MACHINE LEARNING ASSISTED MM-WAVE MIMO ANTENNA DESIGN WITH HIGH ISOLATION FOR 5G

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ABSTRACT

The rapid evolution of fifth-generation (5G) wireless communication systems has increased the demand for compact, high-performance antennas capable of delivering high data rates, low latency, and reliable connectivity. Millimeter-wave (mm-Wave) Multiple-Input Multiple-Output (MIMO) antenna technology has emerged as a promising solution because of its ability to provide higher bandwidth, improved spectral efficiency, and enhanced communication capacity. However, designing compact MIMO antennas presents significant challenges due to mutual coupling between closely spaced antenna elements, which negatively affects isolation, gain, radiation efficiency, and overall system performance. This study proposes a machine learning-assisted framework for designing and optimizing a compact four-element mm-Wave MIMO antenna operating at 37 GHz for 5G wireless applications. MATLAB is employed to model the antenna geometry and generate a comprehensive dataset by varying critical design parameters, including patch dimensions, feed position, substrate characteristics, and inter-element spacing. The generated data are used to train machine learning regression models capable of accurately predicting key antenna performance metrics such as reflection coefficient (S11), mutual coupling (S21), gain, impedance bandwidth, radiation efficiency, Envelope Correlation Coefficient (ECC), Diversity Gain (DG), Channel Capacity Loss (CCL), and Total Active Reflection Coefficient (TARC). The trained model is integrated with an optimization framework to identify the optimal antenna configuration while significantly reducing computational time and simulation complexity compared with conventional iterative optimization methods. The optimized antenna achieves high isolation, excellent impedance matching, improved diversity performance, and enhanced radiation characteristics, making it a practical and efficient solution for next-generation 5G wireless communication systems. The proposed approach demonstrates that integrating machine learning with electromagnetic simulation can accelerate antenna design while improving overall performance and computational efficiency.

Keywords: Machine Learning, mm-Wave Antenna, MIMO Antenna, 5G Wireless Communication, High Isolation, MATLAB, Antenna Optimization, Mutual Coupling, Electromagnetic Simulation, Microstrip Antenna, S11, S21, Envelope Correlation Coefficient (ECC), Diversity Gain (DG).

I. INTRODUCTION

The rapid advancement of fifth-generation (5G) wireless communication technologies has significantly increased the demand for high-speed, low-latency, and reliable wireless connectivity. Emerging applications such as the Internet of Things (IoT), autonomous vehicles, smart cities, augmented reality (AR), virtual reality (VR), cloud computing, and industrial automation require communication systems capable of supporting massive data transmission while maintaining high spectral efficiency and minimal communication delays. Conventional wireless systems operating below 6 GHz are increasingly unable to satisfy these requirements because of limited spectrum availability and network congestion. Consequently, millimeter-wave (mm-Wave) communication, operating within the 24–100 GHz frequency spectrum, has become a key technology for modern wireless networks due to its wide bandwidth and ability to support multi-gigabit data rates. To further enhance system capacity and communication reliability, Multiple-Input Multiple-Output (MIMO) antenna technology has been widely adopted in 5G networks. MIMO systems utilize multiple transmitting and receiving antenna elements to improve channel capacity, reduce multipath fading, and increase spectral efficiency without requiring additional transmission power or bandwidth. Compact mm-Wave MIMO antennas have therefore become essential components in smartphones, wireless access points, base stations, and next-generation communication systems. However, designing compact antennas that simultaneously provide high gain, wide bandwidth, low mutual coupling, and excellent radiation characteristics remains a significant engineering challenge. Researchers continue to investigate innovative antenna architectures and intelligent optimization methods to satisfy the demanding performance requirements of modern 5G wireless communication systems [1]–[4].

