactions on Antennas and Propagation*, vol. 72, no. 12, pp. 9347–9354, Dec. 2024, https://doi.org/10.1109/TAP.2024.3481663.

[18] B. Han, Q. Wu, C. Yu, H. Wang, and W. Hong, "Low-Wind-Load Broadband Dual-Polarized Antenna and Array Designs Using Sequential Multiphysics Machine-Learning-Assisted Optimization," *IEEE Transactions on Antennas and Propagation*, vol. 73, no. 1, pp. 135–148, Jan. 2025, https://doi.org/10.1109/TAP.2024.3503916.

[19] W. Li, Q. Li, J. Zhou, L. Ye, and Y. Liu, "Wideband Patch Antenna With Ground Radiation Mode and Patch Radiation Mode," *IEEE Access*, vol. 7, pp. 173358–173365, 2019, https://doi.org/10.1109/ACCESS.2019.2957117.

[20] M. Joler and L. Mihalić, "A Subtlety of Sizing the Inset Gap Width of a Microstrip Antenna When Built on an Ultra-Thin Substrate in the S-Band," *Sensors*, vol. 23, no. 1, Jan. 2023, Art. no. 213, https://doi.org/10.3390/s23010213.

[21] Q. Wu, Y. Cao, H. Wang, and W. Hong, "Machine-learning-assisted optimization and its application to antenna designs: Opportunities and challenges," *China Communications*, vol. 17, no. 4, pp. 152–164, Apr. 2020, https://doi.org/10.23919/JCC.2020.04.014.

[22] Q. Niu, W. Shi, Y. Xu, and W. Wen, "High-accuracy NLOS identification based on random forest and high-precision positioning on 60 GHz millimeter wave," *China Communications*, vol. 20, no. 12, pp. 96–110, Dec. 2023, https://doi.org/10.23919/JCC.fa.2021-0742.202312.