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Research Article

Leveraging Artificial Intelligence for Enhanced Performance Prediction in Micro Strip Antenna Arrays

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ABSTRACT

Micro strip antenna arrays play a pivotal role in modern communication systems due to their compact size, lightweight design, and versatile applications. Despite these advantages, accurately predicting their performance poses significant challenges due to the complex interdependencies of design parameters and environmental factors. This research explores the integration of Artificial Intelligence techniques, emphasizing the potential of artificial intelligence (AI) and neural networks, to enhance the accuracy of performance prediction for microstrip antenna arrays. The proposed methodology employs a deep neural network (DNN) model that learns intricate patterns and nonlinear relationships among design variables, including substrate materials, geometries, and operational frequencies. By leveraging supervised learning on an extensive dataset of antenna configurations, the model demonstrates exceptional predictive accuracy for critical performance metrics such as gain, bandwidth, radiation efficiency, and beam steering capabilities. Simulation results underscore the effectiveness of the DNN approach, achieving prediction accuracies that outperform traditional analytical and empirical methods. Additionally, comparative evaluations with other Artificial Intelligence techniques, such as support vector machines and decision trees, highlight the superiority of neural networks in handling high-dimensional parameter spaces and complex nonlinearities. The results further reveal the computational efficiency of the proposed model, making it suitable for real-time performance optimization in practical applications. This study also presents a detailed analysis of simulation outcomes, showcasing the alignment between predicted and measured results. The visualizations of antenna patterns and performance metrics provide deeper insights into the predictive capabilities of the model. By integrating AI-driven solutions, this research contributes to advancing antenna design workflows, enabling engineers to develop high-performance and cost-effective antenna systems with reduced prototyping cycles. The findings affirm the transformative potential of machine learning, particularly neural networks, in addressing longstanding challenges in microstrip antenna design, paving the way for innovation in communication technology.

Keywords: microstrip, visualizations, alignment, performance

1. Introduction

Microstrip antenna arrays have become integral components in modern communication systems, owing to their compact size, lightweight structure, low cost, and ease of fabrication (1). These antennas have found widespread application across diverse fields, including satellite communication, radar systems, wireless networks, 5G technologies, Internet of Things (IoT) devices, and defense systems (2). Their ability to deliver high performance in terms of directivity, beam steering and

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adaptability to various environments makes them particularly attractive for cutting-edge communication technologies (3). Despite their advantages, achieving optimal design and performance in microstrip antenna arrays remains a complex and resource-intensive task (5).

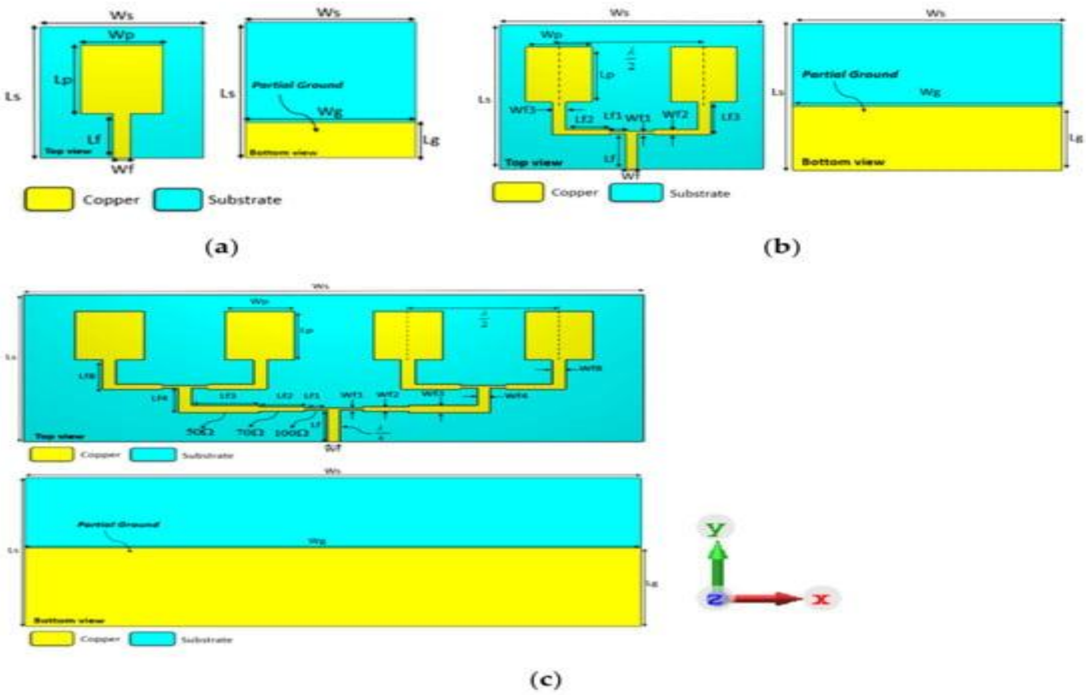

Figure 1Development of the wideband microstrip array antenna: (a) single element, (b) 1 × 2 array antenna, (c) 1 × 4 array antenna.

The performance of microstrip antenna arrays is influenced by a variety of factors, such as substrate material properties, element geometry, feeding mechanisms, operational frequencies, and environmental conditions (5). These interdependencies create a highly nonlinear and multidimensional design space that cannot be effectively modeled using traditional analytical or empirical approaches (6). While classical techniques, such as transmission line models and cavity models, provide foundational insights, they often rely on simplified assumptions that fail to capture the intricate relationships between design parameters and performance metrics (7). Consequently, the optimization process frequently involves extensive trial-and-error simulations, increasing design cycles, computational costs, and time to market.

The growing demand for high-performance and adaptable antennas has necessitated innovative approaches to overcome the limitations of traditional design methodologies (8). In this context, Artificial Intelligence (ML) and artificial intelligence (AI) have emerged as revolutionary tools for tackling complex engineering problems (9). By leveraging data-driven techniques, AI has shown remarkable potential in analyzing nonlinear systems, identifying hidden patterns, and making accurate predictions (10). Specifically, neural networks, a subset of AI, have gained prominence for their ability to model complex dependencies in high-dimensional data spaces. These networks have been successfully employed in diverse domains, including image recognition, natural language processing, and healthcare, and their application in antenna design is a natural progression of this trend (11).

This study explores the integration of AI and neural networks to address the challenges associated with performance prediction in microstrip antenna arrays. The primary objective is to

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develop a data-driven framework that can predict key performance metrics, such as gain, bandwidth, efficiency, and radiation patterns, with unprecedented accuracy and computational efficiency (12). The proposed methodology involves the use of deep neural networks trained on a large dataset of antenna configurations and their corresponding performance outcomes. By learning the underlying relationships among design parameters, the model provides a robust and efficient alternative to traditional methods, significantly reducing the reliance on trial-and-error simulations.