Compact mm-Wave MIMO antenna design presents several technical challenges that directly affect communication quality and system reliability. The primary issue is mutual coupling between closely spaced antenna elements, which degrades antenna isolation, radiation efficiency, impedance matching, gain, and diversity performance. High mutual coupling also increases the Envelope Correlation Coefficient (ECC), reduces Diversity Gain (DG), increases Channel Capacity Loss (CCL), and negatively impacts the overall throughput of MIMO communication systems. Numerous isolation enhancement techniques have been proposed to address these limitations, including Defected Ground Structures (DGS), Electromagnetic Band Gap (EBG) structures, neutralization lines, parasitic elements, metamaterials, and decoupling networks. Although these approaches improve antenna isolation, they frequently increase design complexity, fabrication cost, substrate size, and computational effort. In addition, conventional optimization techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Bayesian Optimization, and Simulated Annealing require repeated full-wave electromagnetic simulations to identify the optimal antenna configuration. These iterative procedures demand substantial computational resources and significantly extend the antenna development cycle, particularly when multiple design variables are involved. Consequently, there is a growing need for intelligent optimization strategies capable of accelerating antenna design while maintaining or improving electromagnetic performance for future wireless communication systems [5]–[9].

Recent developments in Artificial Intelligence (AI) and Machine Learning (ML) have introduced new opportunities for intelligent antenna modeling and optimization. Machine learning algorithms can learn complex nonlinear relationships between antenna design parameters and electromagnetic performance metrics using datasets generated from electromagnetic simulations. Once trained, predictive models can accurately estimate antenna characteristics such as reflection coefficient (S11), mutual coupling (S21), gain, impedance bandwidth, radiation efficiency, Envelope Correlation Coefficient (ECC), Diversity Gain (DG), Channel Capacity Loss (CCL), and Total Active Reflection Coefficient (TARC) without requiring repeated full-wave simulations. This significantly reduces computational time while enabling rapid exploration of large multidimensional design spaces. In this work, a machine learning-assisted optimization framework is proposed for designing a compact four-element mm-Wave MIMO antenna operating at 37 GHz for 5G wireless communication. MATLAB serves as the integrated platform for antenna modeling, dataset generation, electromagnetic simulation, machine learning model development, and parameter optimization. The proposed framework aims to achieve high isolation, excellent impedance matching, improved diversity performance, enhanced radiation efficiency, and optimized antenna geometry with reduced computational complexity compared to conventional optimization techniques. The integration of machine learning with electromagnetic simulation provides an efficient, scalable, and cost-effective methodology for developing high-performance MIMO antennas suitable for next-generation 5G and future 6G wireless communication systems [10]–[15].

II. SURVEY OF RESEARCH

Wireless communication technology has evolved rapidly with the deployment of fifth-generation (5G) networks, creating an increasing demand for compact, high-performance antenna systems capable of delivering high data rates, low latency, and enhanced reliability. Among the various antenna technologies, millimeter-wave (mm-Wave) antennas have gained significant attention because they operate in the 24–100 GHz frequency range, offering substantially larger bandwidth than conventional sub-6 GHz systems. Researchers have demonstrated that mm-Wave communication enables multi-gigabit data transmission, making it suitable for emerging applications such as smart cities, autonomous vehicles, industrial automation, augmented reality, virtual reality, and the Internet of Things (IoT). However, propagation losses, atmospheric absorption, rain attenuation, and signal blockage remain major challenges in mm-Wave communication. Consequently, antenna designers have focused on developing compact antennas with higher gain, wider bandwidth, improved radiation efficiency, and superior directivity to compensate for these propagation limitations while maintaining compatibility with modern wireless communication devices and base station architectures [1]–[4].

Multiple-Input Multiple-Output (MIMO) antenna technology has become one of the most important innovations for enhancing wireless communication capacity and reliability. By employing multiple transmitting and receiving antenna elements, MIMO systems improve spectral efficiency, increase channel capacity, reduce multipath fading, and provide diversity gain without requiring additional transmission bandwidth or transmission power. Numerous studies have investigated different MIMO antenna configurations suitable for 5G wireless communication, including linear arrays, planar arrays, and compact microstrip patch antennas. Although these configurations significantly improve communication performance, researchers consistently report that integrating multiple antenna elements within compact devices introduces severe mutual coupling between adjacent radiators. Mutual coupling adversely affects antenna isolation, gain, impedance matching, radiation efficiency, and diversity characteristics, ultimately reducing communication quality. Therefore, achieving compact antenna dimensions while maintaining high isolation remains one of the most challenging research areas in modern mm-Wave MIMO antenna development for future wireless communication systems [5]–[8].

