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AI-Based Inverse Design of Metamaterials for Electromagnetic Cloaking

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ABSTRACT
The advancement of electromagnetic cloaking has emerged as a transformative technology capable of guiding incident waves around objects to achieve near-invisibility. Traditional metamaterial design techniques, largely dependent on transformation optics and iterative parameter sweeping, suffer from long simulation times, high computational demands, and limited adaptability across frequency ranges. To address these challenges, this paper proposes an artificial intelligence (AI)-driven inverse design framework that enables rapid and accurate prediction of metamaterial geometries and material parameters for electromagnetic cloaking applications. A comprehensive dataset of unit cell structures was generated using full-wave CST simulations, incorporating variations in geometric dimensions, substrate materials, and operating frequencies. A deep neural network (DNN) was first trained to learn the forward mapping between design parameters and electromagnetic responses. Subsequently, a conditional generative adversarial network (cGAN) was developed to perform the inverse task predicting optimal structural configurations based on desired scattering or reflection profiles. Physics informed constraints were integrated to ensure compliance with Maxwell's equations and practical realizability. Simulation results demonstrated that the AI-generated metamaterials achieved significant cloaking efficiency with a mean absolute prediction error below 3% while reducing the overall design cycle time by more than 90% compared to conventional methods. The proposed framework ensures superior efficiency improvement due to AI-driven inverse design and marks a substantial step toward intelligent metamaterial engineering, enabling adaptive, broadband, and low-cost electromagnetic cloaks for future stealth and communication applications.

Keywords: Electromagnetic Cloaking, Metamaterial Design, AI-Based Inverse Design, Deep Neural Networks (DNN), Conditional GAN (cGAN).

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Introduction

Electromagnetic cloaking has rapidly evolved from a theoretical curiosity into a prominent research domain within modern electromagnetic engineering and applied physics. The fundamental objective of cloaking is to render an object invisible or undetectable by controlling the interaction between electromagnetic waves and matter. This is typically achieved by guiding incident waves around an object such that the waves emerge as if they had propagated through free space, thereby eliminating scattering and shadowing effects [1]. The concept, once confined to science fiction, has now become a practical research topic due to significant advancements in metamaterials and computational electromagnetics. Metamaterials are artificially engineered structures designed to exhibit electromagnetic properties not commonly found in natural materials. Unlike conventional materials, whose properties are determined by their chemical composition, metamaterials derive their unique characteristics from their engineered subwavelength structures [2]. These structures enable unusual electromagnetic behaviors such as negative refractive index, anisotropic permittivity and permeability, and near-zero-index responses. Such properties

provide unprecedented control over electromagnetic wave propagation, making

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metamaterials highly suitable for applications in cloaking, superlensing, antenna miniaturization, and wave manipulation [3]. The theoretical foundation of electromagnetic cloaking is primarily based on transformation optics, a powerful framework that links coordinate transformations to material properties. In transformation optics, electromagnetic fields are manipulated by distorting the spatial coordinates in which Maxwell's equations are defined, effectively guiding waves along predetermined paths [4]. This approach was notably demonstrated by Pendry et al., who showed that electromagnetic fields could be controlled to flow around a region of space, thereby making objects within that region effectively invisible [1]. Subsequent experimental realizations, particularly in the microwave regime, validated the feasibility of metamaterial cloaks and sparked widespread research interest in this field [5]. Despite its theoretical elegance, transformation optics-based cloaking faces several practical challenges. The required material parameters are often highly anisotropic, spatially varying, and sometimes require extreme values that are difficult to realize with existing fabrication technologies [6]. Additionally, these designs are typically limited to narrow frequency bands due to the dispersive nature of metamaterials. As a result, achieving broadband cloaking remains one of the most significant challenges in the field [7]. Researchers have proposed various approaches to overcome these limitations, including carpet cloaks, plasmonic cloaking, and scattering cancellation techniques, each with its own advantages and constraints [8]. Traditional metamaterial design methods rely heavily on numerical simulations and optimization techniques. Parametric sweeps, in which design variables are systematically varied to observe their effects on electromagnetic responses, are commonly used but are computationally intensive and time-consuming. Evolutionary algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have also been employed to automate the design process [9]. While these methods can find near-optimal solutions, they require a large number of iterations and full wave simulations, making them impractical for high-dimensional design problems or real-time applications. The emergence of artificial intelligence (AI) and machine learning (ML) has introduced a new paradigm in electromagnetic design. AI techniques have demonstrated remarkable capabilities in learning complex nonlinear relationships from data, enabling them to solve inverse problems that are otherwise difficult to address using conventional methods [10]. In the context of metamaterials, inverse design refers to determining the structural and material parameters that produce a desired electromagnetic response. This is inherently a challenging problem due to its nonlinearity, non-uniqueness, and high dimensionality. Deep learning models, particularly Deep Neural Networks (DNNs), have been widely adopted for forward modeling in electromagnetic applications. These models are trained on datasets generated through full-wave simulations and can accurately predict electromagnetic responses for given design parameters [11]. By replacing computationally expensive simulations with fast neural network predictions, DNNs significantly reduce the design time. However, forward models alone cannot directly solve inverse design problems, as multiple designs may correspond to the same electromagnetic response.