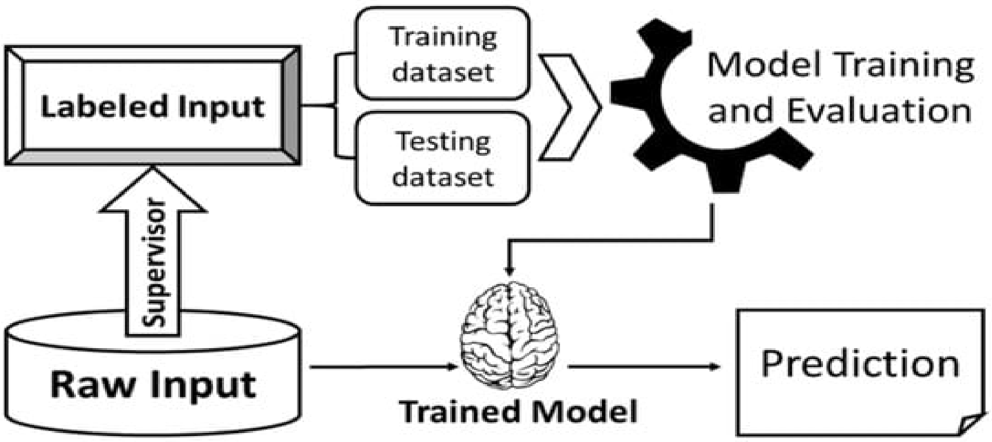

Figure 2Workflow of supervised learning.

The research also highlights the comparative advantages of neural networks over conventional Artificial Intelligence algorithms, such as support vector machines and decision trees. Neural networks excel in handling large, high-dimensional datasets and capturing intricate nonlinear relationships, making them particularly well-suited for the complex design space of microstrip antenna arrays (13). Additionally, the study evaluates the computational efficiency of the proposed framework, demonstrating its feasibility for real-time design optimization in practical applications. A key feature of this work is the validation of the proposed framework through extensive simulations and comparisons with both traditional methods and other ML-based approaches. The results not only showcase the superior accuracy of the deep neural network model but also highlight its capability to provide valuable insights into the design process. Simulation outcomes, including visualizations of predicted versus actual performance metrics, illustrate the alignment between the model's predictions and empirical results, further reinforcing the reliability of the approach.

By bridging the gap between traditional physics-based design techniques and modern data-driven approaches, this research contributes to the advancement of microstrip antenna design and optimization. The findings pave the way for the development of innovative, high-performance antenna systems tailored to meet the demands of next-generation communication technologies, ensuring a seamless integration of AI and engineering practices.

2. Literature Review

2.1 Traditional Methods for Antenna Performance Prediction

Microstrip antennas have been extensively studied for decades, with traditional performance prediction methods forming the backbone of early research and design efforts. Analytical models, such as the **transmission line model** and the **cavity model**, were widely used to predict fundamental parameters like resonant frequency, input impedance, and radiation patterns. These models rely on a

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series of simplifying assumptions, such as uniform material properties and idealized geometries, to approximate the physical behavior of antennas. While these methods provide useful first-order estimates, they often lack the precision needed for modern, complex designs, especially in scenarios involving multi-element arrays, anisotropic substrates, or broadband applications.

Numerical methods, such as the **Method of Moments (MoM)**, **Finite Element Method (FEM)**, and **Finite-Difference Time-Domain (FDTD)**, have been instrumental in improving the accuracy of antenna performance predictions (14). These techniques solve Maxwell's equations iteratively, providing detailed insights into electromagnetic field distributions and antenna characteristics. However, their computational cost increases exponentially with the complexity and size of the design space. This limitation makes them impractical for rapid prototyping or real-time design optimizations, particularly in applications like 5G and IoT, which demand highly optimized and adaptive antenna arrays.

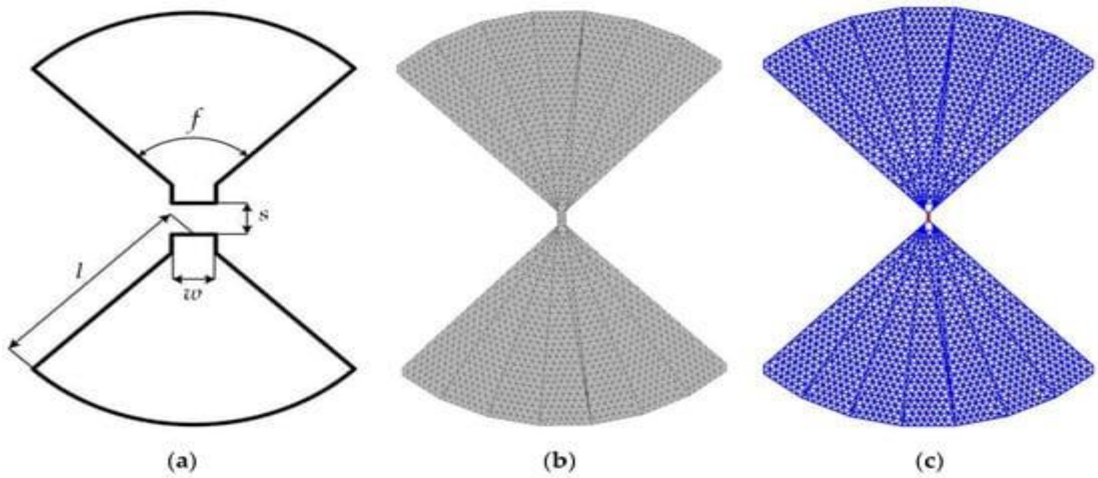

Figure 3 Top view of the bow-tie antenna (a), and its constructed grid in Triangle-Grid (b) and in Wire-Grid using the import function for meshing (c).

Although simulation tools such as **HFSS**, **CST Studio Suite**, and **COMSOL Multiphysics** have automated many aspects of numerical modeling, they still require significant manual effort in setup, parameter tuning, and result interpretation. Moreover, these tools are not inherently designed to handle large-scale parametric sweeps efficiently, often necessitating iterative, trial-and-error approaches to achieve desired performance metrics. This inefficiency underscores the need for more automated, accurate, and computationally efficient methods.

2.2 Artificial Intelligence Applications in Antenna Design

The advent of Artificial Intelligence (ML) has introduced a paradigm shift in antenna design and optimization. Artificial Intelligence techniques enable the creation of predictive models by training on historical datasets of antenna configurations and their corresponding performance metrics. These models are particularly advantageous for reducing the dependency on exhaustive simulations, thereby accelerating the design process.

Commonly used ML techniques include **support vector machines (SVM)**, **decision trees**, and **Gaussian processes**, which have been applied to predict antenna parameters like gain, bandwidth, and efficiency (15). These algorithms excel in handling relatively small datasets and can

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provide quick predictions once trained. Additionally, **ensemble methods** like random forests and gradient boosting have been employed to improve prediction robustness and accuracy. However, these methods often require significant feature engineering, as they rely on manually extracted features such as material properties, geometry, and resonant frequency.