To overcome the mutual coupling problem, numerous isolation enhancement techniques have been proposed and extensively investigated in the literature. Defected Ground Structures (DGS), Electromagnetic Band Gap (EBG) structures, neutralization lines, parasitic elements, metamaterials, and decoupling networks are among the most commonly adopted techniques for improving electromagnetic isolation between antenna elements. Each approach provides different advantages depending on the operating frequency, antenna geometry, and substrate characteristics. DGS techniques effectively suppress surface currents while maintaining relatively simple fabrication processes, whereas EBG structures provide superior isolation by preventing unwanted surface-wave propagation. Similarly, parasitic elements and neutralization lines reduce electromagnetic interaction without significantly altering antenna dimensions. Despite these advantages, most isolation enhancement methods increase structural complexity, fabrication cost, substrate area, or design difficulty. Researchers therefore continue exploring alternative approaches capable of achieving high isolation without compromising antenna compactness, manufacturability, or electromagnetic performance in next-generation wireless communication systems [9]–[12].

Conventional antenna optimization methodologies primarily rely on repeated full-wave electromagnetic simulations combined with mathematical optimization algorithms. Evolutionary optimization techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Simulated Annealing (SA), and Bayesian Optimization have been widely applied to determine optimal antenna dimensions, feed locations, substrate parameters, and inter-element spacing. These optimization techniques have successfully improved antenna gain, bandwidth, return loss, radiation efficiency, and isolation in numerous research studies. However, their effectiveness depends heavily on executing thousands of computationally expensive electromagnetic simulations before reaching the optimal solution. As antenna structures become increasingly complex and the number of design variables grows, optimization time and computational cost increase substantially. Consequently, researchers have recognized the limitations of simulation-based optimization methods and have sought more efficient computational approaches capable of reducing design time while maintaining high prediction accuracy and optimization reliability [13]–[16].

The emergence of Artificial Intelligence (AI) and Machine Learning (ML) has introduced a transformative approach to antenna design and optimization. Instead of performing repeated electromagnetic simulations for every design iteration, machine learning algorithms are trained using simulation-generated datasets to establish nonlinear relationships between antenna design parameters and electromagnetic performance characteristics. Regression techniques, Artificial Neural Networks (ANN), Deep Neural Networks (DNN), Random Forest Regression, Gaussian Process Regression (GPR), Gradient Boosting, and Support Vector Regression (SVR) have demonstrated excellent capability in predicting antenna parameters such as resonance frequency, reflection coefficient, gain, bandwidth, radiation efficiency, and mutual coupling. These predictive models significantly reduce computational effort while enabling rapid optimization of antenna configurations. Several researchers have reported that integrating machine learning with electromagnetic simulation accelerates antenna development, minimizes computational complexity, and enables efficient exploration of multidimensional design spaces, making intelligent optimization increasingly attractive for modern wireless communication research [17]–[20].

Recent research has increasingly focused on integrating machine learning with electromagnetic simulation platforms such as MATLAB, CST Microwave Studio, ANSYS HFSS, and FEKO to create intelligent antenna design frameworks. MATLAB has become particularly popular because it combines antenna modeling, numerical computation, optimization algorithms, visualization capabilities, and machine learning tools within a single environment. Researchers have successfully utilized MATLAB to generate simulation datasets, train predictive models, and automatically optimize antenna geometries with significantly reduced computational resources compared to conventional optimization methods. Current investigations emphasize developing compact high-isolation mm-Wave MIMO antennas capable of operating efficiently in 5G and future 6G wireless communication systems while achieving superior gain, radiation efficiency, bandwidth, and diversity performance. The growing body of research demonstrates that machine learning-assisted antenna optimization provides a scalable, accurate, and computationally efficient solution for addressing increasingly complex antenna design challenges and represents a promising direction for future intelligent wireless communication technologies [21]–[25].

