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Design Optimization of Rectangular Microstrip Antenna Using Deep Neural Network for 3 GHz Applications in Support of SDG 9

Riski Ramadani[1*], Afiyah Nikmah[1], Arum Vonie Rachmawati[1], Rohim Aminullah Firdaus[1], Noer Risky Ramadhani[2]

[1]Universitas Negeri Surabaya, Surabaya, Indonesia
[2]Universität für Weiterbildung Krems, Krems an der Donau, Austria

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ABSTRACT

Objective: *This study aims to investigate the effectiveness of Deep Neural Networks (DNN) for optimizing the design of a rectangular microstrip antenna operating at a target frequency of 3 GHz. The research focuses on improving antenna design efficiency by predicting antenna performance parameters based on geometric characteristics.* ***Method:*** *The study employed a computational simulation approach combined with machine learning techniques. A synthetic dataset consisting of 6000 antenna configurations was generated using analytical microstrip antenna equations. The dataset included geometric parameters such as dielectric constant, substrate thickness, patch width, patch length, and inset feed position. A Deep Neural Network model was trained to predict resonant frequency, return loss, and input impedance. The trained model was then used as a surrogate model to evaluate 30,000 candidate antenna designs and identify the optimal configuration.* ***Result:*** *The proposed model achieved high predictive accuracy with R^2values of 0.9987 for resonant frequency prediction and 0.9988 for input impedance prediction. The optimized antenna design produced a resonant frequency of 2.996 GHz, return loss of −18.70 dB, and input impedance of 53.95 Ω, which closely match the target specifications for S-band wireless applications.* ***Novelty:*** *The study demonstrates that Deep Neural Networks can significantly accelerate antenna design optimization by replacing repetitive electromagnetic simulations with data-driven prediction models.*

INTRODUCTION

The development of wireless communication technology in the era of digital transformation demands increasingly efficient, adaptive hardware systems capable of supporting high-speed connectivity. Antennas are a crucial component of modern communication systems, acting as a link between electronic systems and the electromagnetic wave propagation medium. Microstrip antennas are a type of antenna widely used in various communication applications due to their compact size, lightweight, ease of fabrication, and ability to integrate with radio frequency circuits in modern electronic devices (Bansal & Sharma, 2021; Singh et al., 2022; Kundu et al., 2023; Rahman et al., 2024). These characteristics make microstrip antennas very popular in various applications such as cellular communications, radar, navigation systems, and Internet of Things (IoT) devices, which have continued to develop in recent decades.

Among the various forms of microstrip antennas, the rectangular microstrip patch antenna is the most commonly used configuration due to its simple structure and ease of analysis using basic theoretical models such as the transmission line model and cavity model. The main dimensions of a rectangular patch antenna, namely the length and width of the patch, significantly determine the antenna's resonant frequency. Therefore, the antenna design process generally involves initial mathematical calculations followed by optimization through electromagnetic simulations using software such as CST, HFSS, or FEKO (Verma et al., 2021; Kumar et al., 2022; Chen et al., 2023; Kaur & Singh, 2024).

While these conventional methods can produce antenna designs with good performance, the optimization process is often time-consuming due to repeated iterations of the antenna's geometric parameters until characteristics meet the desired specifications.

At frequencies around 3 GHz, microstrip antennas have great potential for various wireless communication applications such as S-band systems, short-range radar, certain satellite communications, and various broadband communication systems. This frequency also falls within a spectrum region widely utilized in research and development of modern communication systems because it offers a good compromise between propagation range and data capacity. However, antenna design at this frequency range still faces several challenges, particularly in achieving optimal geometric dimensions to achieve the correct resonant frequency, good impedance matching, and low return loss. The relationship between antenna geometric parameters and performance characteristics is nonlinear, making conventional trial-and-error-based design methods less efficient as the design space becomes larger (Ahmed et al., 2022; Zhang et al., 2023; Wu et al., 2024; Fernandez et al., 2025).

In recent years, artificial intelligence-based approaches have begun to be used to accelerate the antenna design and optimization process. Machine learning and deep learning methods allow modeling the complex relationships between antenna design parameters and electromagnetic performance without the need for full electromagnetic simulations for each design configuration. Deep Neural Networks (DNNs), a popular deep learning technique, have the ability to learn complex nonlinear relationships through training on large datasets. Therefore, DNNs can be utilized as surrogate models that predict antenna performance based on given geometric parameters, allowing for faster design optimization compared to conventional simulation approaches (Li et al., 2021; Zhao et al., 2022; Wang et al., 2023; Prabhakar et al., 2024; Chen et al., 2025).