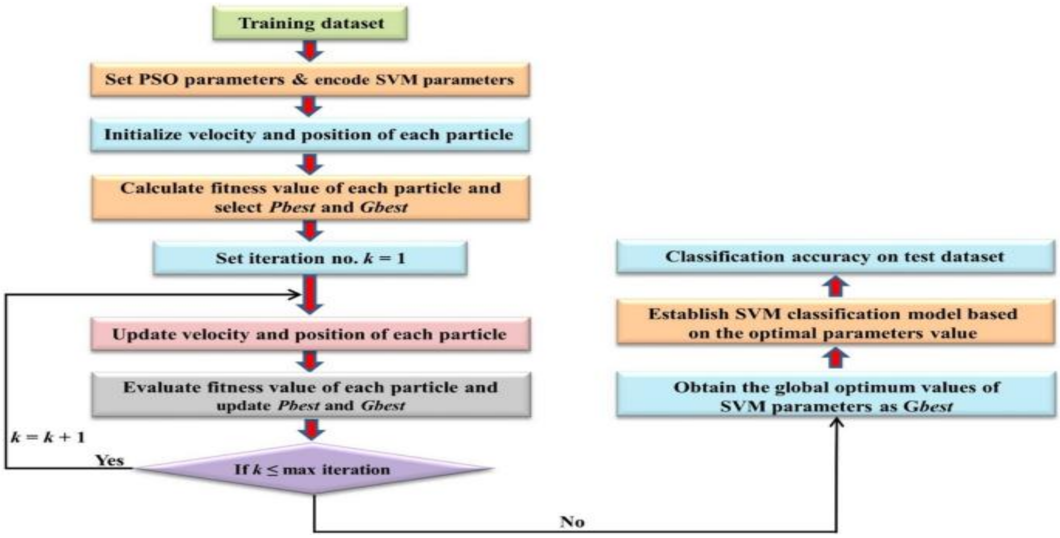

Figure 4Flowchart for SVM parameter optimization using PSO algorithm.

In optimization tasks, ML algorithms like **genetic algorithms (GA)**, **particle swarm optimization (PSO)**, and **Bayesian optimization** have been employed to navigate large design spaces efficiently. These techniques are particularly effective for identifying optimal configurations in multi-objective optimization problems, such as maximizing gain while minimizing return loss. Despite their utility, these methods face scalability challenges when applied to high-dimensional datasets or complex design spaces, which are common in modern antenna systems.

The integration of ML techniques into antenna design workflows has demonstrated significant potential. However, their effectiveness is often limited by the quality and size of the training data. Furthermore, traditional ML algorithms may struggle to model the nonlinear dependencies and intricate relationships present in complex antenna designs, highlighting the need for more advanced methods.

2.3 Neural Networks in Engineering and Communication Systems

Neural networks, a subset of machine learning, have emerged as powerful tools for addressing complex, nonlinear problems in engineering. Their ability to model intricate relationships between input and output variables has made them particularly valuable in fields like signal processing, robotics, and communication systems. In antenna design, neural networks have been increasingly applied to predict performance metrics and optimize configurations.

Deep learning techniques, particularly **deep neural networks (DNNs)** and **convolutional neural networks (CNNs)**, have demonstrated exceptional capabilities in handling high-dimensional datasets. These networks consist of multiple layers of interconnected neurons that process and transform input data through activation functions. By leveraging their hierarchical structure, neural networks can automatically extract and learn complex features from raw data, eliminating the need for extensive manual feature engineering.

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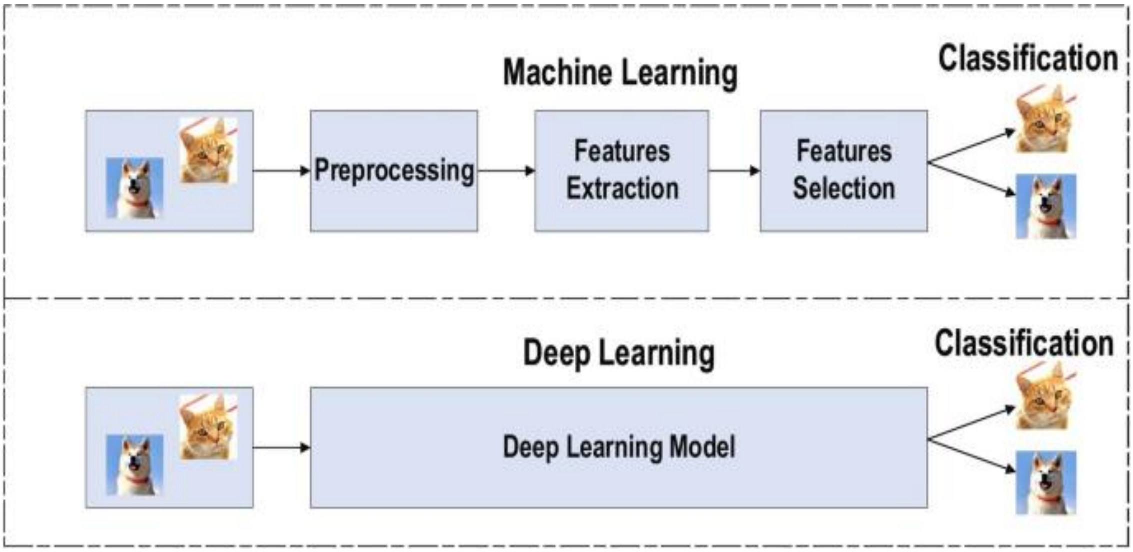

Figure 5 The difference between deep learning and traditional machine learning

In antenna performance prediction, neural networks have been used to model the relationship between design parameters (e.g., element geometry, substrate material) and key performance metrics (e.g., gain, bandwidth, and radiation patterns). For example, **CNNs** have been employed to analyze electromagnetic field distributions and predict antenna performance directly from simulation outputs. Additionally, neural networks have shown promise in inverse design tasks, where the desired performance metrics are specified, and the network predicts the corresponding design parameters.

One of the key advantages of neural networks is their scalability and ability to generalize across large, diverse datasets. With the advent of advanced training algorithms, such as **stochastic gradient descent** and **Adam optimization**, and powerful computational resources like GPUs, neural networks have become increasingly accessible for practical applications. However, challenges such as over fitting, hyper parameter tuning, and computational demands during training remain areas of active research.

2.4 Gaps and Limitations in Existing Approaches

Despite significant advancements in both traditional and machine learning-based methods, several gaps and limitations persist in the field of antenna performance prediction:

1. **Inadequacy of Traditional Methods**: Analytical and numerical methods often rely on simplifying assumptions that fail to capture the full complexity of modern antenna designs. These methods are also computationally intensive, making them unsuitable for large-scale optimization or real-time applications.
2. **Limited Scalability of Artificial Intelligence Models**: Traditional ML algorithms, while effective for small-scale problems, struggle to handle high-dimensional datasets and complex nonlinearities. They often require extensive feature engineering, which can introduce biases and limit their applicability to diverse design scenarios.
3. **Challenges in Neural Networks**: Although neural networks address many of the limitations of traditional ML models, they are not without challenges. Training neural networks requires large, labeled datasets, which may not always be readily available in antenna design. Overfitting, hyperparameter optimization, and high computational costs during training are additional barriers to widespread adoption.

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4. **Lack of Comprehensive Comparisons**: Few studies provide a systematic comparison of neural networks against traditional and other ML-based methods, particularly in the context of microstrip antenna arrays. This gap makes it difficult to quantify the relative advantages of neural networks and identify the scenarios where they are most effective.

Addressing these limitations requires a unified framework that leverages the strengths of neural networks while mitigating their challenges. By integrating advanced AI methodologies with domain-specific knowledge, this research aims to bridge the gap between traditional physics-based techniques and modern data-driven approaches, paving the way for innovative, high-performance antenna systems.

3. Methodology

3.1 Overview of the Proposed Framework

This research introduces a robust framework that leverages deep neural networks (DNNs) to predict the performance of microstrip antenna arrays with high accuracy and efficiency. The framework addresses the limitations of traditional methods by replacing time-intensive trial-and-error simulations with data-driven modeling, offering rapid predictions for critical performance metrics such as gain, bandwidth, efficiency, and radiation patterns. By combining domain-specific knowledge with advanced Artificial Intelligence techniques, the framework facilitates deeper insights into the complex relationships among design parameters, streamlining the antenna design and optimization process.