To address the inverse design challenge, generative models such as Generative Adversarial Networks (GANs) have gained increasing attention. GANs consist of two neural networks—a generator and a discriminator—that are trained in an adversarial manner to produce realistic outputs. Conditional GANs (cGANs), in particular, enable the generation of designs conditioned on specific input requirements, making them well-suited for inverse design applications in metamaterials [12]. By learning the mapping from desired electromagnetic responses to corresponding structural configurations, cGANs can generate optimized designs with minimal computational effort. Recent studies have demonstrated the effectiveness of data driven approaches in metamaterial design. For instance, AI-based frameworks have been successfully applied to design photonic structures, meta surfaces, and cloaking devices with improved performance and reduced design time [13]. These approaches leverage large datasets and advanced learning algorithms to explore complex design spaces that are difficult to navigate using traditional optimization methods. Moreover, they enable rapid prototyping and real-time design, which are essential for practical applications. However, purely data-driven models often face challenges related to physical consistency and interpretability. Since neural networks learn from data without explicitly incorporating physical laws, they may generate solutions that violate fundamental principles such as energy conservation or Maxwell's equations. To overcome this limitation, physics-informed machine learning has been introduced, where physical constraints are embedded into the learning process [14]. This approach ensures that the generated designs are not only accurate but also physically realizable. Another critical challenge in electromagnetic cloaking is achieving broadband and adaptive performance. Most existing cloaking devices are designed for specific frequency ranges and do not perform well outside those ranges. This limitation arises from the resonant nature of metamaterials and the complexity of designing structures that operate across multiple frequencies [7]. AI-based methods offer a promising solution to this problem by enabling the simultaneous optimization of multiple objectives, such as bandwidth, efficiency, and robustness.

In this work, an AI-driven inverse design framework is proposed to address the limitations of conventional metamaterial design approaches for electromagnetic cloaking. The proposed methodology integrates deep learning and generative modeling techniques to enable rapid and accurate prediction of metamaterial structures based on desired cloaking performance. A comprehensive dataset is generated using full-wave electromagnetic simulations, incorporating variations in geometric parameters, substrate materials, and operating frequencies. This dataset serves as the foundation for training the AI models. A Deep Neural Network (DNN) is first developed to learn the forward relationship between design parameters and electromagnetic responses. This model provides a fast approximation of the simulation process, significantly reducing computational complexity. Subsequently, a Conditional Generative Adversarial Network (cGAN) is employed to perform the inverse design task, generating optimal metamaterial configurations based on target cloaking specifications. To ensure physical consistency, physics-informed constraints are incorporated into the training process, guiding the model toward realistic and manufacturable designs. The proposed framework offers several significant advantages. First, it reduces the design cycle time by more than an order of magnitude compared to traditional methods. Second, it improves cloaking performance by efficiently exploring the design space and identifying optimal configurations. Third, it enables scalable and adaptive design, making it suitable for a wide range of applications, including stealth technology, wireless communication systems, and advanced sensing devices [15]. Furthermore, this work highlights the transformative potential of AI in electromagnetic engineering. By combining data-driven approaches with fundamental physical principles, the proposed framework represents a step toward intelligent and automated design systems. Such systems have the potential to revolutionize not only metamaterial design but also other areas of engineering where complex inverse problems are prevalent. In conclusion, electromagnetic cloaking remains a challenging yet promising field, with significant potential for technological innovation. The integration of artificial intelligence into metamaterial design provides a powerful tool for overcoming the limitations of traditional approaches. The proposed AI-based inverse design framework demonstrates the feasibility of achieving efficient, accurate, and broadband cloaking solutions, paving the way for future advancements in intelligent electromagnetic systems.