The use of DNNs in antenna design also opens up opportunities for inverse design, which involves determining antenna geometric parameters based on specific performance targets, such as resonant frequency, bandwidth, or desired return loss. This approach allows for a broader exploration of the design space with more efficient computational time. Several studies have shown that integrating machine learning methods with electromagnetic simulation can significantly improve the efficiency of the antenna design optimization process, especially in the early design stages before more detailed electromagnetic simulations are performed (Wang et al., 2023; Prabhakar et al., 2024; Chen et al., 2025; Fernandez et al., 2025). In addition to contributing to the fields of antenna engineering and artificial intelligence, research on antenna design optimization is also relevant to the global sustainable development agenda. In the context of the Sustainable Development Goals (SDGs), particularly SDG 9: Industry, Innovation, and Infrastructure, the development of efficient and innovative communications technology is a crucial factor in supporting inclusive and sustainable digital infrastructure development. Reliable telecommunications infrastructure enables increased access to information, the development of technology-based industries, and the acceleration of digital transformation across various economic and social sectors (ITU, 2022; United Nations, 2023; World Bank, 2024). Therefore, research focused on innovative design of basic communication system components, such as antennas, can be viewed as part of a scientific contribution to strengthening the technology ecosystem and digital infrastructure that support the achievement of these sustainable development goals.

Based on this background, this research aims to develop a design optimization method for rectangular microstrip antennas at 3 GHz using a Deep Neural Network approach. A

DNN model is used to study the relationship between antenna geometric parameters and their performance characteristics, thereby accelerating the search for optimal designs. By utilizing an artificial intelligence-based approach, it is hoped that the antenna design process can be more efficient, adaptive, and innovative. Furthermore, this research is also expected to contribute to the development of communications technologies that support industrial innovation and digital infrastructure, in line with SDG 9.

RESEARCH METHOD

This study uses a computational simulation and artificial intelligence-based modeling approach to optimize the design of rectangular microstrip antennas at an operating frequency of 3 GHz. This approach integrates analytical microstrip antenna design methods with Deep Neural Network (DNN) techniques to model the relationship between antenna geometry parameters and performance characteristics. Through this approach, the design optimization process can be carried out more efficiently than conventional methods that rely on repeated electromagnetic simulations. The overall research methodology flow is shown in Figure 1, which illustrates the computational stages from parameter initialization to obtaining the optimal antenna design. This research was conducted through several main stages, namely antenna design parameter design, antenna design dataset generation, Deep Neural Network model training, model performance evaluation, and antenna design optimization based on the trained model. This method enables a faster exploration of the vast antenna design space by utilizing machine learning models as surrogate models to predict antenna performance. As shown in Figure 1, the research process begins with the parameter initialization stage, which is the determination of basic system parameters such as target frequency, substrate dielectric constant, substrate thickness, and initial antenna dimensions.

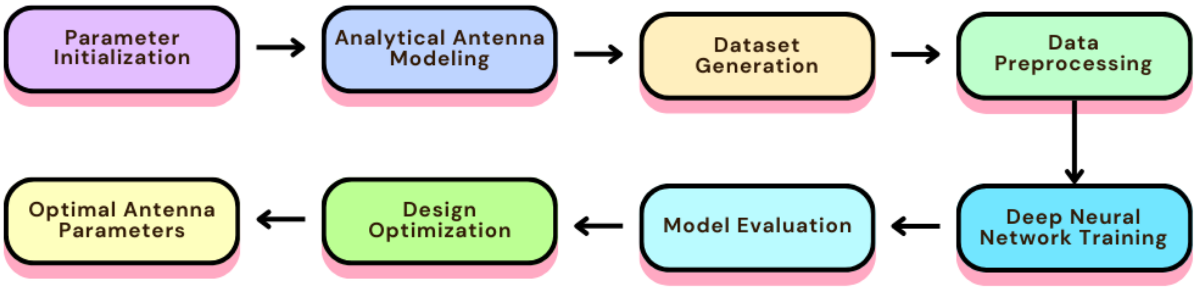

Figure 1. Research methodology flow

The next stage is analytical antenna modeling, which is the process of calculating the basic characteristics of a rectangular microstrip antenna using a microstrip antenna analytical model. This model is used to calculate the dimensions of the antenna patch and initial performance characteristics such as resonance frequency and input impedance. The results of this stage are then used in the dataset generation process, which involves generating an antenna design dataset by varying the antenna geometry parameters within a certain range to produce various antenna design configurations. The resulting dataset is then processed in the data preprocessing stage, which includes data normalization and the division of the dataset into training and testing data. This stage aims to improve the stability and accuracy of the machine learning model training process. Next, the dataset is used in the deep neural network training stage, which is the process of training the DNN model to learn the relationship between antenna geometry parameters and its performance characteristics.

The trained model is then evaluated in the model evaluation stage to measure the model's prediction performance using evaluation metrics such as prediction error and model accuracy. Once the model is deemed to have adequate performance, it is used in the design optimization stage, which is the process of searching for antenna design configurations that produce the best performance based on a predetermined objective function. The final result of this process is optimal antenna parameters, namely rectangular microstrip antenna design parameters that produce optimal performance at a target frequency of 3 GHz.