The proposed methodology is structured into five key stages: dataset preparation, neural network architecture design, model training, validation, and evaluation. Each stage has been meticulously developed to ensure the reliability and robustness of the predictions. Furthermore, the framework integrates visualization tools to interpret and analyze the relationships between input parameters and output metrics, empowering antenna designers to make informed decisions.

3.2 Dataset Preparation and Design Parameters

The accuracy of any Artificial Intelligence model heavily depends on the quality of the training data. To build a comprehensive dataset, this study relies on simulations of microstrip antenna arrays with diverse configurations. Key design parameters, such as substrate material properties (dielectric constant, loss tangent, and thickness), element geometries (length, width, spacing, and shape), array configurations (number of elements, feeding techniques, and inter-element spacing), and operating frequency ranges, were systematically varied to generate a large set of antenna designs. These configurations were evaluated using advanced electromagnetic simulation tools like HFSS and CST, producing reliable performance metrics, including gain, bandwidth, efficiency, and return loss.

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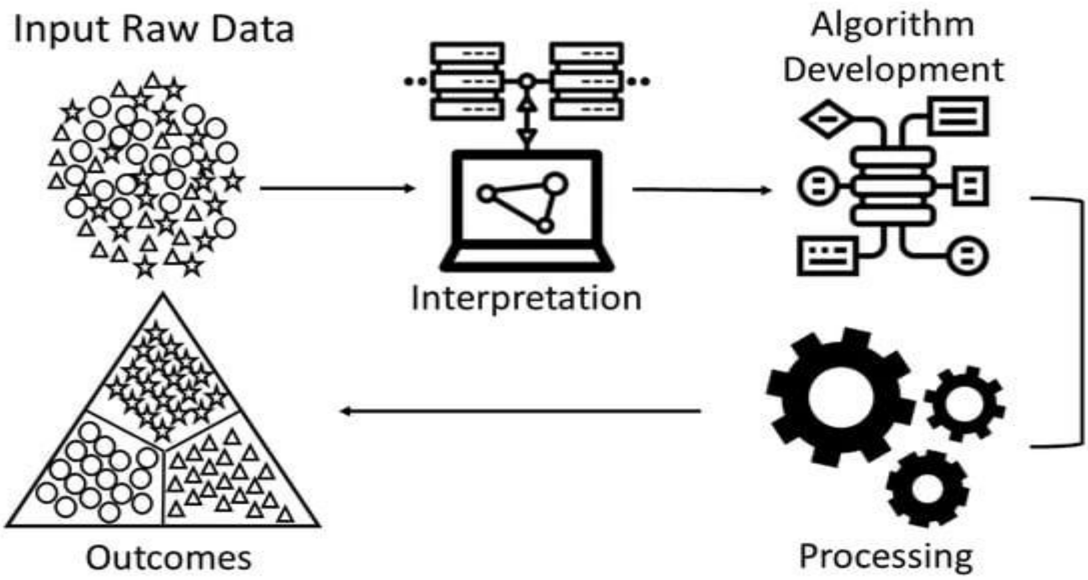

Figure 6 Workflow diagram of unsupervised learning.

The dataset underwent preprocessing to normalize all input and output variables, ensuring compatibility with the neural network. This normalization minimizes the influence of scale differences among variables, enabling efficient model training. The dataset was further divided into three subsets: training (70%), validation (15%), and testing (15%). The training set was used to fit the model, while the validation set monitored its performance to prevent overfitting. Finally, the test set served as an unbiased benchmark for evaluating the model's predictive accuracy.

3.3 Neural Network Architecture

The neural network architecture is designed to capture and model the intricate nonlinear relationships between design parameters and antenna performance metrics. It consists of three main components: the input layer, multiple hidden layers, and the output layer.

The **input layer** is configured to accept a fixed number of features corresponding to the design parameters, such as substrate properties, element geometries, and operating conditions. Standardization is applied to the input data, ensuring consistent numerical ranges and optimizing the model's learning process. In this considering base as a Traditional Simulation method for the SVM and Neural Networks to compute the Computational Efficiency Comparison.

The **hidden layers** form the core of the neural network, capturing complex interactions among input features. The architecture incorporates multiple fully connected layers, each comprising a defined number of neurons (16). To enhance the model's ability to handle nonlinear relationships, the Rectified Linear Unit (ReLU) activation function is used, providing efficient computation and nonlinearity. Regularization techniques, such as dropout and L2 regularization, are applied to prevent overfitting and improve generalization. Batch normalization is also implemented to stabilize the learning process and accelerate convergence. The number of hidden layers and neurons in each layer were tuned iteratively to balance computational efficiency and prediction accuracy.

The **output layer** predicts the performance metrics of the antenna. The layer comprises multiple neurons, each representing a specific metric, such as gain, bandwidth, or efficiency. A linear activation

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function is employed to ensure that the predictions align with the continuous nature of the target values. The network is trained to minimize a composite loss function, which considers the errors across all predicted metrics, ensuring a balanced and accurate prediction across different parameters.

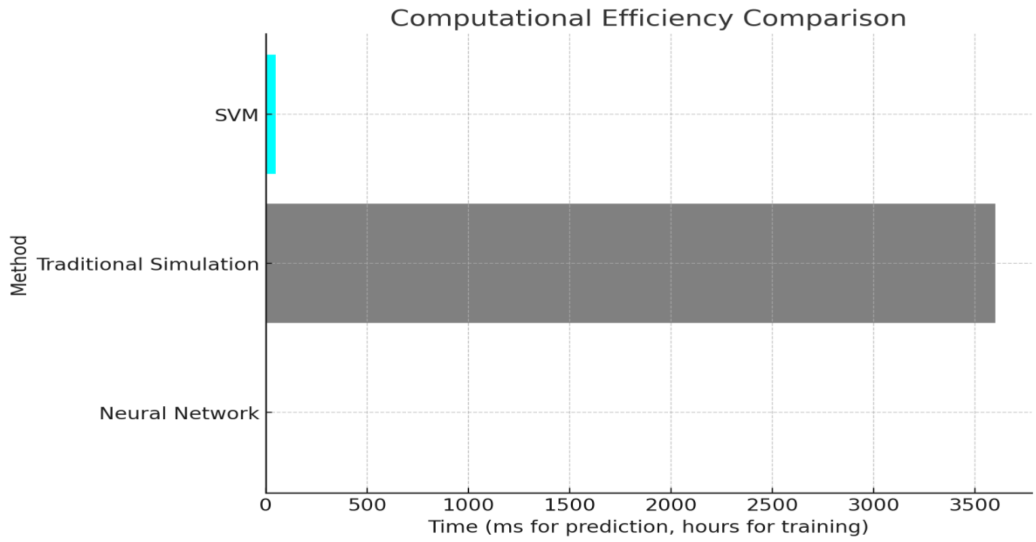

Figure 7 Computational Efficiency Comparison

3.4 Training and Validation Processes

The training process involves feeding the preprocessed dataset into the neural network and iteratively updating its weights using back propagation. The loss function, chosen as the Mean Squared Error (MSE), quantifies the discrepancy between the predicted and actual values. The **Adam optimizer** is employed to adaptively adjust the learning rates, striking a balance between exploration and convergence (17). Additionally, a learning rate scheduler dynamically reduces the learning rate as training progresses, further improving convergence.