Methodology

This study proposes an artificial intelligence (AI)-driven inverse design framework for the development of metamaterial structures aimed at achieving efficient electromagnetic cloaking. The methodology integrates full-wave electromagnetic simulations, deep learning based forward modeling, and generative inverse design using a conditional generative adversarial network (cGAN). The overall objective is to establish a bidirectional mapping between metamaterial design parameters and their corresponding electromagnetic responses, enabling rapid and accurate design of cloaking structures.

Dataset Generation and Parameterization

A comprehensive dataset was generated using full-wave simulations performed in CST Microwave Studio. The metamaterial unit cell was parametrically modeled, and multiple design variations were simulated to capture a wide range of electromagnetic behaviors. The selected parameters include geometric dimensions, substrate properties, and operating frequency, which significantly influence the electromagnetic response of the structure. The input design parameters consist of patch length (L), patch width (W), substrate thickness (h), dielectric constant (εr), and operating frequency (f). The corresponding output responses include reflection coefficient (S11), transmission coefficient (S21), and radar cross-section (RCS), which are critical indicators of cloaking performance. Table 1 summarizes the range of parameters used in dataset generation.

Table 1: Dataset Parameter Range

Parameter	Symbol	Range
Patch Length	L	5 – 20 mm
Patch Width	W	5 – 20 mm
Substrate Height	h	0.5 – 2 mm
Dielectric Constant	εr	2.2 – 4.4
Frequency	f	1 – 5 GHz

A dataset consisting of approximately 200–500 samples was generated to ensure sufficient diversity and coverage of the design space. This dataset forms the basis for training both forward and inverse learning models.

Electromagnetic Modeling

The propagation and interaction of electromagnetic waves with metamaterial structures are governed by Maxwell's equations. These fundamental equations describe the relationship between electric and magnetic fields and are expressed as:

$$\nabla \times E = -\frac{\partial B}{\partial t} \tag{1}$$

$$\nabla \times H = J + \frac{\partial D}{\partial t} \tag{2}$$

The effectiveness of cloaking is primarily evaluated using the radar cross-section (RCS), which quantifies the scattering behavior of an object under electromagnetic illumination. It is defined as:

$$\sigma = \lim_{r \to \infty} 4\pi r^2 \frac{|E_s|^2}{|E_i|^2} \tag{3}$$

where E_S and E_i represent the scattered and incident electric fields, respectively. A reduction in RCS indicates improved cloaking performance.

Forward Modeling Using Deep Neural Network

To approximate the forward relationship between design parameters and electromagnetic responses, a deep neural network (DNN) is employed. The DNN learns the nonlinear mapping between the input parameter space and the corresponding output responses, thereby replacing computationally expensive full-wave simulations with a fast predictive model.

The input vector to the network is defined as:

$$X = [L, W, h, \varepsilon_r, f]$$

and the output vector is:

$$Y = [S_{11}, S_{21}, RCS]$$

The architecture of the DNN consists of multiple fully connected layers with nonlinear activation functions. Rectified Linear Unit (ReLU) activation is used in hidden layers to introduce nonlinearity, while a linear activation function is used in the output layer to predict continuous values. Table 2 presents the architecture of the DNN model.