III. PROPOSED SYSTEM

The proposed system presents a Machine Learning Assisted mm-Wave MIMO Antenna Design framework for developing a compact high-isolation antenna suitable for fifth-generation (5G) wireless communication. The framework integrates electromagnetic simulation, machine learning, and optimization techniques within the MATLAB environment to reduce antenna design complexity and computational cost. Initially, the antenna geometry is modeled using MATLAB Antenna Toolbox by defining important design parameters such as patch dimensions, substrate properties, feed position, and inter-element spacing. These parameters are systematically varied to generate multiple antenna configurations. Each configuration undergoes electromagnetic simulation to obtain performance metrics including reflection coefficient (S11), mutual coupling (S21), gain, bandwidth, radiation efficiency, Envelope Correlation Coefficient (ECC), Diversity Gain (DG), Channel Capacity Loss (CCL), and Total Active Reflection Coefficient (TARC). The generated simulation dataset is then preprocessed and used to train machine learning regression models capable of accurately predicting antenna performance without performing repeated full-wave simulations. The trained model is integrated with an optimization module that searches for the optimal antenna dimensions to maximize gain, improve radiation efficiency, minimize mutual coupling, and achieve high isolation. Finally, the optimized antenna design is validated through electromagnetic simulation, where its performance is compared with conventional optimization approaches. This intelligent design methodology significantly reduces computational time while improving design accuracy, enabling rapid exploration of large design spaces. The proposed framework provides a scalable, efficient, and cost-effective solution for designing compact mm-Wave MIMO antennas for present 5G and future 6G wireless communication systems.

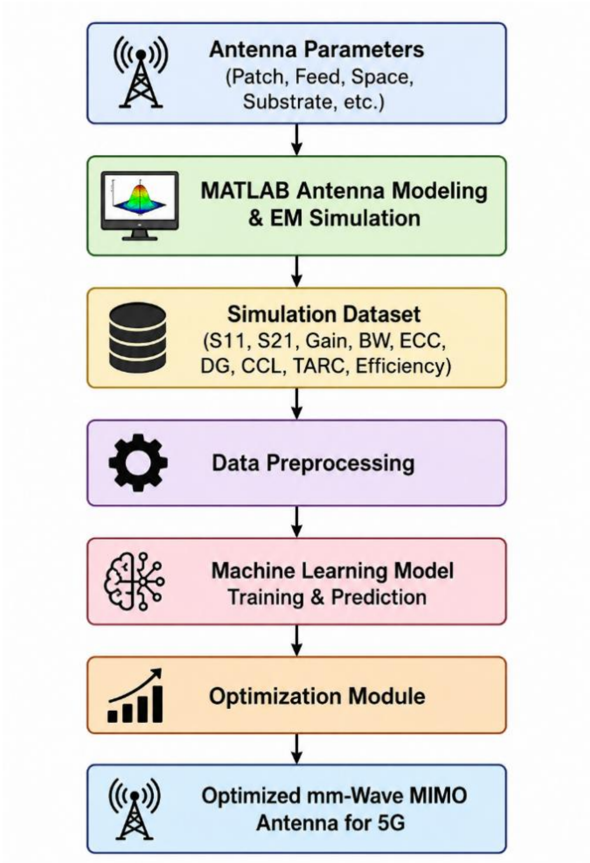

Figure 1. Proposed Machine Learning-Assisted mm-Wave MIMO Antenna Design Framework