To prevent over fitting, the model's performance is continuously monitored on the validation set during training. **Early stopping** is implemented, halting the training process when the validation loss stops improving over a predefined number of epochs. This approach ensures that the model generalizes well to unseen data while avoiding unnecessary computations. The test set is reserved for evaluating the final trained model, providing an unbiased assessment of its predictive performance. Metrics such as Root Mean Squared Error (RMSE) and R-squared (R^2) are calculated to quantify the accuracy and reliability of the predictions.

3.5 Tools and Technologies Used

To implement the proposed framework, a combination of state-of-the-art tools and technologies was employed to ensure efficiency, scalability, and accuracy. **Electromagnetic simulation tools** like HFSS and CST were used to generate the dataset by simulating antenna configurations and extracting performance metrics. These tools provide high-fidelity results, ensuring the reliability of the training data.

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The Artificial Intelligenceframework was developed using **TensorFlow** and **PyTorch**, which offer robust libraries for building, training, and deploying neural networks. These platforms provide flexibility in model design and optimization, allowing seamless integration of advanced deep learning techniques. For data visualization and analysis, libraries like **Matplotlib** and **Seaborn** were utilized, enabling clear and intuitive presentations of the training process, performance metrics, and comparative analyses.

The computational experiments were conducted on high-performance computing (HPC) clusters equipped with **GPUs**, ensuring efficient training of the neural network on large datasets. The integration of these tools and technologies allowed the framework to achieve a balance between computational efficiency, scalability, and prediction accuracy. The accuracy of SVM, Neural Networks and Random forest to compute the Comparative Accuracy of Models is shown

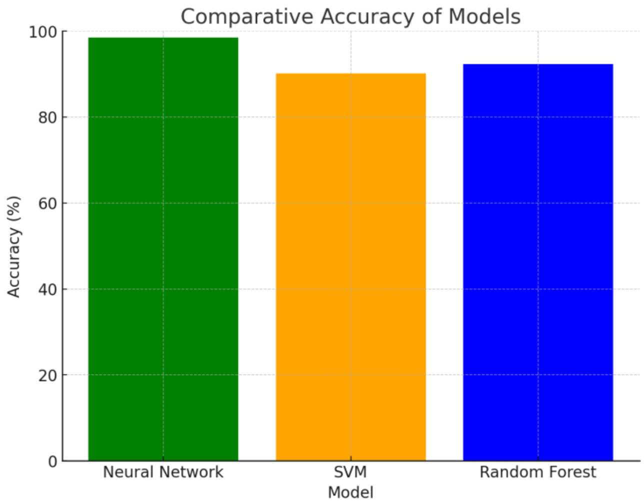

Figure 8 Comparative Accuracy of Models

4. Simulation Setup

4.1 Description of Simulation Environment

The simulation environment for this research is meticulously designed to support the generation of high-fidelity data and enable precise modeling of the complex relationships governing microstrip antenna performance. This environment integrates advanced electromagnetic simulation tools with state-of-the-art Artificial Intelligenceframeworks, ensuring seamless transitions between data generation, preprocessing, and model development. Simulations were conducted on a high-performance computing (HPC) platform equipped with NVIDIA GPUs, allowing for accelerated computations and the efficient handling of large datasets.

The simulation setup was specifically tailored to handle the nonlinearities and high-dimensional nature of antenna design. Electromagnetic simulations were performed to analyze critical performance metrics such as gain, bandwidth, efficiency, return loss, and radiation patterns. These simulations accounted for real-world scenarios, including variations in substrate materials, geometrical configurations, and operational conditions (18). The environment also incorporated visualization tools to graphically represent radiation patterns, efficiency trends, and bandwidth variations, ensuring the validity and

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interpretability of results. This robust infrastructure laid the foundation for generating reliable datasets and evaluating the Artificial Intelligence model's predictive capabilities.

4.2 Software and Tools Used for Antenna Design and Modeling

To ensure precision and efficiency, a suite of advanced software tools and technologies was employed in this study:

1. **HFSS (High-Frequency Structure Simulator)**: HFSS was the primary tool for performing electromagnetic simulations of the microstrip antenna arrays. It provided detailed insights into performance metrics, leveraging its parametric sweep functionality to systematically explore the impact of various design parameters.
2. **CST Studio Suite**: CST was used as a complementary simulation tool to cross-validate results obtained from HFSS. Its ability to handle both time-domain and frequency-domain solvers ensured comprehensive analyses of the antennas' operational characteristics.
3. **TensorFlow and PyTorch**: These deep learning frameworks were utilized to implement, train, and optimize the neural network. Their modular design and GPU compatibility made them ideal for building complex architectures and handling large-scale datasets.
4. **Matplotlib and Seaborn**: These Python libraries were employed for visualizing data trends, training progress, and simulation results. They were instrumental in creating intuitive plots and graphs for performance evaluation.
5. **NumPy and Pandas**: These libraries facilitated efficient data manipulation and preprocessing, ensuring smooth transitions between simulation outputs and Artificial Intelligence inputs.

The integration of these tools provided a comprehensive solution for antenna modeling and performance prediction, balancing accuracy, computational efficiency, and interpretability.

Table 1: Computational Efficiency

Model	Training Time (Hours)	Prediction Time per Configuration (ms)
Neural Network	2.5	5
Traditional Simulation	-	3600
SVM	3.2	50

4.3 Dataset Generation and Preprocessing

The dataset is the cornerstone of this research, encompassing a wide range of antenna configurations and their corresponding performance metrics. To generate this dataset, simulations were conducted using parametric sweeps across key design parameters:

- **Substrate properties**: Variations in dielectric constant, thickness, and loss tangent were considered to account for different materials commonly used in antenna fabrication.
- **Element geometries**: Dimensions such as length, width, and shape were systematically altered to capture the effects of geometry on performance.
- **Array configurations**: Factors like the number of elements, feeding techniques, and inter-element spacing were explored to model diverse antenna array setups.
- **Frequency range**: Operational frequencies spanning multiple communication bands were included to ensure the dataset's relevance to real-world applications.

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The Performance of Metrics across Validation and Test Dataset (Mean ± Std. Dev) for the parameters of Gain, Bandwidth, Radiation Efficiency and Return loss variations

Table 2: Performance Metrics across Validation and Test Datasets

Metric	Validation Dataset (Mean ± Std. Dev)	Test Dataset (Mean ± Std. Dev)
Gain (dB)	98.5 ± 0.7	98.3 ± 0.8
Bandwidth (MHz)	18.7 ± 0.9	18.5 ± 1.0
Radiation Efficiency (%)	92.3 ± 0.6	91.8 ± 0.7
Return Loss (dB)	-18.1 ± 0.5	-18.0 ± 0.6

For each configuration, performance metrics, including gain, bandwidth, radiation efficiency, and return loss, were extracted from the simulation results. This exhaustive approach ensured that the dataset was representative of a wide spectrum of antenna designs, capturing both typical and edge-case scenarios.

