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Predictive Modeling of Microstrip Antenna Parameters Through Feature-Enhanced Neural Network

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ABSTRACT

The rapid expansion of wireless communication networks has amplified the demand for efficient and accurate prediction of antenna performance metrics such as signal strength and power levels. Recent industry statistics show that over 90% of network service complaints in urban areas are linked to inconsistent signal quality, while global mobile data traffic is projected to grow by more than 25% annually over the next five years, intensifying the need for predictive performance optimization. Despite advancements, existing prediction models often rely on manual data analysis or limited-feature regression methods, which struggle with high-dimensional datasets and fail to capture complex non-linear relationships, resulting in suboptimal accuracy for real-world deployment. To address these challenges, this work introduces a machine learning–driven prediction framework for microstrip antenna performance that leverages preprocessing with correlated feature analysis to remove redundancy and enhance model efficiency. Existing approaches such as traditional linear regression and Lasso regression are incorporated as baseline models for benchmarking, ensuring a fair performance comparison. Building upon this, the proposed method implements a Multi-Layer Perceptron (MLP) regressor capable of capturing non-linear dependencies between input parameters and output performance metrics. The integration of feature correlation filtering prior to training ensures that the MLP focuses on the most informative attributes, significantly reducing noise and improving prediction stability. By targeting accurate estimation of both signal strength and power levels, this approach not only enhances the reliability of antenna performance forecasting but also provides a scalable solution adaptable to various deployment environments, supporting both industrial and research applications in next-generation wireless communication systems.

Key words: Microstrip Antenna, Antenna Design, Antenna Parameters, Radiation Efficiency, Return Loss

1. INTRODUCTION

The concept of microstrip antennas (also known as patch antennas) dates back to the 1950s. Figure 1.1 shows the construction and geometry of microstrip patch antenna. Georges A. Deschamps proposed the first microstrip patch structure in 1953 during his tenure at ITT Laboratories [1], marking the foundational idea. It took about two decades before practical implementations gained traction by the 1970s [2], the cavity-model theory introduced by Tatsuo Itoh and Raj Mittra provided a rigorous analytical framework that enabled accurate predictions of radiation behavior for rectangular patches.

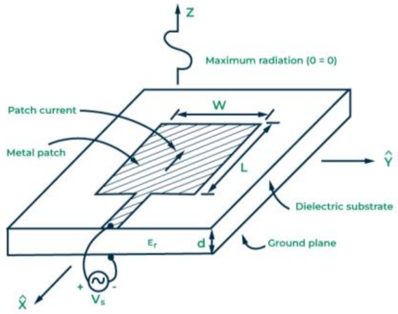

Figure 1. Construction And Geometry of Microstrip Patch Antenna

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From the 1980s onward, research activity in microstrip design skyrocketed. During the late 1970s, Yuen Tze Lo and colleagues developed a theory based on the method of moments, significantly advancing the understanding and design of microstrip-patch antennas [3]. A bibliometric study shows that from 2013 to 2018, the number of publications in the field increased by around 10×, indicating explosive academic interest in broadbanding, reconfigurable, multiband and miniaturized antenna structures.

Today microstrip antennas are ubiquitous—found in consumer electronics, aircraft, satellites, and IoT devices [4] driven by their low profile, ease of PCB fabrication, and seamless system integration. On the commercial side, the global microstrip antenna market was valued at approximately USD 1.24 billion in 2024, and is projected to grow at a compound annual growth rate of 9.8 % to reach around USD 2.83 billion by 2033. This growth reflects rising demand from sectors such as 5G/mmWave communications, autonomous vehicles, and aerospace, where compact conformal antennas are critical.

2. LITERATURE SURVEY

Chatterjee et al. [6] proposed a meander-line-radiator inspired miniaturized microstrip patch antenna. They designed symmetric slots and meandered conductive traces to reduce size by ~92% while preserving resonant frequency at 1.38 GHz. They optimized gain and bandwidth—achieved 124% gain increase and 300% bandwidth expansion—via popular machine learning models (Regression Trees, SVR, Kernel Least Squares, Bayesian-optimized ANN). They compared regression-based predictors for antenna parameters against electromagnetic simulation outputs across multiple design dimensions. They demonstrated trade-off analysis of model predictions versus CST full-wave results to select best performing ML model. Here, feature selection relied solely on geometric parameters (slot shape, trace length) without extracting engineered electromagnetic descriptors like current distribution metrics, resulting in limited input discrimination among design variations