The antenna designed in this study is a rectangular microstrip patch antenna that operates at a target frequency of 3 GHz. The main parameters used in the design process include the substrate dielectric constant ε_r, substrate thickness h, antenna patch width W, antenna patch length L, and inset feed position y_0. These parameters were selected because they have a significant effect on antenna performance characteristics, particularly resonance frequency, impedance matching, and return loss values. In this study, the antenna substrate is assumed to have a dielectric constant within the range commonly used in commercial microstrip antennas, while the dimensions of the patch antenna are calculated based on the basic analytical model of a microstrip antenna.

The resonance frequency of a rectangular microstrip antenna can be calculated using the following formula (1).

$$W = \frac{c}{2f_r}\sqrt{\frac{2}{\varepsilon_r+1}} \quad (1)$$

$$\varepsilon_{\text{eff}} = \frac{\varepsilon_r+1}{2} + \frac{\varepsilon_r-1}{2}\left(1+\frac{12h}{W}\right)^{-1/2} \quad (2)$$

$$L = \frac{c}{2f_r\sqrt{\varepsilon_{\text{eff}}}} - 2\Delta L \quad (3)$$

Where c is the speed of light, f_r is the antenna resonance frequency, and ΔL is the length correction due to the fringing field effect. The antenna design dataset in this study was computationally generated using an analytical microstrip antenna model. Design parameters such as dielectric constant, substrate thickness, patch width, patch length, and feed inset position were varied within certain ranges to produce a number of antenna design configurations. Each design configuration was then used to analytically calculate the antenna performance characteristics, including the antenna resonance frequency f_r, antenna input impedance Z_{in}, return loss value S_{11}, and antenna bandwidth. The resulting dataset was then used as training data for the Deep Neural Network model so that the model could learn the nonlinear relationship between antenna design parameters and performance characteristics.

The Deep Neural Network model used in this study was built using a feed-forward neural network architecture with several hidden layers. The network architecture consisted of an input layer representing the antenna design parameters, hidden layers using the ReLU activation function, and an output layer predicting the antenna performance parameters. The input parameters used in the model included equation (4).

$$X = [\varepsilon_r, h, W, L, y_0] \tag{4}$$

While the output parameters predicted by the model with equation (5)

$$Y = [f_r, S_{11}, Z_{in}] \tag{5}$$

The model was trained using the Adam optimizer algorithm with a mean squared error (MSE) loss function. The training process was carried out until the model achieved stable convergence between the training data and validation data. After the Deep Neural Network model was trained, it was used as a surrogate model to quickly evaluate thousands of antenna design candidates. The optimization process was carried out by generating a number of random antenna design configurations within a predetermined parameter space. Each design candidate was then evaluated using the DNN model to predict antenna performance. The optimization objective function was formulated as follows equation (6)

$$J = w_1|f_{\text{pred}} - f_{\text{target}}| + w_2|S_{11} + 20| + w_3|Z_{in} - 50| \tag{6}$$

With f_{target}=3 GHz , the target S_{11} value is around -20 dB, and the input impedance is close to 50 Ω. The design with the smallest objective function value is selected as the optimum antenna design.

RESULTS AND DISCUSSION

Result

Dataset and model training

The dataset used in this study consisted of 6000 rectangular microstrip antenna design configurations generated synthetically using an analytical microstrip antenna model. Each data sample contained five input parameters, namely the substrate dielectric constant (ε_r), substrate thickness (h), patch width (W), patch length (L), and inset feed position (y_0). The output parameters predicted by the model included resonant frequency (f_r), return loss (S_{11}), and input impedance (Z_{in}). This synthetic dataset-based approach is commonly employed in antenna design optimization because it enables broad exploration of the design space without requiring repeated electromagnetic simulations (Li et al., 2021; Wu et al., 2024).

The Deep Neural Network (DNN) model used in this study employed an architecture with three hidden layers configured as 128-128-64 neurons. This architecture enabled the neural network to model the nonlinear relationship between antenna design parameters and performance characteristics effectively, as also reported in previous studies on deep learning-based antenna optimization (Wang et al., 2023; Zhang et al., 2023).

Training performance of the DNN model

Figure 1 shows the training loss and validation loss curves during the training process of the Deep Neural Network model. In the early epochs, the loss values decreased significantly from approximately 0.37 to around 0.20, indicating that the model began to learn the relationship between the antenna geometry parameters and its performance characteristics. As the number of epochs increased, both training loss and validation loss continued to decrease until reaching a convergent condition in the range of 0.01-0.03. The closeness of these two curves indicates that the model had good generalization capability and did not experience significant overfitting. Although slight fluctuations appeared in the validation loss at later epochs, the overall pattern remained stable and did not show any substantial increase. This result suggests that the adopted network architecture was capable of effectively modeling the nonlinear relationship between antenna design parameters and antenna performance (Wang et al., 2023).

