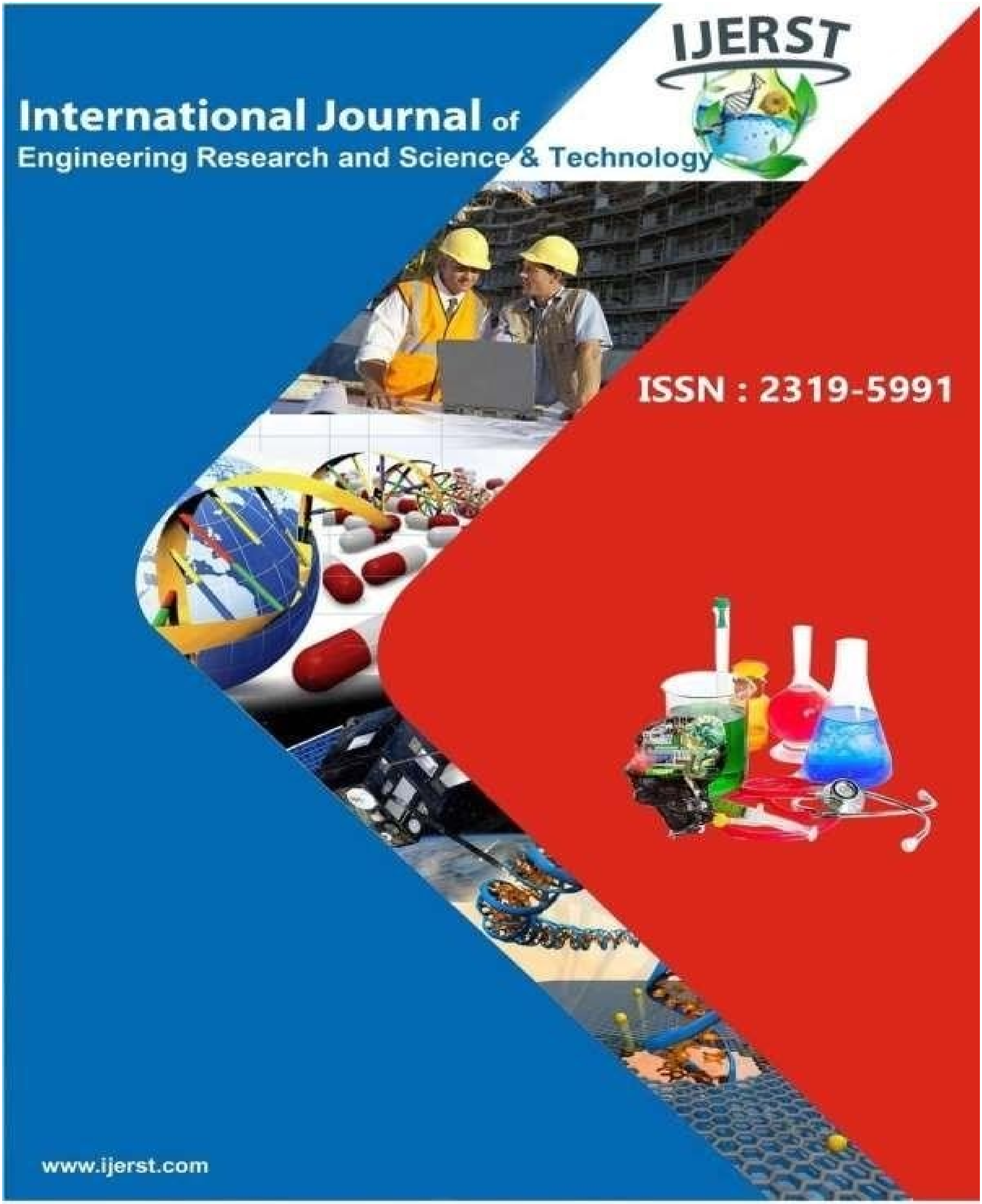


IJERST

International Journal of
Engineering Research and Science & Technology

ISSN : 2319-5991

www.ijerst.com

Email: editor@ijerst.com or editor.ijerst@gmail.com

Int. J. Eng. Res. & Sci. & Tech. 2025

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

Vol. 21, Issue 2, 2025

Deep Learning Based Data-Driven InsightsInto Microstrip Antenna Performance

Muddagouni Yashvardhan[1], Arepally Teja [2], Gudavalli Prabhu Kiran[3], Mr. Gabbeta Ramesh [4]
[1,2,3] UG Scholar, Dept. of ECE, St. Martin's Engineering College, Secunderabad, Telangana, India, 500100
[4]Assistant Professor, Dept. of ECE, St. Martin's Engineering College, Secunderabad, Telangana, India, 500100
yashu.muddagouni@gmail.com