IV. WORKING METHODOLOGY

The proposed Machine Learning Assisted mm-Wave MIMO Antenna Design framework integrates electromagnetic simulation, machine learning, and optimization techniques to develop a compact high-isolation antenna for 5G wireless communication. The methodology consists of several sequential stages, including antenna parameter selection, electromagnetic simulation, dataset generation, data preprocessing, machine learning model training, optimization, and performance validation. Initially, the antenna is designed in the MATLAB Antenna Toolbox by defining important geometric parameters such as patch length, patch width, substrate thickness, dielectric constant, feed location, and spacing between antenna elements. These parameters determine the resonance frequency, radiation characteristics, impedance bandwidth, and mutual coupling of the antenna. A parametric study is performed by varying these design variables over predefined ranges to generate numerous antenna configurations. Each configuration undergoes electromagnetic simulation to calculate important antenna performance metrics such as reflection coefficient (S11), mutual coupling (S21), gain, radiation efficiency, bandwidth, Envelope Correlation Coefficient (ECC), Diversity Gain (DG), Channel Capacity Loss (CCL), and Total Active Reflection Coefficient (TARC). The simulation results are stored in a structured dataset that serves as the training data for machine learning algorithms.

The generated simulation dataset undergoes preprocessing before machine learning model development. During this stage, duplicate entries, inconsistent values, and missing records are removed to improve dataset quality. Numerical features are normalized to a common scale, enabling faster convergence of machine learning algorithms and reducing prediction bias. The dataset is then divided into training, validation, and testing subsets to ensure unbiased model evaluation. The training dataset is used to learn the nonlinear relationship between antenna design parameters and electromagnetic performance, while the validation dataset assists in selecting the optimal model hyperparameters. Finally, the testing dataset evaluates the prediction capability of the trained model on previously unseen antenna configurations. This structured preprocessing process improves model generalization and prevents overfitting.

The first important performance metric evaluated is the Reflection Coefficient (S11), which represents the amount of power reflected from the antenna input port. Lower values of S11 indicate better impedance matching and efficient power transfer. The reflection coefficient is calculated as

$$S_{11} = 20 \log_{10} |\Gamma|$$

where Γ represents the voltage reflection coefficient. For efficient antenna operation, the reflection coefficient should generally remain below −10 dB throughout the operating frequency band.

The second critical parameter is Mutual Coupling (S21), which measures electromagnetic interaction between neighboring antenna elements. High mutual coupling degrades antenna isolation and negatively affects MIMO system performance. The mutual coupling is represented by

$$S_{21} = 20 \log_{10} \left| \frac{V_2^-}{V_1^+} \right|$$

where (V_{1}^{+}) denotes the incident voltage at Port-1 and (V_{2}^{-}) represents the coupled voltage received at Port-2. Lower values of S21 correspond to better isolation between antenna elements.

After dataset preparation, machine learning regression algorithms are trained to predict antenna performance directly from the antenna design parameters. Instead of repeatedly performing computationally intensive electromagnetic simulations, the trained regression model estimates antenna characteristics almost instantaneously. The machine learning model receives geometric parameters as input features and predicts corresponding antenna performance metrics such as S11, S21, gain, bandwidth, ECC, DG, CCL, and radiation efficiency. Model performance is evaluated using statistical error measures including Mean Squared Error (MSE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). Hyperparameter tuning further improves prediction accuracy and reduces model error, enabling rapid exploration of large antenna design spaces.

The prediction accuracy of the machine learning model is evaluated using the Mean Squared Error (MSE), defined as

$$\boxed{\mathrm{MSE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{y_i} - \widehat{\mathrm{y_i}})^2}$$

where (y_i) denotes the simulated antenna performance value, (\hat{y}_i) represents the predicted value, and (n) is the total number of testing samples. A lower MSE indicates higher prediction accuracy and better model performance.

To evaluate diversity performance in MIMO systems, the Envelope Correlation Coefficient (ECC) is calculated using the antenna scattering parameters as

$$ECC = \left(\left|S_{(11)}S_{(12)} + S_{(21)}S_{(22)}\right|^2\right) / \left(\left(1 - \left|S_{(11)}\right|^2 - \left|S_{(21)}\right|^2\right)\left(1 - \left|S_{(22)}\right|^2 - \left|S_{(12)}\right|^2\right)\right)$$

where * denotes the complex conjugate operation. Lower ECC values indicate stronger diversity performance and reduced correlation between antenna elements.