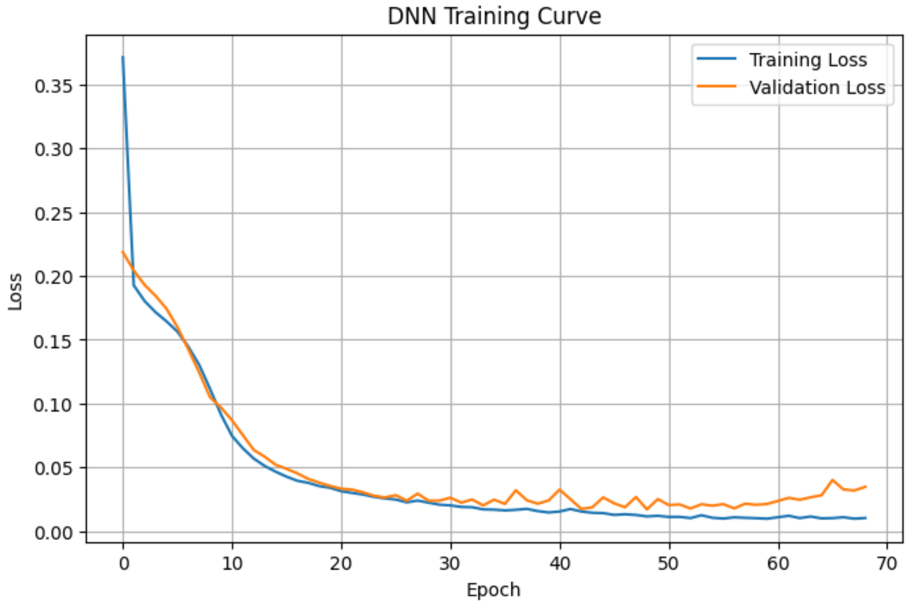

Figure 1. Training and validation loss curves of the deep neural network during the training process.

Model performance evaluation

The performance of the DNN model was evaluated using three main metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). The model evaluation results are presented in Table 1.

Table 1. Evaluation of DNN model performance

Parameter	MAE	RMSE	R^2
Resonant frequency	1.1634×10^7 Hz	1.4856×10^7 Hz	0.9987
Return loss (S_{11})	0.677 dB	1.986 dB	0.9261
Input impedance	4.69 Ω	6.23 Ω	0.9988

Based on Table 1, the model showed very high accuracy in predicting the antenna resonant frequency. The MAE of 11.63 MHz and RMSE of 14.86 MHz at a frequency around 3 GHz indicate that the relative prediction error was very small. The value of $R^2 = 0.9987$ further indicates that nearly all variation in the resonant frequency data could be explained by the model. For the input impedance parameter, the model also demonstrated excellent performance with $R^2 = 0.9988$. The MAE value of approximately 4.69 Ω indicates that the model was able to predict the antenna impedance with high accuracy, which is particularly important for impedance matching with the standard 50 Ω transmission line. High prediction accuracy for antenna parameters using machine learning methods has also been reported in previous studies on AI-based antenna design optimization (Prabhakar et al., 2024; Merino-Fernandez et al., 2025). Meanwhile, the prediction of return loss (S_{11}) yielded $R^2 = 0.9261$ with an MAE of 0.677 dB. Although this performance was slightly lower than that of the other parameters, it still indicates good predictive capability. This can be explained by the fact that the return loss parameter is highly sensitive to small variations in feed position and the electromagnetic field distribution over the antenna patch (Kaur & Singh, 2024).

Prediction accuracy of resonant frequency

Figure 2 shows the relationship between the actual resonant frequency values and the predicted resonant frequency values generated by the model. As shown in the figure, most data points are located very close to the diagonal line, indicating strong agreement between the actual and predicted values. The distribution of points along the diagonal line demonstrates that the model had a very high predictive capability for the resonant frequency of the antenna. This finding is also consistent with the evaluation results presented in Table 1, where the R^2 value approached 1. These results confirm that the DNN model was able to learn the relationship between antenna geometry parameters, such as patch length, patch width, and substrate dielectric constant, and the antenna resonant frequency with very high accuracy (Li et al., 2021).

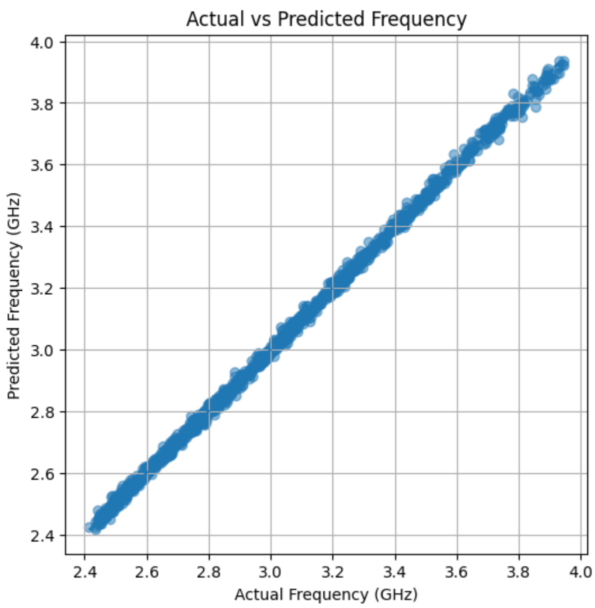

Figure 2. Comparison between actual and predicted resonant frequency values

Prediction performance for return loss

The relationship between the actual return loss (S_{11}) values and the predicted values is shown in Figure 3. The figure indicates that most data points are still distributed around the diagonal line, suggesting that the model was able to predict S_{11} values with good accuracy. However, compared with the resonant frequency plot, the spread of points in this figure is slightly wider. This indicates that the prediction of return loss had a somewhat higher degree of variation. This behavior can be attributed to the fact that the return loss parameter is strongly influenced by the antenna feed position as well as the more complex electromagnetic field distribution on the antenna patch (Kaur & Singh, 2024).