Abstract:

Microstrip antennas are widely used in modern communication systems due to their low profile, lightweight, and ease of integration with circuits. However, predicting their performance across various parameters such as bandwidth, gain, and VSWR remains a challenge, traditionally relying on empirical methods and complex simulations. Over the years, advancements in deep learning have opened new avenues for more accurate and efficient prediction models. The traditional approach to antenna design typically involved time- consuming and resource-intensive processes, including manual tuning, trial-and-error, and reliance on antenna simulation software. These methods, though effective, are limited in scalability and accuracy when dealing with vast design variations. In this research, we propose a data-driven approach using Multi-Layer Perceptron (MLP) regression models to predict key performance metrics of microstrip antennas. By training on a dataset containing diverse antenna parameters, this model offers improved accuracy and prediction speed over traditional methods. The proposed system aims to provide designers with a robust tool for optimizing antenna performance, reducing reliance on simulations, and expediting the design process. This deep learning- based solution demonstrates the potential for enhancing microstrip antenna design, making it more efficient, scalable, and precise.

1. INTRODUCTION

Microstrip antennas (MSAs) have been an essential component in modern wireless communication systems due to their compact size, lightweight nature, and ease of fabrication. Since their introduction in the 1950s and subsequent advancements in the 1970s, MSAs have been widely adopted in applications such as satellite communication, radar systems, mobile networks, and IoT devices. In India, the rapid expansion of 5G networks and satellite communication has significantly increased the demand for efficient antenna design. According to market reports, the Indian telecom sector witnessed a 13.7% CAGR growth in 2022, with a rising focus on antenna miniaturization and performance optimization. Traditional microstrip antenna design relies heavily on iterative simulations using tools like HFSS and CST, which require extensive computational resources and expert knowledge. The growing complexity of wireless applications has highlighted the limitations of conventional methods, as engineers struggle to optimize parameters like bandwidth, gain, and VSWR efficiently. The advent of deep learning, particularly data-driven regression models, provides a promising alternative by enabling rapid and accurate performance prediction. This study explores the role of Multi-Layer Perceptron (MLP) regression models in time, techniques, this research aims to transform antenna development, making it faster and more accessible while maintaining high accuracyand efficiency.

2. LITERATURE SURVEY

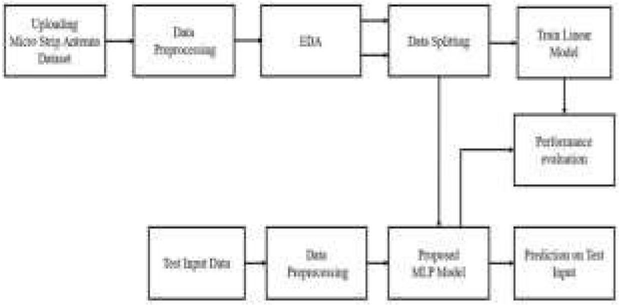
Cui et al. [1] During the last decade, a variety of optimization methods have absorbed the attention of designers to tackle the drawbacks of EDA tools in this sense. Some of the various reported optimization methods are: surrogate-based optimization particle swarm optimization spider monkey optimization genetic algorithm optimization and K-nearest neighbor algorithm. In the Research of Ossa-Molina et al. [2]. Microstrip antennas are fabricated by a copper-etched printed circuit board (PCB) through an exact patch shapes that are arranged at one side and ground planes are arranged at other side. Sharma and Pandey [3] have presented an application of Gaussian Process Regression machine learning algorithms with artificial neural network for computing resonant frequency at square patch dimensions of compact microstrip antenna (SPCMA), slot dimensions of square patch, and dominant mode at 0.4856–7.8476 GHz frequency band was presented. The presented Gaussian process regression (GPR) model was evaluated through fabricating as well as categorizing microstrip antenna prototype. The performance of the fabricated antenna was near to the structured antenna and forecasted through Gaussian Process Regression. It provides less predicted accuracy.Han et al. [6] have presented a resonant frequency modelling of MSA based on deep kernel learning (DKL). It was one of the most time consuming process to obtain train samples through labels from the software of full- wave electromagnetic simulation, after modelling and optimizing electromagnetic components. Hence, artificial neural network and Gaussian process (GP) kernel learning model, DKL technique with multiple-nonlinear-mapping layers was presented related to particle swarm optimization algorithm. The DKL performance model was evaluated through the resonant frequency of 2 Yagi micro strip antennas and the expected outcome of the deep kernel learning technique. It provides high feedline length. Qian et al. [7] have presented a surrogate-assisted defected ground structure (DGS) design for suppressing E- plane couplings and H- plane couplings simultaneously in two × two MSA array at 2.45 GHz. The magnetic current and mode theory basis, the DGS was designed and analyzed. Moreover, machine learning was used for sweeping the defected ground structure parameters amongst determined limits and fine-tunes for obtaining optimum design, predominantly shortens the defected ground structure design time. To corroborate the performance of the presented method, the 2 MSA antennas were used as test case. Thus, the simulation and measurement outcomes at trains that the presented defected ground structure can suggestively decrease E- and H- plane couplings. It provides high patch width.