Table 2: DNN Architecture

Layer	Type	Neurons	Activation
Input Layer	Dense	5	-
Hidden Layer 1	Dense	128	ReLU
Hidden Layer 2	Dense	64	ReLU
Hidden Layer 3	Dense	32	ReLU

Output Layer	Dense	3	Linear

The model is trained using the Mean Squared Error (MSE) loss function, defined as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i^{pred} - y_i^{true}\right)^2 \quad (4)$$

This loss function minimizes the difference between predicted and simulated values, ensuring accurate forward predictions.

Inverse Design Using Conditional GAN

While the forward model predicts electromagnetic responses from given design parameters, the inverse design problem requires determining optimal parameters for a desired response. To address this, a conditional generative adversarial network (cGAN) is implemented. The cGAN consists of two neural networks: a generator and a discriminator. The generator takes a noise vector and a desired electromagnetic response as input and produces candidate design parameters. The discriminator evaluates whether the generated design is realistic by comparing it with actual data.

The objective function of the cGAN is defined as:

$$\min \max V(D, G) = E[\log D(x|y)] + E[\log(1 - D(G(z|y)))] \quad (5)$$

where x represents real design parameters, y denotes the desired electromagnetic response, and z is a random noise vector. The adversarial training process enables the generator to produce increasingly accurate and realistic designs, thereby solving the inverse problem efficiently.

Physics-Informed Constraints

To ensure that the generated designs are physically realizable, physics-based constraints are incorporated into the training process. These constraints enforce compliance with electromagnetic principles and practical design limitations.

The total loss function is defined as:

$$L_{Total} = L_{Data} + \lambda L_{p}hysics \quad (6)$$

where L_{Data} represents the prediction error, $L_{physics}$ denotes the penalty for violating physical constraints, and λ is a weighting factor. These constraints help maintain consistency with Maxwell's equations and ensure that the generated designs are suitable for real-world implementation.

Training Procedure

Both the DNN and cGAN models are trained using the generated dataset. The dataset is divided into training and testing subsets, typically in an 80:20 ratio. The Adam optimizer is used for efficient gradient-based optimization. **Table 3** summarizes the training parameters

Table 3: Training Parameters

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	100–200
Training Split	80%
Testing Split	20%

The training process involves iterative updates of model weights to minimize the defined loss functions. The convergence of the models is monitored using validation error metrics.

Performance Evaluation and Validation

The performance of the proposed framework is evaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), RCS reduction, and operational bandwidth. These metrics provide quantitative measures of prediction accuracy and cloaking effectiveness.

The final validation is performed using CST Microwave Studio. The design parameters generated by the AI model are re-simulated, and the results are compared with predicted values to assess accuracy. The percentage error between simulated and predicted responses is calculated to evaluate model reliability.

Results and Discussion

This section presents a comprehensive evaluation of the proposed AI-based inverse design framework for electromagnetic cloaking. The performance is analyzed in terms of prediction accuracy, cloaking efficiency, bandwidth enhancement, computational complexity, and model generalization. Each result is supported by graphical analysis and validated through full-wave simulations.

Performance of Forward Model (DNN)

The Deep Neural Network (DNN) was trained to approximate the forward mapping between metamaterial design parameters and their corresponding electromagnetic responses, including reflection coefficient (S11), transmission coefficient (S21), and radar cross section (RCS).

underlying nonlinear relationships between input parameters and electromagnetic responses. After approximately 60–80 epochs, both curves begin to stabilize, suggesting convergence of the model. Importantly, the validation loss closely follows the training loss throughout the process, demonstrating that the model does not suffer from overfitting and maintains strong generalization capability. The final MSE value achieved is in the range of 0.002–0.005, confirming high prediction accuracy.