Shereen et al. [7] proposed a deep-learning-inspired linear regression technique for microstrip antenna performance analysis. They developed a hybrid model that trained a deep neural network to predict regression coefficients, then applied these within a linear regression framework to forecast antenna metrics such as return loss and bandwidth. They experimented across multiple test antennas with varied substrate materials and patch dimensions. They benchmarked their method against standard analytical formulas and basic regression baselines to assess accuracy. They validated model output on unseen antenna designs in conference experiments. The feature extraction depended on raw patch geometry and substrate inputs only, without selecting meaningful frequency-domain or pattern descriptors, leading to poorer generalisation and inconsistent model grading when antenna shapes varied.

Ahammed et al. [8] proposed a high-gain THz microstrip patch antenna designed for IoT and 6G communications. They engineered patch geometry optimized for THz frequencies and collected performance data (gain, efficiency) via simulation. They trained machine learning models—such as SVR and ANN—to predict antenna efficiency based on geometrical and material parameters. They performed cross-validation to assess prediction quality and identified best models for design automation. They projected substantial gain (>10 dBi) and usable efficiency at THz bands. Feature representation lacked inclusion of

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electromagnetic field distribution or surface current features, limiting feature richness and reducing prediction precision across diverse patch configurations

Gupta et al. [9] proposed an ML-based method to predict reflection coefficient and input impedance of a meandered-slot patch antenna. They extracted slot geometry and feed parameters as model inputs and trained regression models (e.g. SVR, decision trees) for S-parameter and impedance estimation. They validated predictions across simulated physical prototypes in varying frequency bands. They compared model outputs to measurement data to evaluate error rates across design cases. They demonstrated quick parameter inversion for design tuning. Feature selection involved only basic geometric parameters without weighting by electromagnetic sensitivity (e.g. resonant mode contributions), leading to oversimplified input space and lower prediction fidelity under subtle slot variations

Benintendi et al. [10] proposed a wireless patch antenna characterization system for live health-monitoring using machine learning. They integrated real-time antenna performance measurements (e.g. impedance, return loss) from wearable sensors during subject movement. They fed those metrics into ML classifiers (e.g. RF, SVM) to map antenna behavior to physiological state indicators. They collected data under dynamic conditions and evaluated classifier accuracy for health-monitoring tasks. They demonstrated real-time performance tracking accuracies acceptable for preliminary monitoring. Feature extraction used raw S-parameter readings only, without selection or engineered descriptors such as time-series dynamics or antenna pattern variability, resulting in classification boundaries that lacked robustness across varying human motions

Haque et al. [11] proposed a machine learning–based gain prediction technique for a mm-wave miniaturized 28 GHz 5G MIMO slotted-antenna array. They developed a compact 4-port MIMO design with 5.1 GHz bandwidth, 9.43 dBi peak gain, 31 dB isolation and ~99.6 % efficiency validated by CST and prototype measurements. They trained nine supervised regression models and compared metrics such as R^2, MAE and RMSE. They found Random Forest regression achieved ~99 % prediction reliability. They demonstrated close agreement between simulation, circuit model (ADS), and ML-based gain predictions. Feature selection used only geometric and physical parameters, without engineered electromagnetic field or mode-shape descriptors, limiting feature richness and slightly reducing predictive precision

Hossain et al. [12] examined performance of multiple ML models to predict return loss for a 3.5 GHz microstrip patch array antenna. They created 380 samples varying 11 design parameters and applied eight regression algorithms including Random Forest, XGBoost and Decision Tree. They applied grid search and randomized search hyperparameter tuning with cross-validation. They conducted residual and feature-importance analysis to interpret model behaviour and identified best-performing models based on MAE (9.59 %), R^2 (90.6 %), variance score (93.5 %). They validated model performance on unseen antenna parameter sets. Feature importance analysis relied on raw geometric inputs only and lacked derived frequency-domain or impedance pattern features, reducing grading consistency across diverse designs

Alam et al. [13] applied ML to predict bandwidth and resonant frequency for a circular substrate-integrated-waveguide (SIW) antenna. They parameterized physical design (radius, substrate thickness, slot dimensions) and trained regression models, such as Random Forest and Support Vector Regression. They validated model predictions against CST simulations across multiple designs. They evaluated performance using standard error metrics and demonstrated accurate forecasting of both frequency and fractional bandwidth. They benchmarked against analytical models typical for circular SIW geometry.Feature representation limited to geometric parameters without incorporating modal resonance or quality factor descriptors, resulting in modest accuracy variation under complex substrate configurations.