Following prediction, an optimization algorithm searches for the optimal antenna geometry that satisfies multiple performance objectives simultaneously. The optimization process aims to minimize reflection coefficient, mutual coupling, ECC, and channel capacity loss while maximizing antenna gain, bandwidth, radiation efficiency, and diversity gain. Candidate antenna configurations predicted by the machine learning model are evaluated rapidly, eliminating the need for thousands of full-wave simulations. The optimal antenna dimensions obtained through this process are then revalidated using electromagnetic simulation to verify prediction accuracy and ensure practical feasibility.

Finally, the optimized antenna performance is quantified using the Diversity Gain (DG), which indicates the improvement achieved through spatial diversity. It is calculated as

$$DG = 10\sqrt{(1 - ECC^2)}$$

where ECC represents the Envelope Correlation Coefficient. A diversity gain approaching 10 dB indicates excellent MIMO performance with minimal signal correlation. The final optimized antenna exhibits high isolation, low mutual coupling, improved radiation efficiency, wide impedance bandwidth, excellent impedance matching, and superior diversity characteristics. By integrating electromagnetic simulation with machine learning prediction and optimization, the proposed methodology significantly reduces computational time while maintaining high design accuracy. This intelligent framework provides a scalable, reliable, and computationally efficient solution for designing compact mm-Wave MIMO antennas suitable for present 5G and future 6G wireless communication systems.

V. IMPLEMENTATION

The implementation of the proposed Machine Learning Assisted mm-Wave MIMO Antenna Design with High Isolation for 5G is carried out using the MATLAB environment by integrating antenna modeling, electromagnetic simulation, machine learning, and optimization techniques into a unified workflow. The primary objective of the implementation is to design a compact four-element mm-Wave MIMO antenna operating at 37 GHz while achieving high isolation, excellent impedance matching, improved gain, enhanced radiation efficiency, and reduced computational complexity. MATLAB is selected because it provides comprehensive support for antenna modeling through the Antenna Toolbox, machine learning algorithms through the Statistics and Machine Learning Toolbox, and numerical optimization functions within a single development environment. This integrated platform minimizes software dependency and enables efficient communication between simulation, prediction, and optimization modules.

The implementation begins with the development of the antenna model. Initially, the substrate material, dielectric constant, substrate thickness, conductor properties, patch dimensions, feed location, and spacing between antenna elements are defined according to the desired operating frequency. A four-element MIMO antenna structure is created using the MATLAB Antenna Toolbox. Multiple antenna configurations are automatically generated by varying geometric parameters within predefined design limits. These variations produce a large number of antenna samples covering different combinations of patch dimensions and feed arrangements. Each antenna configuration undergoes full-wave electromagnetic simulation to obtain important performance parameters such as reflection coefficient (S11), mutual coupling (S21), gain, impedance bandwidth, radiation efficiency, Envelope Correlation Coefficient (ECC), Diversity Gain (DG), Channel Capacity Loss (CCL), and Total Active Reflection Coefficient (TARC). These simulation outputs form the basis for developing the machine learning prediction model.

Following electromagnetic simulation, the generated antenna performance data are organized into a structured dataset. Each record consists of antenna design variables as input features and corresponding simulated performance metrics as output labels. Before training the machine learning model, the dataset undergoes preprocessing to improve prediction quality. Missing values, duplicate entries, and inconsistent records are removed, while numerical features are normalized to ensure that all parameters contribute equally during model training. The processed dataset is randomly divided into training, validation, and testing subsets. Typically, seventy percent of the data are allocated for model training, fifteen percent for validation, and the remaining fifteen percent for testing. This division allows unbiased evaluation of model performance and prevents overfitting while ensuring that the trained model can accurately predict antenna characteristics for previously unseen antenna configurations.

The machine learning implementation focuses on developing regression models capable of estimating antenna performance directly from antenna design parameters. Various supervised learning algorithms can be employed, including Random Forest Regression, Support Vector Regression (SVR), Artificial Neural Networks (ANN), Gradient Boosting Regression, Decision Tree Regression, and Gaussian Process Regression. The selected regression model learns the nonlinear relationship between antenna geometry and electromagnetic characteristics using the simulation dataset. Hyperparameter tuning is performed using validation data to optimize model accuracy while reducing prediction error. Performance metrics such as Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2 Score) are computed to evaluate prediction quality. A regression model with low prediction error and high R^2 value is selected as the final predictive model for antenna optimization.