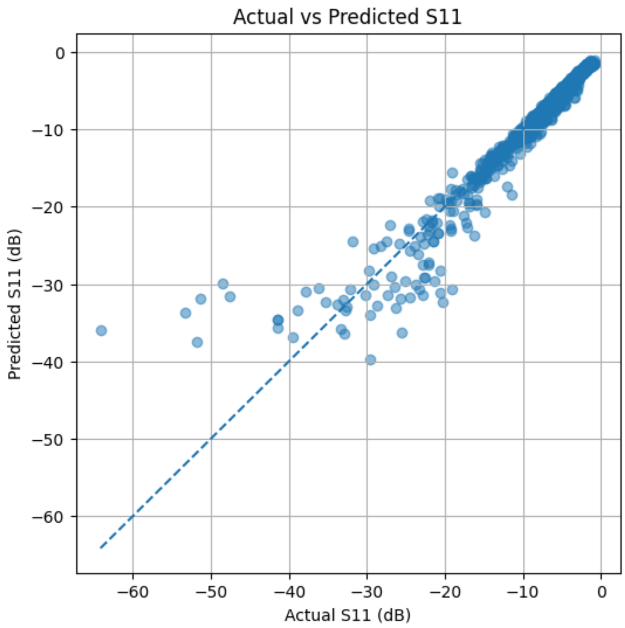

Figure 3. Comparison between actual and predicted S_{11} values

Optimized antenna geometry

The optimization result of the rectangular microstrip antenna design using the DNN model is shown in Figure 4, which illustrates the optimum antenna geometry obtained from the optimization process. Based on the optimization results, the obtained antenna patch dimensions were a patch width of 28.34 mm and a patch length of 24.40 mm, with an inset feed position of approximately 9.55 mm from the patch edge. These dimensions are consistent with the characteristics of microstrip antennas designed to operate at around 3 GHz, which generally have patch sizes in the range of tens of millimeters depending on the dielectric constant of the substrate used (Ahmed et al., 2022; Singh et al., 2022). The optimum design produced a resonant frequency of 2.996 GHz, which is very close to the target frequency of 3 GHz. In addition, the return loss of -18.70 dB indicates that the antenna had reasonably good impedance matching. The input impedance of 53.95 Ω was also close to the standard 50 Ω, indicating that this antenna design is suitable for wireless communication applications in the S-band (Kumar et al., 2022).

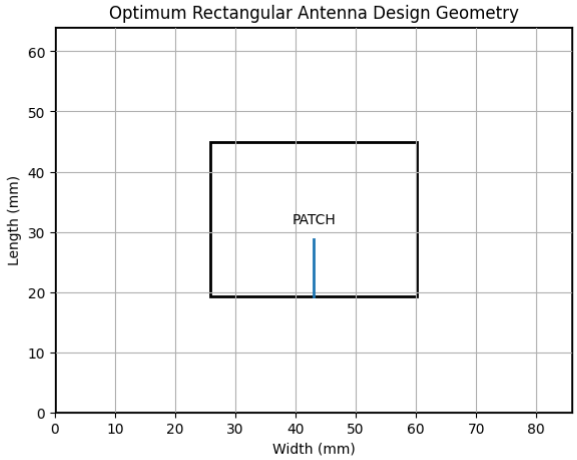

Figure 4. Geometry of the optimized rectangular microstrip antenna obtained using the DNN-based optimization method

The results presented in this section demonstrate that the proposed DNN-based approach was able to accurately predict key antenna parameters and effectively identify an optimized rectangular microstrip antenna design for operation near the 3 GHz target frequency.

Discussion

Effectiveness of deep neural networks for antenna design

The results of this study demonstrate that the Deep Neural Network (DNN) model is capable of predicting the characteristics of a rectangular microstrip antenna with a very high level of accuracy. This capability is reflected in the coefficient of determination R^2 values of 0.9987 for resonant frequency and 0.9988 for input impedance, indicating that nearly all variations in the dataset can be explained by the model. Such high R^2 values suggest that the DNN model successfully captured the nonlinear relationship between antenna design parameters and the resulting electromagnetic performance. The relatively small prediction error further confirms that the trained model can function effectively as a surrogate model for antenna design optimization.