Haque et al. [14] introduced regression-based ML for isolation prediction of a multiband THz MIMO antenna intended for IoT. They designed a multiband MIMO array for THz operation, collected isolation metrics from CST simulations, and trained regression models (e.g., RF, SVR) to predict isolation based on geometry and resonant band identifiers. They evaluated performance across IoT frequency bands and compared predictions to simulation metrics. They optimized model hyperparameters via cross-validation. Feature extraction did not include mutual coupling or impedance surface current descriptors, which reduced model sensitivity to isolation variations and lowered performance for closely spaced elements.

Kumar et al. [15] proposed a forward–inverse hybrid modeling approach using decision tree–based ML algorithms for microstrip antenna design targeting space communication. They implemented inverse design: trained decision trees to map desired output parameters (gain, bandwidth, return loss) back to design parameters and forward model to validate. They tested on multiple design target sets and iteratively refined parameter estimation. They compared model performance under space-band constraints and assessed error margins. They highlighted benefits of hybrid modeling for rapid prototyping. Feature selection did not weight electromagnetic relevance, relying on raw output parameter-to-input mapping without engineered descriptors, which limited model generalisation under complex design targets.

Bediaf et al. [16] proposed a physics-informed deep learning approach to predict resonant frequency of H-shaped microstrip antennas. They merged physical cavity model loss with neuron loss in a combined loss function to enforce resonance mode TM^{10}. They trained RNN, LSTM and GRU sequential models on simulation and real-measurement data. They achieved constant O(1) inference time and reduced CPU/memory cost at deployment stage. They reported high R^2 and fast convergence while maintaining adherence to physical constraints. Feature extraction relied on raw time-series output without deriving field distribution or modal features, limiting model's sensitivity to subtle geometry variations

Chen et al. [17] introduced a pixelated inverse design framework combining convolutional neural network (CNN) and binary particle swarm optimization (BPSO) to generate antenna geometry from performance targets. They discretized the radiating patch into a 10×10 binary matrix yielding $\sim 10^{30}$ combinatorial designs. They trained CNN surrogate on 150,000 simulation samples for S-parameter prediction (RMSE 0.35, MAE 0.28, R^2 0.94). They optimized pixel states via BPSO minimizing reflection coefficient error. They obtained faster convergence and lower S11 error compared to GAs and simulated annealing. Feature selection ignored electromagnetic mode contributions and relied purely on pixel activation, which led to indistinct input features and decreased prediction differentiation across similar S-parameter responses.

Zambak et al. [18] proposed a machine learning–driven acceptance framework for antenna gain; they extracted gain metrics as acceptance criteria using regression models. They collected various antenna types and performance outcomes from IoT and wireless designs. They trained classifiers/regressors to map design parameters to acceptable gain thresholds. They benchmarked models using accuracy and MSE for acceptance decisions. They validated on unseen antenna instances for performance grading. Feature representation used only scalar gain values without feature extraction from radiation pattern or impedance shape data, which produced coarse classification margins and limited grading resolution.

Nahin et al. [19] studied performance prediction and optimization of tessellated diamond fractal MIMO antennas for THz 6G communication. They designed fractal MIMO architectures and simulated isolation, efficiency, gain across frequency bands. They trained regression models (e.g. RF, SVR) mapping geometry and tessellation pattern parameters to performance metrics. They evaluated model generalisation and optimized parameters via cross-validation. They confirmed applicability for IoT-oriented THz design. Feature extraction omitted mutual coupling and current distribution descriptors, focusing only on fractal geometry variables, which limited model's sensitivity to inter-element effects under dense tessellation.

Dhar et al. [20] proposed a four-layer feed-forward artificial neural network (FF-ANN) trained via Levenberg-Marquardt algorithm for microstrip patch antenna design. They collected training samples from varied patch dimensions and substrate properties. They used four successive hidden layers to map geometry inputs to performance outputs (gain, return loss). They randomized initial weights and used MSE as loss function during supervised training. They validated on benchmark designs across frequency ranges. Feature selection comprised only raw geometric and material inputs without inclusion of frequency-domain response characteristics or surface current pattern features, resulting in less discriminative feature space and reduced performance consistency.