3. PROPOSED METHODOLOGY

In the traditional system of microstrip antenna design, performance prediction relies heavily on empirical methods, manual tuning, and electromagnetic simulation software like HFSS or CST Studio. These methods have long been the foundation of antenna design, using detailed physical models to estimate key performance metrics such as gain, bandwidth, and VSWR. Engineers typically adjust design parameters through trial-and-error or iterative simulations, drawing from prior knowledge and past data to refine the design. While this approach has been effective, it comes with several inherent limitations that hinder efficiency and innovation.

One major drawback is the time and computational resources required for simulation-based design. Modelling complex antenna structures, especially when running multiple iterations, can significantly prolong the design cycle, delaying product development. Additionally, high-performance computing resources are often necessary to conduct detailed electromagnetic simulations, making the process resource- intensive and costly. As the number of design parameters increases, traditional methods struggle to handle large datasets efficiently, reducing scalability and limiting the ability to explore a wide range ofpotential designs.

Furthermore, the reliance on empirical tuning and trial-and-error methods frequently results in suboptimal antenna designs. Engineers may overlook configurations that could yield better performance, particularly when working with novel or unconventional designs. Empirical methods can also introduce inaccuracies, as they may fail to capture complex relationships between design parameters and performance. Additionally, simulation-based predictions often do not fully align with real-world behavior, necessitating costly physical prototyping and experimental validation. This not only increases expenses but also slows down the iterative design process, making it challenging to optimize antenna performance effectively.



The given flowchart illustrates the process of predicting microstrip antenna performance using machine learning models. It begins with uploading the dataset, followed by data preprocessing and exploratory data analysis (EDA) to extract insights. The data is then split into training and testing sets, where a linear model is trained and evaluated for performance. Simultaneously, a proposed MLP (Multi-Layer Perceptron) model is developed using processed test input data. The model undergoes further data preprocessing before making predictions on the test input. This structured approach ensures accurate performance evaluation and comparison between the linear and MLP models.

Applications:

Microstrip antennas play a crucial role in advancing 5G and wireless networks by optimizing high-frequency applications to ensure better signal propagation and reduced interference. These antennas are designed to meet the demands of next-generation communication systems, offering improved bandwidth and efficiency. Similarly, in the Internet of Things (IoT) and smart devices, small-form antennas are essential for compact IoT modules, enhancing connectivity and operational efficiency in various smart applications. Their integration allows for seamless communication between devices, making them fundamental in the growing landscape of interconnected technologies.

In satellite communication, high-gain microstrip antennas are engineered for space applications, ensuring robust signal strength and efficient data transmission. These antennas contribute to improved connectivity in remote areas and enhance global communication networks. In defence and aerospace, advanced radar and communication antennas are vital for military applications, providing enhanced surveillance and security. Their reliability and precision make them indispensable for defence systems, enabling effective monitoring and threat detection.

Microstrip antennas also find applications in biomedical fields, where wearable and implantable antennas support wireless health monitoring. These antennas enable real-time patient monitoring and data transmission, improving healthcare accessibility and efficiency. In the automotive industry, their integration in vehicular communication systems (V2X) enhances navigation and supports autonomous driving technologies. Additionally, high-efficiency antennas are widely used in RFID and sensor networks for inventory tracking, asset management, and environmental monitoring, demonstrating their versatility across various industries.