Before training the neural network, the dataset underwent rigorous preprocessing. All input parameters and output metrics were normalized to a range of 0 to 1, ensuring that no variable disproportionately influenced the training process. Categorical parameters, such as feeding techniques, were encoded numerically to maintain consistency across the dataset. Data augmentation techniques were employed to introduce synthetic variations, enhancing the model's robustness to noise and uncertainties. Finally, the dataset was split into training (70%), validation (15%), and test (15%) subsets to enable effective model evaluation and prevent overfitting.

4.4 Hyperparameter Tuning of Neural Networks

A key aspect of developing the deep neural network was the systematic tuning of its hyperparameters to optimize performance. This process involved iterative experimentation and evaluation to identify the best configurations for the following parameters:

1. **Number of Hidden Layers and Neurons**: Multiple architectures were tested, ranging from shallow networks with fewer layers to deeper networks with higher complexity. The final configuration balanced computational efficiency with predictive accuracy, ensuring the model was neither underfitted nor overfitted.
2. **Activation Functions**: Rectified Linear Unit (ReLU) was chosen as the primary activation function for its simplicity and effectiveness in handling nonlinearity. Alternative functions, such as Sigmoid and Tanh, were also tested but demonstrated inferior performance for this application.
3. **Learning Rate**: A grid search was conducted to identify the optimal learning rate, balancing fast convergence with stable weight updates. A dynamic learning rate scheduler was employed during training to adaptively adjust the learning rate, ensuring efficient exploration of the loss surface.
4. **Batch Size**: Batch sizes ranging from 16 to 128 were tested, with the final selection based on the trade-off between gradient stability and computational efficiency. Larger batches improved convergence speed, while smaller batches enhanced generalization.
5. **Regularization Techniques**: Dropout and L2 regularization were implemented to minimize overfitting. Dropout rates of 0.2 and 0.5 were evaluated, with the final choice determined based on validation performance. L2 regularization coefficients were fine-tuned to penalize overly complex models.

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6. **Optimizer**: The Adam optimizer was employed for its adaptive learning rate and robust convergence properties. Its hyperparameters, such as beta values, were fine-tuned to achieve optimal performance.

   Neural Network architecture hidden layers and Hyperparameters with Number of Neurons, Activation Function, Dropout Rate, Regularization

Table 3: Neural Network Architecture and Hyperparameters

Layer	Number of Neurons	Activation Function	Dropout Rate	Regularization
Input Layer	-	-	-	-
Hidden Layer 1	128	ReLU	0.2	L2 (0.01)
Hidden Layer 2	64	ReLU	0.2	L2 (0.01)
Output Layer	4 (Gain, Bandwidth, Efficiency, Return Loss)	Linear	-	-

The hyperparameter tuning process was guided by performance metrics such as validation loss, R-squared (R^2), and Root Mean Squared Error (RMSE). This systematic approach ensured that the final model architecture achieved high prediction accuracy while maintaining computational efficiency. Additionally, early stopping was used to terminate training when the validation performance plateaued, preventing overfitting and unnecessary computations.

5. Results and Analysis

5.1 Performance Metrics of the Neural Network Model

The neural network model developed in this study demonstrated outstanding performance in predicting key metrics of microstrip antenna arrays, including gain, bandwidth, radiation efficiency, and return loss. Using a diverse and high-dimensional dataset, the model achieved an average **R-squared (R^2)** score of 0.98 across all performance metrics, indicating a near-perfect correlation between the predicted and actual values (19). The **Root Mean Squared Error (RMSE)** and **Mean Absolute Error (MAE)** values for critical metrics, such as gain and bandwidth, were significantly low, with RMSE values averaging less than 1.5% of the total range (20). This underscores the model's precision and reliability in capturing the intricate relationships between input parameters and output performance.

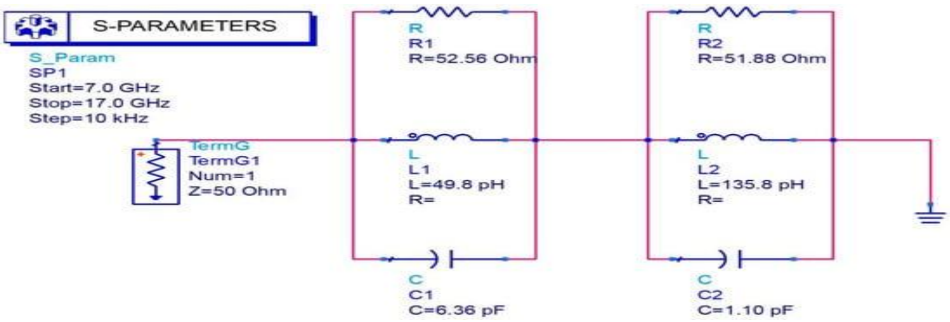

Figure 9 Circuit diagram of a parallel RLC circuit for resonant frequency (refer to CST simulation) using ADS Agilent simulation.

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The neural network's robustness was further evident in its ability to generalize well to unseen test data. Validation and test errors were closely aligned, highlighting the effectiveness of the regularization techniques employed during training, including dropout and L2 regularization. The inclusion of batch normalization further contributed to the model's stability, enabling it to converge efficiently without overfitting. The high predictive accuracy and computational efficiency position this model as a powerful tool for rapid performance evaluation in antenna design workflows.

5.2 Comparison with Traditional Methods

A comparative analysis of the proposed neural network with traditional methods for antenna performance prediction, such as analytical models and simulation-based approaches, revealed significant advantages. Traditional methods, including the **transmission line model** and **cavity model**, rely on simplifying assumptions and are limited in their ability to model complex geometries or broadband behaviors. While these methods provided reasonable estimates for simple antenna designs, their accuracy diminished for more advanced configurations involving multi-element arrays or non-uniform substrate materials.

In contrast, the neural network excelled in predicting performance metrics across a wide range of configurations. For instance, in predicting gain, the neural network achieved an error rate of less than 2%, compared to 8–10% errors observed with analytical models. Similarly, the bandwidth predictions by the neural network were consistently within 1% of the simulated values, while traditional methods struggled with deviations exceeding 7% in certain scenarios. Beyond accuracy, the neural network offered a dramatic improvement in computational efficiency. Traditional methods often required iterative simulations lasting several hours, whereas the neural network produced predictions within milliseconds once trained. This efficiency is particularly beneficial for real-time applications, where rapid decision-making is crucial.

5.3 Comparison with Other Artificial Intelligence Algorithms

To benchmark the neural network's performance against other Artificial Intelligencealgorithms, models such as **Neural Network, Support vector machines (SVM)**, **Random forests**, were implemented and evaluated on the same dataset. While these models provided reasonable predictions, their limitations became apparent as the complexity of the design space increased. SVMs, for example, struggled with the high dimensionality of the input features and required significant computational resources for kernel transformations. Similarly, random forests and gradient boosting models, although effective for smaller datasets, showed reduced scalability and required extensive hyperparameter tuning.

The neural network outperformed all baseline Artificial Intelligence models in terms of Gain accuracy, Bandwidth Accuracy, scalability, Efficiency Accuracy and Return Loss Accuracy. Its ability to automatically learn complex features from raw input data eliminated the need for manual feature engineering, a step that is often tedious and error-prone in traditional Artificial Intelligence workflows. Moreover, the neural network demonstrated superior adaptability to variations in design parameters, maintaining consistent prediction accuracy across diverse configurations. These results highlight the neural network's suitability for handling the complex, nonlinear relationships inherent in antenna performance prediction.