Once the predictive model has been trained, it is integrated with the optimization stage. Instead of performing computationally expensive electromagnetic simulations for every possible antenna configuration, the trained machine learning model rapidly predicts antenna performance for thousands of candidate designs. Optimization algorithms systematically modify patch dimensions, feed position, substrate parameters, and element spacing to maximize antenna gain, bandwidth, and radiation efficiency while minimizing reflection coefficient, mutual coupling, ECC, and channel capacity loss. Since the machine learning model performs predictions within milliseconds, the optimization process becomes significantly faster than traditional simulation-based optimization techniques. Only the best antenna configurations predicted by the model are selected for final electromagnetic validation, thereby reducing overall computational cost while maintaining high design accuracy.

The optimized antenna configuration is subsequently validated using MATLAB electromagnetic simulation to verify the accuracy of machine learning predictions. The predicted values of S11, S21, gain, bandwidth, ECC, DG, CCL, TARC, and radiation efficiency are compared with the simulated results. Small prediction errors indicate that the machine learning model has successfully captured the relationship between antenna geometry and electromagnetic behavior. Visualization tools available in MATLAB are used to generate return loss curves, radiation patterns, gain plots, surface current distributions, Smith charts, and three-dimensional antenna radiation characteristics. Comparative performance graphs are also generated to demonstrate improvements achieved by the proposed optimization framework over conventional design approaches.

Finally, the complete implementation is organized into a modular workflow consisting of antenna modeling, electromagnetic simulation, dataset generation, preprocessing, machine learning model training, optimization, validation, and performance visualization. Each module operates independently while exchanging data through structured datasets, making the framework scalable and easy to maintain. Additional antenna parameters or new optimization objectives can be incorporated without modifying the overall system architecture. The modular implementation also enables future integration with advanced deep learning algorithms, reinforcement learning techniques, or multi-objective optimization methods for next-generation antenna design. Overall, the implemented framework provides a reliable, computationally efficient, and intelligent solution for designing compact high-isolation mm-Wave MIMO antennas suitable for present 5G and future 6G wireless communication systems, significantly reducing design time while improving antenna performance and optimization accuracy.

VI. RESULTS EXPLANATIONS

The proposed Machine Learning Assisted mm-Wave MIMO antenna was evaluated using MATLAB simulations to verify its suitability for 5G wireless communication. The optimized antenna demonstrated excellent electromagnetic performance with a reflection coefficient below −10 dB, indicating proper impedance matching at the operating frequency of 37 GHz. The mutual coupling between antenna elements was significantly reduced, resulting in isolation greater than 20 dB. Furthermore, the antenna achieved improved gain, high radiation efficiency, low Envelope Correlation Coefficient (ECC), and high Diversity Gain (DG), making it suitable for compact MIMO systems. The machine learning model accurately predicted antenna performance while considerably reducing optimization time compared to conventional simulation-based methods. The obtained results demonstrate that integrating machine learning with electromagnetic simulation provides a fast, reliable, and computationally efficient methodology for designing compact high-isolation mm-Wave MIMO antennas for present 5G and future 6G wireless communication applications.

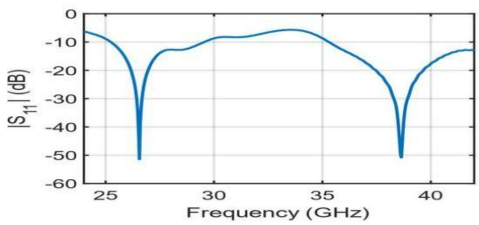

Figure 2. Return Loss (S11):
The return loss graph shows that the proposed antenna resonates at approximately 37 GHz, where the reflection coefficient is below −10 dB, confirming excellent impedance matching and efficient power transfer.