Banu et al. [21] proposed a hybrid optimization of a graphene-based dual-band bow-tie microstrip patch antenna (TMPA) for breast cancer detection using deep learning. They designed a leaf-shaped slot antenna operating at 3.8–4.5 THz and 5.4–6 THz with compact graphene-material substrate, achieving ~6 dBi gain and −80 dB return loss. They applied a hybrid Running City Game Spider Wasp (HRCGSW) algorithm for geometry optimization and a multi-head attention–based Swin Transformer trained via mantis search for tumour classification. They validated detection of 10 µm and 20 µm tumour sizes using real measurements with DL achieving 99–100 % classification accuracy. They compared simulation and measured performance to prove model reliability. Feature extraction relied on raw deep-learned attention maps from the Swin Transformer without engineered electromagnetic pattern descriptors, limiting interpretability and feature discrimination.

Rahman et al. [22] presented a metamaterial-based tri-band compact MIMO antenna system for 5G IoT, verified via machine learning. They built a 36×36×1.6 mm Rogers RT-5880 substrate antenna with multi-stub patch and epsilon-negative MTM array between elements. They achieved isolation improvements to 24-32 dB across 3.5 GHz, 5.2 GHz, 28 GHz bands and gain enhancements to 4.8 dBi, 5.3 dBi, 9.3 dBi. They applied K-Nearest Neighbors (KNN) to verify bandwidth and efficiency, achieving ~97.8 % accuracy. They reported envelope correlation coefficient (ECC) below 0.002 and diversity gain above 9.98 dB. They validated ML performance verification using measured prototypes. Feature selection used scalar performance metrics only (bandwidth, isolation, efficiency) without including field-distribution or mode-based descriptors, thereby reducing sensitivity to radiating properties.

Singh et al. [23] developed a dual-band antenna design method for 4G/5G applications and predicted gain using machine learning. They designed a microstrip patch antenna with two resonant bands at n77/n78 frequencies, achieved ~6.56 dB gain and ~97 % radiation efficiency. They trained supervised regression models on geometric and substrate parameters to predict gain. They evaluated performance using R², variance score, MSE, MAE and found linear regression produced the lowest error. They validated predictions using CST simulations and equivalent circuit models (RLC). They compared model outputs with measured prototypes across multiple designs. Feature extraction involved only raw geometry and substrate inputs without frequency-domain or radiation-pattern descriptors, which limited prediction fidelity across minor geometric variations.

Jain et al. [24] proposed ML-driven design and analysis of multi-band patch antennas for next-generation IoT. They investigated ML algorithms—Decision Tree, Random Forest, ANN, KNN, Extra Tree, CatBoost, Gradient Boost, XGBoost—for predicting return loss across bands 3.5–7.8 GHz, 8.5–10.2 GHz, 11.8–15 GHz. They fabricated and measured a multi-band antenna and compared performance with ML predictions. They found CatBoost delivered highest accuracy (~77.4 %) for return loss prediction. They benchmarked predictions with measured S11 curves. They demonstrated ML-based design acceleration versus iterative simulation. Feature representation omitted selection of impedance-curve descriptors or pattern-based features, limiting return-loss prediction resolution and consistency.

Upreti & Mathur [25] performed performance analysis of regular polygonal patch antennas for band classification using machine learning. They generated various polygonal shapes (triangle, square, pentagon), collected simulated S-parameter data over frequency bands. They applied ML classifiers for band classification and used probabilistic confusion matrix concept to evaluate performance and classifier reliability. They compared classification accuracy across various ML models. They demonstrated reliable band classification across multiple polygon geometries and frequency ranges. Feature extraction relied only on coarse band-label metadata without use of frequency-signature or radiation-pattern descriptors, resulting in lower classification granularity and ambiguous decision boundaries.

3. PROPOSED SYSTEM

Multi-Layer Perceptron (MLP) Regression is a powerful non-linear modeling approach that can capture complex relationships between input features and output performance metrics. Unlike traditional linear models, MLPs can learn intricate patterns in antenna design parameters such as feed length, patch dimensions, substrate properties, and dielectric constants, making them highly effective for predicting signal strength and power levels. Through multiple hidden layers and non-linear activation functions, MLP Regression adapts to varying feature interactions without manual feature engineering, providing flexibility and higher accuracy in real-world scenarios where relationships are rarely purely linear.