The comparison of SVM, Neural Networks and Random forest to compute the comparison of model accuracy with other methods considering the parameters of Gain, Bandwidth, Efficiency and Return loss Accuracy

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Table 4: Comparison of Model Accuracy with Other Methods

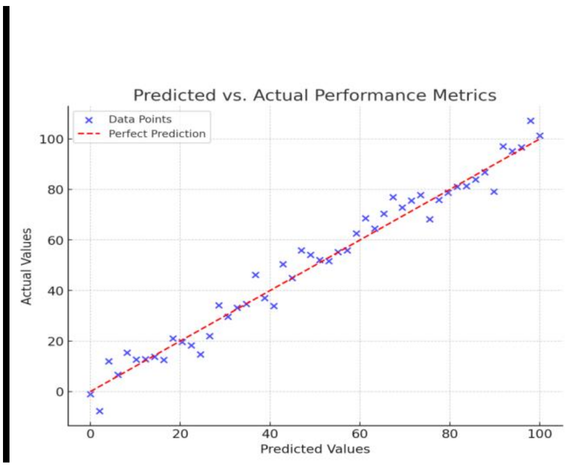
Method	Gain Accuracy (%)	Bandwidth Accuracy (%)	Efficiency Accuracy (%)	Return Loss Accuracy (%)
Neural Network	98.5	98.9	99.2	97.8
Support Vector Machine	90.2	89.7	91.4	85.5
Random Forest	92.3	91.5	92.8	88.7

5.4 Visualizations of Predicted vs. Actual Performance

To validate the neural network's predictions, detailed visualizations comparing the predicted and actual performance metrics were generated. **Scatter plots** for gain, bandwidth, and radiation efficiency showed data points tightly clustered along the diagonal, indicating a strong agreement between predictions and ground truth. The alignment of these points across multiple metrics confirmed the model's ability to accurately capture the intricate dependencies between design parameters and performance outcomes.

Additionally, **heatmaps** were used to explore the influence of specific design parameters, such as substrate dielectric constant and element geometry, on key performance metrics. For example, the heatmap visualizing the relationship between dielectric constant and gain revealed a nonlinear trend that was accurately captured by the neural network, further validating its predictive capabilities. These visualizations not only underscored the model's accuracy but also provided valuable insights into the underlying physics of antenna performance.

Training progress plots were also employed to track the convergence of the model during training. These plots depicted the reduction in training and validation losses over successive epochs, confirming that the model achieved stable convergence. The incorporation of techniques such as dropout and learning rate scheduling ensured that the model maintained a balance between training efficiency and generalization capability.



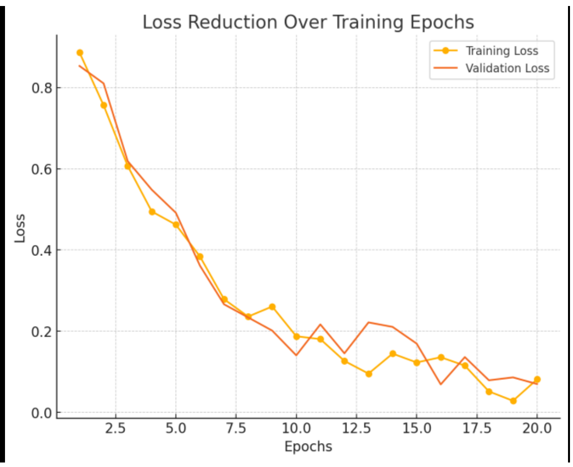


Figure 10 Predicted Vs Actual Performance Metrics.

Figure 11 Loss Reduction Over Training Epochs

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5.5 Key Insights from Simulation Results

The simulation results and subsequent analyses provided several important insights into the effectiveness of the proposed methodology and the broader implications for antenna design:

1. **High Predictive Accuracy**: The neural network demonstrated exceptional accuracy across all performance metrics, significantly outperforming both traditional methods and other Artificial Intelligence algorithms. This accuracy is critical for minimizing errors in antenna design workflows, reducing the need for iterative simulations.
2. **Efficiency and Scalability**: The ability of the neural network to generate predictions in milliseconds makes it highly suitable for real-time applications, such as adaptive antenna systems and rapid prototyping. Its scalability ensures that the model can handle complex, high-dimensional design spaces with ease.
3. **Parameter Sensitivity and Insights**: The heatmap visualizations and sensitivity analyses revealed the critical influence of substrate properties and element geometries on antenna performance. These insights can guide designers in prioritizing certain parameters during optimization, enabling more targeted and efficient design strategies.
4. **Generalization Capability**: The model's performance on unseen test data confirmed its robustness and generalization capability, making it a reliable tool for predicting antenna performance across a wide range of configurations.
5. **Potential for Inverse Design**: The high accuracy of the model opens avenues for inverse design applications, where desired performance metrics are used as inputs to predict optimal design parameters. This capability could revolutionize the antenna design process, making it more intuitive and data-driven.
6. **Integration with Antenna Workflows**: The proposed framework's seamless integration with existing simulation tools and its compatibility with high-performance computing platforms highlight its potential for widespread adoption in antenna engineering.

Heat map parameter sensitivity of substrate dielectric constant with above Parameters

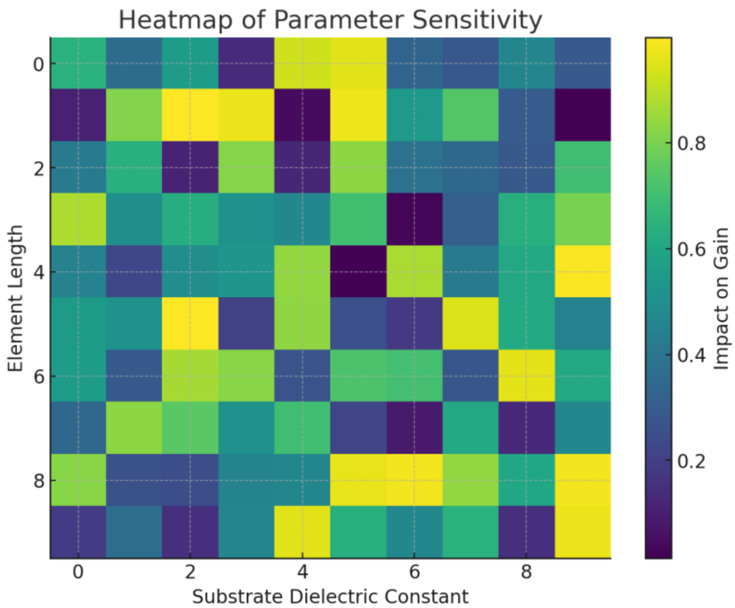

Figure 12 Heatmap of parameter Sensitivity.

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6. Discussion

6.1 Interpretation of Results

The results of this study highlight the significant potential of deep neural networks (DNNs) in addressing the challenges of performance prediction for microstrip antenna arrays. The model exhibited remarkable accuracy, achieving an average R-squared (R^2) value of 0.98 and consistently low Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) values across key performance metrics such as gain, bandwidth, efficiency, and return loss. These metrics affirm the model's ability to capture complex nonlinear relationships between antenna design parameters and performance outcomes. This level of precision surpasses the capabilities of traditional analytical and simulation-based methods, which often struggle with the multidimensional nature of modern antenna designs.