In conventional antenna design approaches, the optimization process is typically performed using full-wave electromagnetic simulations such as CST Microwave Studio or HFSS. Although these simulation tools provide highly accurate results, they often require significant computational time, especially when exploring a large design space with many geometric parameters. Each design iteration may involve several minutes or even hours of simulation time depending on the complexity of the antenna structure. As a result, the optimization process can become computationally expensive and time-consuming.

The use of machine learning models, particularly Deep Neural Networks, offers a promising alternative to overcome these limitations. Once trained, a DNN model can evaluate thousands of antenna design configurations in a very short time, often within milliseconds. This significantly accelerates the design exploration process and enables researchers to identify promising antenna configurations more efficiently. Similar findings have been reported in previous studies, where deep learning techniques were successfully applied to predict antenna parameters and accelerate the design optimization process (Li et al., 2021; Wang et al., 2023). Another important observation from this study is the stability of the training process. As shown in Figure 1, the training and validation loss curves gradually decrease and eventually converge within a relatively narrow range. The close proximity between the two curves indicates that the model does not experience significant overfitting and is capable of generalizing well to unseen data. This suggests that the dataset generated using the analytical antenna model was sufficiently representative for training the neural network.

Furthermore, the ability of the DNN model to learn complex relationships between geometric parameters and antenna performance highlights the potential of artificial intelligence techniques in electromagnetic engineering. Antenna performance is inherently influenced by nonlinear interactions among multiple parameters, including substrate properties, patch dimensions, and feed structure. Traditional analytical models may provide approximate solutions, but they often become less accurate when the antenna geometry becomes more complex. In contrast, deep learning models can learn these nonlinear interactions directly from data, enabling more accurate and flexible prediction models.

Prediction accuracy of antenna parameters

The model evaluation results presented in Table 1 show that the proposed DNN model achieves very high accuracy in predicting the resonant frequency of the antenna. The MAE value of 11.63 MHz at an operating frequency around 3 GHz corresponds to a relative prediction error of approximately 0.39%, which is considered very small for antenna design applications. This result indicates that the geometric parameters of the antenna, particularly patch length and dielectric constant, have a strong and predictable influence on the resonant frequency. The relationship between the actual resonant frequency values and the predicted values is further illustrated in Figure 2, where most of the data points lie very close to the diagonal reference line. This strong alignment indicates that the model predictions closely match the actual values generated from the analytical antenna model. Such behavior confirms that the neural network successfully learned the mapping between input parameters and output performance metrics.

The high prediction accuracy of resonant frequency can be explained by the strong theoretical relationship between patch dimensions and the fundamental resonant mode of a microstrip antenna. According to microstrip antenna theory, the resonant frequency is primarily determined by the effective electrical length of the patch and the effective dielectric constant of the substrate. Because these parameters have a well-defined mathematical relationship, the neural network can effectively learn this relationship during training. In contrast, the prediction accuracy for return loss S_{11} is slightly lower, with an R^2 value of 0.9261. Although this value still indicates strong predictive performance, it is lower than that observed for resonant frequency and input impedance. The scatter plot shown in Figure 3 reveals that the predicted S_{11} values exhibit a slightly wider distribution around the diagonal line. This behavior suggests that the return loss parameter is more difficult to predict compared with resonant frequency. One possible explanation for this phenomenon is that return loss is strongly influenced by the antenna feeding mechanism and the distribution of electromagnetic fields within the patch structure. Small variations in the feed position or slight changes in the current distribution on the patch surface can significantly affect the impedance matching condition. As a result, the relationship between geometric parameters and S_{11} tends to be more complex and nonlinear compared with the relationship governing resonant frequency (Kaur & Singh, 2024).

Nevertheless, the prediction performance obtained in this study still demonstrates that the DNN model is capable of estimating return loss with sufficient accuracy for preliminary antenna design optimization. Such predictions can serve as an initial guide for selecting promising antenna configurations before performing detailed electromagnetic simulations.

Analysis of the optimized antenna design

The antenna design optimization process performed using the trained DNN model produced an optimal antenna configuration with patch dimensions of 28.34 mm × 24.40 mm and an inset feed position of approximately 9.55 mm from the patch edge. These dimensions fall within the typical range of rectangular microstrip antennas designed to operate in the S-band frequency range (2–4 GHz). Previous studies have also reported that microstrip patch antennas operating around 3 GHz generally have patch dimensions in the order of tens of millimeters, depending on the substrate dielectric constant and thickness (Ahmed et al., 2022; Singh et al., 2022).

The optimized antenna design produced a resonant frequency of 2.996 GHz, which is extremely close to the target frequency of 3 GHz. The very small deviation from the target frequency indicates that the optimization process was able to successfully identify an antenna configuration that satisfies the design requirements. This result demonstrates the effectiveness of using DNN-based optimization techniques in identifying suitable antenna design parameters. In addition to achieving the desired resonant frequency, the optimized antenna also exhibits a return loss of −18.70 dB, indicating good impedance matching. In antenna engineering, a return loss below −10 dB is generally considered acceptable for practical applications, as it indicates that most of the input power is successfully radiated by the antenna rather than being reflected back to the source. Therefore, the obtained return loss value suggests that the antenna design has satisfactory radiation efficiency.