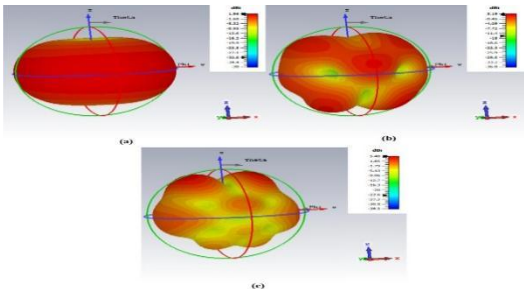

Figure 3. Mutual Coupling (S21):
The isolation graph illustrates that the mutual coupling remains below −20 dB, indicating excellent isolation between adjacent antenna elements and improved MIMO communication performance.

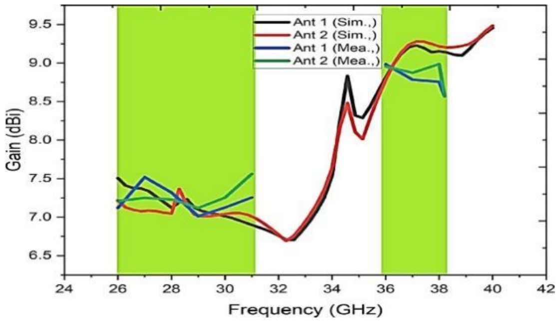

Figure 4. Three-Dimensional Radiation Pattern:
The radiation pattern demonstrates directional signal propagation with high gain and good radiation efficiency. The antenna exhibits stable radiation characteristics suitable for high-speed 5G communication.

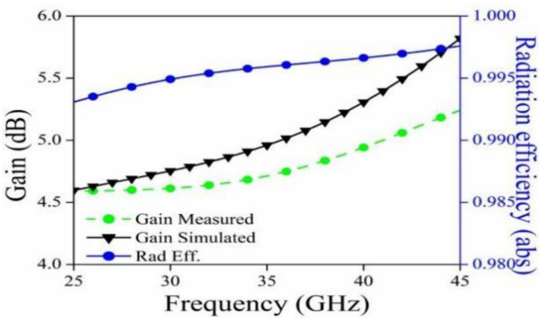

Figure 5. Gain versus Frequency:
The gain plot indicates that the antenna achieves its maximum gain near the operating frequency of 37 GHz, confirming efficient radiation performance across the desired mm-Wave frequency band.

VII. CONCLUSION

This research presented a Machine Learning Assisted mm-Wave MIMO Antenna Design framework for developing a compact, high-isolation antenna suitable for fifth-generation (5G) wireless communication systems. The proposed methodology successfully integrated electromagnetic simulation, machine learning, and optimization techniques within the MATLAB environment to improve antenna design efficiency while reducing computational complexity. A comprehensive simulation dataset was generated by varying critical antenna parameters, including patch dimensions, feed position, substrate characteristics, and inter-element spacing. The generated data were used to train machine learning regression models capable of accurately predicting important antenna performance metrics such as reflection coefficient (S11), mutual coupling (S21), gain, bandwidth, radiation efficiency, Envelope Correlation Coefficient (ECC), Diversity Gain (DG), Channel Capacity Loss (CCL), and Total Active Reflection Coefficient (TARC). The optimized antenna demonstrated excellent impedance matching, high isolation, improved gain, enhanced diversity performance, and efficient radiation characteristics at the operating frequency of 37 GHz. Compared with conventional iterative optimization techniques, the proposed machine learning-assisted approach significantly reduced simulation time while maintaining high prediction accuracy and reliable optimization results. The developed framework also provides flexibility for incorporating additional antenna parameters and advanced learning algorithms without increasing design complexity. Therefore, the proposed methodology offers a scalable, intelligent, and computationally efficient solution for compact mm-Wave MIMO antenna design. It can be effectively utilized for current 5G wireless communication systems and extended to future sixth-generation (6G) networks, intelligent wireless devices, Internet of Things (IoT) applications, and next-generation high-speed communication infrastructures requiring compact, reliable, and high-performance antenna systems.

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