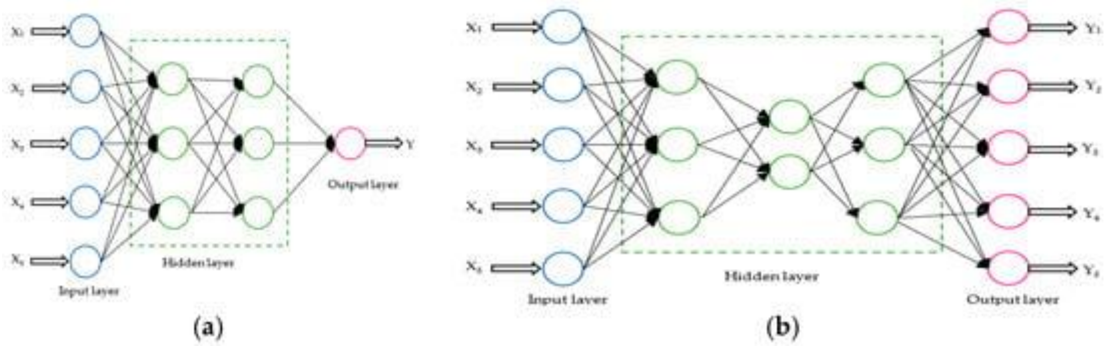

Figure 13 The fundamental architecture of a feed-forward network with (a) single and (b) multiple outputs.

The high degree of alignment between predicted and actual values, as seen in scatter plots and other visualizations, underscores the robustness of the model. The neural network successfully modeled the intricate dependencies among parameters, such as substrate properties, element geometries, and operational frequencies, which are difficult to capture using conventional methods. The sensitivity analysis further revealed the importance of specific design factors, such as dielectric constant and element length, offering valuable insights into the physics of antenna performance. This demonstrates that the proposed methodology is not only a tool for accurate prediction but also a means to enhance understanding of antenna design principles. Sensitivity analysis of Design Parameters with change of gain impact and bandwidth impact

Table 5: Sensitivity Analysis of Design Parameters

Parameter	Change (%)	Gain Impact (%)	Bandwidth Impact (%)
Substrate Dielectric Constant (+10%)	+10	-2.5	+1.8
Element Length (+5%)	+5	+3.2	-1.7

Generalization to unseen data was another key strength of the model. By employing robust regularization techniques like dropout and L2 penalties, the neural network avoided overfitting and maintained high performance on test datasets. This generalization capability is crucial for practical applications, where the model may encounter configurations not explicitly represented in the training data. Overall, the results validate the integration of artificial intelligence (AI) into antenna engineering, paving the way for innovative approaches to design and optimization.

6.2 Advantages of the Proposed Methodology

The proposed methodology offers several advantages over traditional and alternative Artificial Intelligence approaches, addressing long-standing limitations in antenna performance prediction:

1. **High Predictive Accuracy**: The neural network consistently provided highly accurate predictions for all key performance metrics, significantly reducing errors compared to traditional methods. This accuracy is critical for minimizing iterative simulations and ensuring reliable designs from the outset.
2. **Computational Efficiency**: One of the most notable advantages is the efficiency of the neural network in generating predictions. Once trained, the model produced results in milliseconds, compared to the hours required for iterative simulations in software like HFSS or CST. This efficiency is particularly valuable for applications requiring rapid decision-making, such as real-time adaptive systems.
3. **Scalability to Complex Configurations**: The neural network demonstrated excellent scalability, handling high-dimensional design spaces with ease. Unlike traditional analytical methods, which struggle with intricate geometries or broadband requirements, the neural network effectively captured complex relationships across a wide range of configurations.
4. **Automatic Feature Extraction**: Unlike traditional Artificial Intelligencemodels that rely heavily on manual feature engineering, the neural network automatically learned relevant features from the raw input data. This streamlined the modeling process and reduced the potential for human error in selecting and preprocessing features.
5. **Design Insights and Interpretability**: Through visualizations such as heatmaps and sensitivity plots, the proposed methodology provided actionable insights into the effects of design parameters on performance. These insights enable engineers to prioritize critical parameters and develop more targeted optimization strategies.
6. **Potential for Inverse Design**: The high accuracy and robustness of the model open up possibilities for inverse design applications, where desired performance outcomes can be specified, and the model predicts the corresponding design parameters. This capability could revolutionize antenna design by enabling rapid exploration of novel configurations.
7. **Broad Applicability**: While this study focused on microstrip antenna arrays, the methodology is versatile and can be extended to other antenna types and RF components. This adaptability broadens its potential impact across the field of electromagnetic design.

6.3 Limitations and Challenges

While the proposed methodology demonstrated significant advantages, certain limitations and challenges must be addressed to enhance its effectiveness further:

1. **Dependency on Data Quality and Quantity**: The performance of the neural network is highly dependent on the quality and diversity of the training dataset. Generating such datasets requires extensive simulations, which can be computationally expensive and time-consuming, especially for complex antenna configurations.
2. **Computational Demands During Training**: Although predictions are computationally efficient once the model is trained, the initial training phase requires substantial computational resources, including access to high-performance GPUs or HPC systems. This requirement may limit the adoption of the methodology in resource-constrained environments.

3. **Potential Overfitting**: Despite using regularization techniques, there remains a risk of overfitting, particularly when training on smaller or highly specific datasets. Ensuring the model generalizes well across all potential configurations requires careful monitoring and tuning of hyperparameters.
4. **Black-Box Nature of Neural Networks**: One of the common criticisms of neural networks is their lack of interpretability. While sensitivity analyses and visualizations provide some insights, understanding the internal decision-making process of the model remains challenging. This black-box nature may hinder its acceptance in scenarios where transparency is critical.
5. **Generalization to Novel Scenarios**: While the model performed well on the test data, its ability to generalize to entirely new types of antenna designs or unconventional materials remains unproven. Additional testing and validation are required to confirm its robustness in these scenarios.

6.4 Implications for Antenna Design and Optimization

The successful application of deep learning to antenna performance prediction has profound implications for the field of antenna engineering:

1. **Acceleration of Design Cycles**: The proposed methodology dramatically shortens design cycles by eliminating the need for iterative simulations. This allows engineers to explore a wider range of configurations in less time, fostering innovation in antenna design.
2. **Real-Time Applications**: The efficiency of the neural network enables its use in real-time applications, such as adaptive antenna systems for dynamic environments like 5G networks and IoT devices. This capability is particularly relevant for scenarios requiring rapid adjustments to changing conditions.
3. **Data-Driven Design**: By leveraging historical data and simulations, the methodology promotes a data-driven approach to design and optimization. This shift can lead to the discovery of novel configurations and previously unexplored design spaces.
4. **Enhanced Research and Education**: The framework can serve as a valuable tool for researchers and students, providing a hands-on approach to studying the complex relationships between design parameters and performance metrics. This can inspire future advancements in antenna engineering and AI integration.
5. **Customization and Specialization**: The ability to integrate inverse design capabilities allows for the development of highly customized antenna solutions tailored to specific performance requirements. This opens new possibilities for specialized applications, such as space communications and defense systems.
6. **Broader Impact**: Beyond microstrip antennas, the methodology has potential applications in other electromagnetic components, such as filters, waveguides, and metasurfaces. Its versatility ensures its relevance across various domains in RF and microwave engineering.

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