Advantages:

Multi-Layer Perceptrons (MLPs) excel at capturing complex non-linear relationships between inputs and outputs, making them far more flexible than traditional linear models. By using multiple hidden layers and activation functions like ReLU or sigmoid, MLPs can approximate intricate patterns that simpler models fail to recognize. This ability is particularly useful in areas like image recognition, finance, and natural language processing, where data relationships are not straightforward.Another key advantage of MLPs is their ability to automatically learn feature interactions, reducing the need for manual feature engineering. The hidden layers combine different features in meaningful ways, uncovering patterns that may not be immediately obvious. This makes MLPs highly effective for handling high- dimensional and complex datasets, such as images, audio, and time- series data. Their ability to generalize across complex patterns allows them to perform well in diverse applications, including medical diagnosis, fraud detection, and speech recognition. A key strength of MLPs lies in their ability to automatically learn feature interactions, reducing the need for extensive manual feature engineering. Through multiple layers of interconnected neurons, the network learns hierarchical representations of data. The hidden layers extract meaningful abstractions by combining different features in ways that may not be immediately obvious to human analysts. This makes MLPs highly effective in handling high-dimensional datasets, such as images, audio, and time-series data, where traditional models struggle to capture underlying dependencies. MLPs are trained using supervised learning techniques, typically with the backpropagation algorithm combined with optimization methods such as Stochastic Gradient Descent (SGD) or Adam. During training, the network adjusts the weights and biases in each layer based on the error between predicted and actual outputs. Loss functions such as mean squared error (MSE) for regression tasks or cross-entropy loss for classification help guide the model in learning meaningful representations. The introduction of techniques like batch normalization and dropout further improves training efficiency and prevents overfitting.

4. EXPERIMENTAL ANALYSIS

This figure illustrates the data preprocessing step within the GUI interface. It shows the various transformations applied to the raw dataset before training the models. These transformations include handling missing values, scaling features, encoding categorical variables, and normalizing data where necessary. The GUI provides real-time feedback, ensuring that the dataset is ready for model training after preprocessing steps are applied.