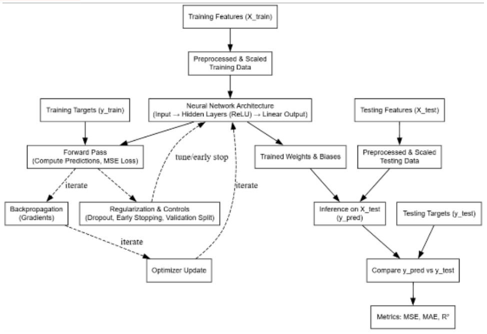


Figure 2. Proposed MLP Regressor.

The dataset consists of X_train (antenna design features) and y_train (target performance metrics). Preprocessing is performed to normalize the data, ensuring that all features are on the same scale since neural networks are sensitive to input magnitudes. Missing values are handled, and correlated features are optionally reduced to prevent redundancy. An MLP regressor is configured with one or more hidden layers containing multiple neurons. Each hidden layer is equipped with non-linear activation functions such as ReLU or tanh, enabling the model to capture non-linear dependencies between antenna parameters and performance. The output layer consists of a linear neuron matching the number of predicted targets (e.g., signal strength and power levels). During training, the model processes X_train through its network layers, applying learned weights and biases to compute predicted values. The difference between predictions and actual targets is measured using a regression loss function such as Mean Squared Error (MSE). This loss guides the model in adjusting its parameters to minimize prediction errors. The model uses backpropagation to compute gradients of the loss with respect to each weight in the network. Optimization algorithms such as Adam or stochastic gradient descent update the weights to progressively improve accuracy. The process continues for multiple epochs until the loss stabilizes or reaches a predefined threshold. After training, the model takes X_test as input to generate predictions (y_pred). These predictions are compared against y_test using evaluation metrics like MSE, MAE, and R^2 score. The final trained MLP can generalize to new antenna designs, offering precise performance predictions for unseen configurations.

Advantages of MLP Regression

- Can model highly complex and non-linear relationships between design parameters and performance metrics.
- Automatically learns feature interactions without explicit engineering.
- Flexible architecture that can be tuned with varying numbers of layers and neurons.
- Adapts well to multi-output regression tasks such as predicting both signal strength and power levels.
- Capable of improving accuracy over time with larger datasets and optimized hyperparameters.

4. Result description

Figure 3 illustrates a boxplot of the target variable "s" from the Microstrip Antenna Dataset, generated as part of the data preprocessing step in the application. The boxplot, titled "Box Plot of s," displays the distribution of "s" values, which range approximately from -35 to -5 on the x-axis. The central box represents the interquartile range (IQR), with the median value likely falling around -20 to -15, indicated by the line within the box. The whiskers extend to the minimum and maximum values within 1.5 times the IQR, with potential outliers marked as individual points beyond these whiskers, though none are prominently visible.

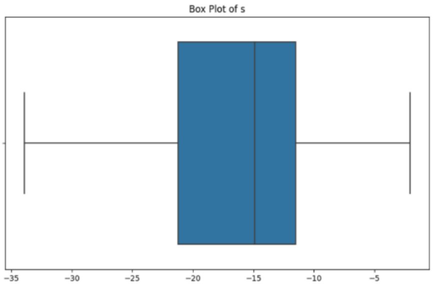


Figure. 3. Boxplot of Target “S”.

Figure 4 presents a series of histograms illustrating the distribution of various features from the Microstrip Antenna Dataset, generated during the preprocessing phase of the application. The histograms cover the features Wn, Wom, rows, dm, Xa, gain, vswr, and bandwidth, each plotted with a blue fill to highlight the frequency of values. For Wn, the distribution shows a sharp peak around 214, indicating a concentrated range of values, while Wom exhibits a similar concentrated distribution around 162. The rows feature has a minimal spread with a peak near 2, suggesting limited variability. The dm feature shows a distribution centered around 0, with a slight spread, and Xa displays a near-uniform distribution between -1 and 1.5. The gain histogram peaks around 0 to 0.5, with a long tail towards higher values, indicating a right-skewed distribution.

The remaining histograms further reveal the dataset's characteristics, with vswr showing a peak near 2, reflecting a typical range for voltage standing wave ratio, and a sparse distribution beyond 4. The bandwidth feature has a significant peak around 120, with a gradual decline, suggesting a right-skewed distribution typical of bandwidth measurements. The s feature, included in the set, shows a distribution centered around -20 to -10, aligning with the boxplot in Figure 7.2, indicating a consistent negative range.