The optimized design also produces an input impedance of 53.95 Ω, which is close to the standard 50 Ω impedance commonly used in RF transmission systems. Maintaining an input impedance close to the transmission line impedance is crucial for minimizing signal reflections and ensuring efficient power transfer between the antenna and the RF circuitry. The close agreement between the optimized impedance value and the standard transmission line impedance further confirms the suitability of the proposed antenna design. The geometric visualization presented in Figure 4 also shows that the resulting antenna structure follows a realistic configuration commonly used in practical microstrip antenna designs. The placement of the patch at the center of the substrate, combined with a larger ground plane, helps maintain stable radiation patterns and reduces unwanted edge effects. The inset feed structure also provides an effective method for achieving impedance matching without requiring additional matching networks.

Implications for antenna design optimization

The findings of this study highlight the significant potential of integrating Deep Neural Networks into the antenna design workflow. By employing a DNN model as a surrogate model, the antenna design process can be significantly accelerated, particularly during the early stages of design exploration. Instead of performing time-consuming full-wave simulations for every design candidate, the trained neural network can quickly evaluate the performance of thousands of potential configurations. This approach enables designers to rapidly explore a wide design space and identify promising antenna geometries before conducting detailed electromagnetic simulations. Once a promising design is identified using the machine learning model, the design can then be further refined and validated using full-wave simulation tools such as CST or HFSS. This hybrid approach combines the speed of machine learning with the accuracy of electromagnetic simulations.

Moreover, the integration of artificial intelligence in antenna design aligns with the growing trend of applying data-driven methods in electromagnetic engineering. Recent research has demonstrated that machine learning techniques can be used not only for antenna parameter prediction but also for tasks such as inverse antenna design, radiation pattern synthesis, and array optimization. These developments indicate that AI-assisted electromagnetic design may play an increasingly important role in future wireless communication technologies (Wu et al., 2024; Chen et al., 2025). Overall, the results of this study suggest that DNN-based optimization methods can serve as an effective tool for accelerating antenna design, reducing computational cost, and improving the efficiency of design exploration. Such approaches are particularly relevant in modern wireless communication systems, where antenna designs must often be optimized across multiple parameters to meet increasingly demanding performance requirements.

CONCLUSION

Fundamental Finding: This study demonstrated the effectiveness of Deep Neural Networks (DNN) for optimizing the design of a rectangular microstrip antenna targeting a frequency of 3 GHz. The proposed model achieved high prediction accuracy with R^2values of 0.9987 for resonant frequency and 0.9988 for input impedance. The optimized antenna design produced a resonant frequency of 2.996 GHz, return loss of −18.70 dB, and input impedance of 53.95 Ω, which closely match the target design specifications for S-band applications. **Implication**: The results indicate that DNN can be effectively used as a surrogate model to accelerate antenna design optimization by reducing the need for repetitive electromagnetic simulations. This approach enables faster exploration of design parameters and supports the integration of artificial intelligence techniques in modern wireless communication system development. **Limitation**: The main limitation of this study is that the dataset was generated from analytical models rather than full-wave electromagnetic simulations or experimental measurements. In addition, the optimization focused primarily on resonant frequency, return loss, and input impedance. **Future Research**: Future work should incorporate full-wave simulation data or experimental validation to improve model reliability. Further studies may also explore advanced deep learning architectures and include additional antenna parameters such as gain, radiation efficiency, and bandwidth in the optimization process.

AUTHOR CONTRIBUTIONS

Riski Ramadani contributed to the conceptual framework, research design, and validation process. **Afiyah Nikmah** was involved in methodology development, data analysis, sourcing references, and drafting the manuscript. **Arum Vonie Rachmawati** handled data management, project coordination, and manuscript drafting. **Rohim Aminullah Firdaus** supervised the research process. **Noer Risky Ramadhani** provided critical revisions, and finalized the manuscript.

CONFLICT OF INTEREST STATEMENT

The authors report no conflicts of interest, either financial or personal, that might have influenced the research process or the outcomes of this study.

STATEMENT ON THE USE OF AI OR DIGITAL TOOLS IN WRITING

The authors acknowledge the use of digital technologies, including AI-assisted tools, to support certain stages of the research and writing process of this article. These tools were utilized to assist with reference organization, language refinement, and structuring of ideas during manuscript preparation. All generated outputs were carefully reviewed, critically evaluated, and revised by the authors to ensure accuracy, academic integrity, and compliance with ethical research standards. The authors take full responsibility for the content, interpretation, and conclusions presented in this manuscript.