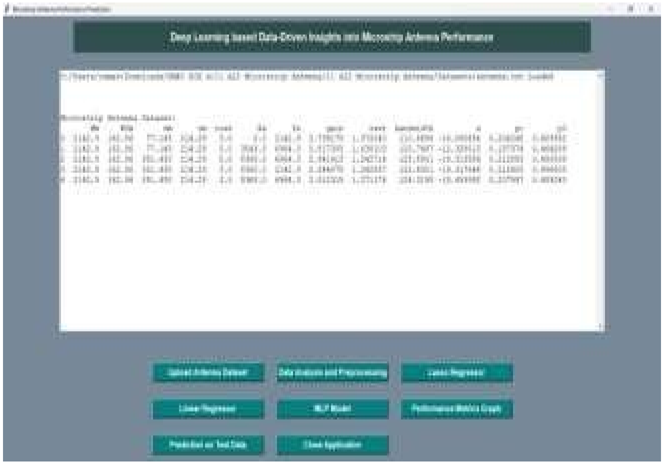


Fig: Data Preprocessing in the GUI

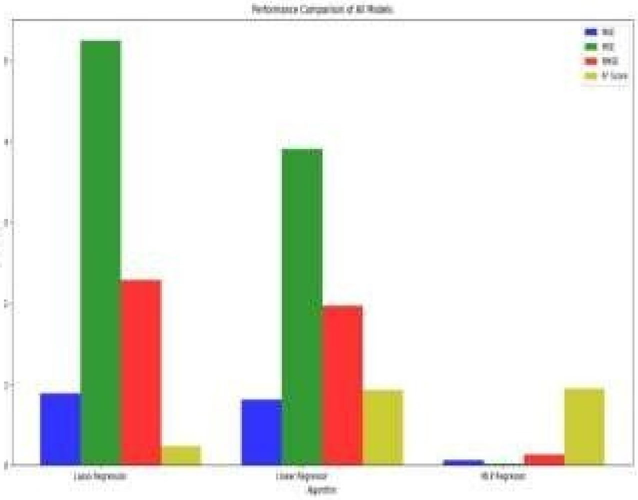


Fig: Performance Comparison Graph for All Models

5. CONCLUSION

This research successfully leveraged machine learning models to predict the performance of microstrip antennas. By analyzing a dataset containing key parameters such as wavelength, distance, gain, VSWR, and bandwidth, valuable insights were gained into antenna behavior. Data preprocessing steps, including cleaning and feature scaling, ensured that the dataset was well-prepared for model training. The use of regression algorithms such as Ridge Regression, Lasso Regression, and MLP Regressor allowed for reliable predictions of antenna performance characteristics, enabling an effective comparison of different modeling approaches. The evaluation of these models helped identify the most efficient technique in terms of accuracy and computational efficiency. The incorporation of deep learning, particularly the MLP Regressor, demonstrated promising results, indicating the potential of advanced machine learning techniques to enhance antenna performance prediction. These findings highlight the advantages of leveraging artificial intelligence in optimizing antenna design and improving predictive accuracy, reducing dependency on traditional empirical methods and time-consuming simulations.

Several avenues exist for future research to expand and improve these findings. Model enhancements could involve exploring advanced machine learning algorithms such as Random Forest Regressor, Support Vector Machines (SVM), and ensemble methods like XG Boost to achieve better accuracy. Integrating deep learning architectures like Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) may help capture more complex patterns in data, particularly in cases where spatial or temporal relationships are crucial. Additionally, real-time prediction capabilities can be developed by integrating sensor networks, enabling continuous performance adjustments based on live data.

Further optimization techniques, such as Genetic Algorithms or Particle Swarm Optimization, could refine antenna parameters, leading to enhanced performance prediction. Acquiring a more diverse and extensive dataset, covering different antenna types, frequencies, and environments, would improve the model's robustness and generalizability. Multi-objective performance metrics can also be incorporated to balance factors like signal loss, bandwidth, and power efficiency. Finally, hardware integration, where real-time measurements from physical antennas are fed into the machine learning models, could provide dynamic performance monitoring, bridging the gap between simulation-based predictions and practical implementations.

REFERENCES

[1] O. Ossa-Molina, J. Duque-Giraldo, E. & eyes-Vera Strain sensor based on rectangular microstrip antenna: Numerical methodologies and experimental validation IEEE Sensors Journal, 21 (20) (2021), pp. 22908-22917.

[2] K. Sharma, G.P. Pandey Efficient modelling of compact microstrip antenna using machine learning AEU-International Journal of Electronics and Communications, 135 (2021), Article 153739.

[3] J. Gao, Y. Tian, X. Chen Antenna optimization based on co-training algorithm of Gaussian process and support vector machine IEEE Access: Practical Innovations, 8 (2020), pp. 211380-211390.

[4] J. Kim, J. Oh Liquid-crystal-embedded aperture-coupled microstrip antenna for 5G applications IEEE antennas and wireless propagation Letters, 19(11) (2020)

[5] S. Han, Y. Tian, W. Ding, P. Li Resonant frequency modelling of microstrip antenna based on deep kernel learning IEEE Access, Practical Innovations, 9(2021), pp.39067-39076.

[6] B. Qian, X. Huang X. Chen, M. Abdullah, L. Zhao, A.A. Kishk surrogate- Assisted defected ground structure design for reducing mutual coupling in 22 microstrip antenna array IEEE Antennas and wireless propagation letters

[7] J.P. Jacobs Accurate modelling by convolutional neural-network regression of resonant frequencies of dual-based pixelated microstrip antenna IEEE Antennas and wireless propagation Letters 20(12)(2021),pp, 2417-2421.

[8] G.C. Wan, M.M. Li, Y.L yang, L. Xie,L. Chen Patch-antenna-based structural strain measurement using optimized energy detection algorithm applied on USRP IEE Internet Of Things Journal, 8(9) (2020), pp. 7476-7484.

[9] D.Khezzar, et al and ray et al. New Design of a broadband PBG-based antenna for THz band applications phonotics and Nanostructures fundamentals and applications 46(2021), Article.100947

[10] Cui, L., Zhang, Y., Zhang, R. & Liu, Q. H. A modified efficient KNN method for antenna optimization and design. IEEE Trans. Antennas Propag. 68, 6858– 6866. https://doi.org/10.1109/TAP.2020.3001743 (2020).