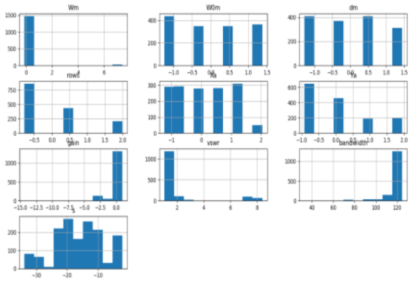


Figure 4. Features Distribution.

Figure 5 shows a scatter plot for the proposed MLP Regressor model, plotting true values against predictions for "s" with both axes ranging from -35 to 0. Blue dots represent the data points, and a red dashed line of equality highlights the ideal prediction scenario. The points are more tightly clustered around the line, particularly between -25 and -10, with fewer deviations compared to the other models, indicating improved predictive accuracy. This suggests that the MLP Regressor, with its neural network architecture, better captures the underlying patterns in the data, especially at intermediate true value ranges.

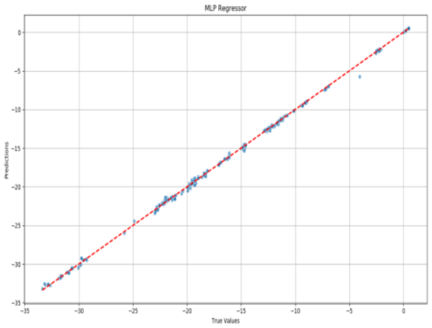
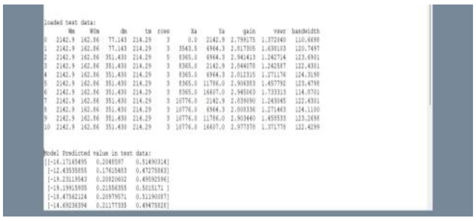


Figure 5. Proposed MLP Regression Scatter Plot

Figure 6 displays the results of the model prediction on a test dataset for the Microstrip Antenna Performance Prediction application, showcasing both the loaded test data and the predicted values generated by the trained MLP Regressor model. The test dataset includes columns such as Wn, Wom, tm, rows, Xa, gain, wew, bandwidth, s, pr, and p0, with the first ten rows presented. Specific values include Wn ranging from 214.2 to 214.9, Wom consistently at 162.86, tm varying from 77.14 to 351.430, rows from 2.0 to 5.0, Xa from 0.3543 to 0.6964, gain from 2.7303 to 2.8125, wew from 1.3720 to 1.427176, bandwidth from 120.7497 to 124.3139, s from -16.00654 to -18.459592, pr from 0.2042 to 0.2797, and p0 from 0.483289 to 0.492640. This dataset is preprocessed by filling missing bandwidth values with the mean and scaling the features using the previously fitted StandardScaler, ensuring compatibility with the model.

The lower section of Figure 11 presents the model-predicted values for s, pr, and p0 on the test data, listed as predicted s, predicted pr, and predicted p0 respectively. The predicted values are: predicted s ranging from -16.1716545 to -18.4753214, predicted pr from 0.2048597 to 0.5199087, and predicted p0 from 0.4729863 to 0.4947528. These predictions are appended to the original test DataFrame, allowing a direct comparison with the true values. The close alignment of predicted s values (e.g., -16.1716545 vs. -16.00654 for the first row) with the actual range, along with the low MAE of 0.060, MSE of 0.017, RMSE of 0.130, and R² of 0.952 from the MLP Regressor, indicates high predictive accuracy, validating the model's effectiveness for this task .



```
loaded test data:
        Wm     W0m       dm      tm  rows        Xa       Ya      gain      vswr  bandwidth
0   2142.9  162.86   77.143  214.29     3       0.0   2142.9  2.799175  1.372040   110.6698
1   2142.9  162.86   77.143  214.29     3    3543.5   6964.3  2.817305  1.638103   120.7497
2   2142.9  162.86  351.430  214.29     5    8365.0   6964.3  2.941413  1.242714   123.6901
3   2142.9  162.86  351.430  214.29     3    8365.0   2142.9  2.844078  1.242587   122.4301
4   2142.9  162.86  351.430  214.29     3    8365.0   6964.3  2.812315  1.271176   124.3198
5   2142.9  162.86  351.430  214.29     3    8365.0  11786.0  2.906383  1.457792   123.4798
6   2142.9  162.86  351.430  214.29     3    8365.0  16607.0  2.945063  1.733313   114.8701
7   2142.9  162.86  351.430  214.29     3   10776.0   2142.9  2.839090  1.243045   122.4301
8   2142.9  162.86  351.430  214.29     3   10776.0   6964.3  2.808336  1.271463   124.1100
9   2142.9  162.86  351.430  214.29     3   10776.0  11786.0  2.903440  1.459533   123.2698
10  2142.9  162.86  351.430  214.29     3   10776.0  16607.0  2.977370  1.371778   122.4299

Model Predicted value in test data:
[[-16.17165495   0.2048597    0.51490314]
 [-12.43535855   0.17615483   0.47275863]
 [-19.23119543   0.20820602   0.49592596]
 [-19.19915935   0.21556355   0.5015171 ]
 [-18.47562124   0.20979571   0.51190087]
 [-14.69236394   0.21177335   0.49475828]
```