REFERENCES

Ahmed, S., Rahman, M. M., & Islam, M. T. (2022). Compact microstrip patch antenna design for S-band wireless applications. *International Journal of RF and Microwave Computer-Aided Engineering, 32*(9), e23241. https://doi.org/10.1002/mmce.23241

Bansal, R., & Sharma, S. (2021). Design and analysis of microstrip patch antenna for wireless communication systems. *Microwave and Optical Technology Letters, 63*(10), 2525–2531. https://doi.org/10.1002/mop.32989

Chen, J. H., Lin, Y. C., & Chen, C. H. (2023). Multiple performance optimization for microstrip patch antennas using design of experiments and response surface methodology. *Sensors, 23*(9), 4278. https://doi.org/10.3390/s23094278

Chen, S., Sun, G. H., & Wang, K. (2025). Inverse design of microstrip antennas based on deep learning. *Electronics, 14*(13), 2510. https://doi.org/10.3390/electronics14132510

Kaur, A., & Singh, G. (2024). Performance analysis of rectangular microstrip patch antennas for S-band wireless communication. *Wireless Personal Communications, 136*(2), 913–925. https://doi.org/10.1007/s11277-023-10564-9

Kumar, A., Singh, D., & Sharma, R. (2022). Design and analysis of microstrip patch antenna for wireless communication applications. *Microwave and Optical Technology Letters, 64*(6), 1627–1634. https://doi.org/10.1002/mop.33201

Kundu, K., Ghosh, S., & Chattopadhyay, S. (2023). Design and analysis of a low-profile microstrip antenna for wireless communication systems. *Journal of Telecommunications and Information Technology, 2023*(3), 45–53. https://doi.org/10.26636/jtit.2023.167423

Li, L., Xu, S., Zhao, Y., & Nie, Z. (2021). Machine learning methods for antenna design and optimization: A review. *IEEE Access, 9*, 125424–125445. https://doi.org/10.1109/ACCESS.2021.3110124

Merino-Fernandez, I., Gomez, J., & Martinez, F. (2025). Design of rectangular patch antennas through machine learning and electromagnetic simulations. *Scientific Reports, 15*, 18939. https://doi.org/10.1038/s41598-025-18939-2

Prabhakar, D., Balaji, P., & Ramesh, K. (2024). Prediction of microstrip antenna dimensions using optimized graph neural networks. *Array, 21*, 100258. https://doi.org/10.1016/j.array.2024.100258

Rahman, M. A., Islam, M. T., & Ullah, M. H. (2024). A compact rectangular microstrip antenna for wireless communication systems. *Progress In Electromagnetics Research C, 134*, 123–134. https://doi.org/10.2528/PIERC23120105

Singh, H., Kumar, P., & Meena, R. (2022). Rectangular microstrip patch antenna design for S-band applications. *AEU – International Journal of Electronics and Communications, 145*, 154090. https://doi.org/10.1016/j.aeue.2022.154090

Wang, Y., Liu, X., & Zhang, H. (2023). Deep learning based surrogate modeling for antenna design optimization. *IEEE Access, 11*, 72844–72855. https://doi.org/10.1109/ACCESS.2023.3290081

Wu, T., Yang, F., & Chen, Y. (2024). Artificial intelligence assisted antenna design: A review and future perspectives. *IEEE Access, 12*, 34512–34530. https://doi.org/10.1109/ACCESS.2024.3365178

Zhang, Q., Liu, Y., & Li, J. (2023). Deep neural network based surrogate modeling for electromagnetic device optimization. *IEEE Transactions on Antennas and Propagation, 71*(4), 3052–3063. https://doi.org/10.1109/TAP.2022.3229897

International Telecommunication Union. (2022). *Digital development report 2022: ICTs for sustainable development*. ITU. https://doi.org/10.1787/9789264499047

United Nations. (2023). *The sustainable development goals report 2023*. United Nations Publications. https://doi.org/10.18356/9789210024914

World Bank. (2024). *Digital development overview 2024*. World Bank. https://doi.org/10.1596/978-1-4648-2076-5

***Riski Ramadani (Corresponding Author)**
Postgraduate Physics, Universitas Negeri Surabaya
Jl. Ketintang, Ketintang, Kec. Gayungan, Surabaya, Jawa Timur 60231
Email: riski.20056@mhs.unesa.ac.id

Afiyah Nikmah
Postgraduate Physics, Universitas Negeri Surabaya
Jl. Ketintang, Ketintang, Kec. Gayungan, Surabaya, Jawa Timur 60231
Email: 24031885002@mhs.unesa.ac.id

Arum Vonie Rachmawati
Postgraduate Physics, Universitas Negeri Surabaya
Jl. Ketintang, Ketintang, Kec. Gayungan, Surabaya, Jawa Timur 60231
Email: 25031885005@mhs.unesa.ac.id

Rohim Aminullah Firdaus
Postgraduate Physics, Universitas Negeri Surabaya
Jl. Ketintang, Ketintang, Kec. Gayungan, Surabaya, Jawa Timur 60231
Email: rohimfirdaus@unesa.ac.id

Noer Risky Ramadhani
Universität für Weiterbildung Krems
Dr.-Karl-Dorrek-Straße 30, 3500 Krems an der Donau, Austria
Email: ramadhanirisky52@gmail.com