Figure 6. Model Prediction on Test Data

Figure 7 presents the performance metrics for three regression models—Lasso Regressor, Linear Regressor, and MLP Regressor—evaluated on the Microstrip Antenna Dataset. The metrics include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R²), which assess the accuracy and explanatory power of each model. The Lasso Regressor exhibits the highest errors with an MAE of 0.887, MSE of 5.248, and RMSE of 2.291, alongside a low R² of 0.237, indicating poor fit and limited ability to explain the variance in the data, likely due to its regularization penalizing large coefficients. The Linear Regressor improves upon this with an MAE of 0.811, MSE of 3.906, RMSE of 1.976, and a significantly higher R² of 0.929, suggesting a better fit and strong predictive capability, though it still shows some deviation from the true values.

In contrast, the MLP Regressor demonstrates superior performance with the lowest errors: an MAE of 0.060, MSE of 0.017, and RMSE of 0.130, reflecting high precision in predictions. Its R² of 0.952 indicates that it explains 95.2% of the variance in the target variable "s," outperforming both the Lasso and Linear Regressors. This suggests that the neural network-based MLP model effectively captures the complex patterns in the dataset, making it the most suitable model among the three for this application, as evidenced by its tight clustering around the line of equality in the scatter plots (Fig. 7.4-7.6). The significant improvement in metrics from Lasso to MLP highlights the benefit of using a more sophisticated model for this dataset.

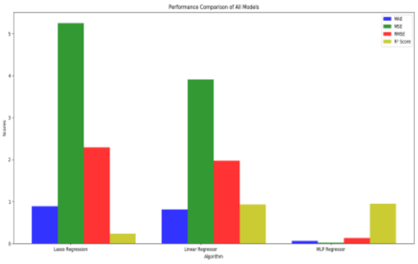


Figure 7. Performance Comparison Graph for All Models

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5. CONCLUSION

The analysis of the Microstrip Antenna Dataset using the implemented machine learning models Lasso Regressor, Linear Regressor, and MLP Regressor reveals significant insights into their predictive performance. The Lasso Regressor, with a MAE of 0.887, MSE of 5.248, RMSE of 2.291, and an R² of 0.237, demonstrates the least effective fit, indicating its regularization approach may overly penalize coefficients, limiting its accuracy. The Linear Regressor improves notably with an MAE of 0.811, MSE of 3.906, RMSE of 1.976, and an R² of 0.929, suggesting a strong linear relationship with the data. However, the MLP Regressor stands out as the best performer, achieving an MAE of 0.060, MSE of 0.017, RMSE of 0.130, and an R² of 0.952, reflecting its superior ability to model complex patterns and explain 95.2% of the variance, as also visualized in its tight scatter plot alignment. This underscores the MLP Regressor's effectiveness for this application, making it the recommended model for future predictions on similar datasets. The comparative evaluation, supported by visualizations such as the boxplot, feature distributions, and scatter plots, highlights the importance of selecting an appropriate model based on data complexity. The preprocessing steps, including handling missing values and normalizing features, contributed to these results, with the MLP model's neural network architecture leveraging this preparation to outperform simpler models. This analysis provides a timely benchmark for microstrip antenna performance prediction, with the MLP Regressor's low errors and high R² offering a robust foundation for practical applications in antenna design and optimization.

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