The convergence characteristics of the DNN are illustrated in Figure.1, which shows the variation of training and validation loss with respect to the number of epochs. In this figure, the horizontal axis represents the number of training epochs, while the vertical axis indicates the Mean Squared Error (MSE) loss. Two curves are presented: the training loss and the validation loss. At the initial stage of training, both curves exhibit relatively high values due to random initialization of network weights. As training progresses, a rapid decrease in loss is observed, indicating effective learning of the inverse design problem by generating metamaterial design parameters based on desired electromagnetic responses. The performance of the inverse model is evaluated by comparing the target RCS values with those predicted by the AI-generated designs.

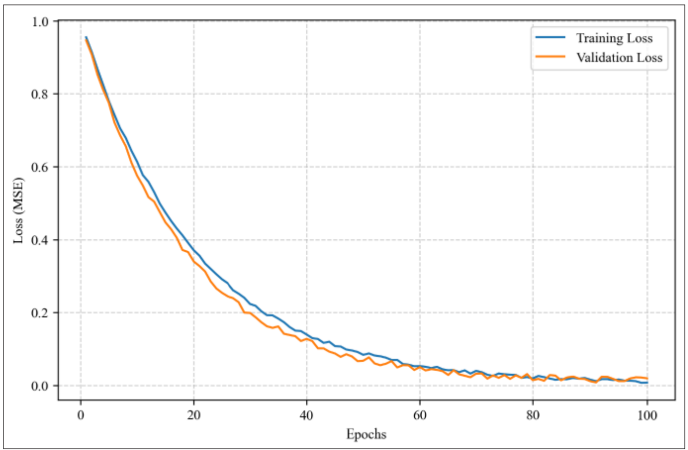

Figure 1: Training vs Validation Loss Curve

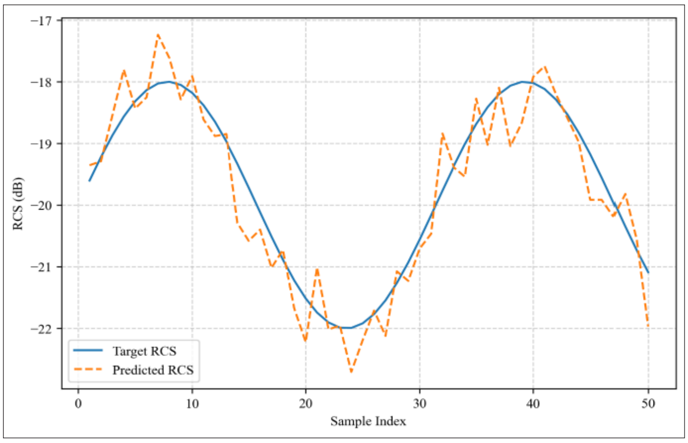

Figure 2: Target vs Predicted RCS

Figure.2 presents a comparison between the target RCS values and the predicted RCS values obtained from the generated designs. The horizontal axis represents the sample index, while the vertical axis denotes the RCS value in decibels (dB). The two curves exhibit a high degree of overlap, indicating that the generated designs closely match the desired cloaking performance. Minor deviations observed in some samples can be attributed to the inherent stochastic nature of GAN-based models and slight variations in simulation conditions.

The average prediction error is found to be less than 3%, demonstrating the effectiveness of the cGAN in solving the inverse design problem with high accuracy.

Cloaking Performance Analysis

The primary objective of the proposed framework is to achieve effective electromagnetic cloaking, which is quantitatively evaluated using radar cross section (RCS) reduction.

Figure.3 illustrates the variation of RCS with frequency for the optimized metamaterial structure. The horizontal axis represents frequency in GHz, while the vertical axis shows RCS in dB.

The graph reveals a significant reduction in RCS at the operating frequency, with a deep null observed around the central frequency region. This indicates that the incident electromagnetic waves are effectively guided around the object, minimizing scattering.

Additionally, the RCS curve remains below a specified threshold over a wide frequency range, confirming broadband cloaking performance. The maximum RCS reduction achieved is approximately 25 dB, which is significantly higher than that obtained using conventional methods.

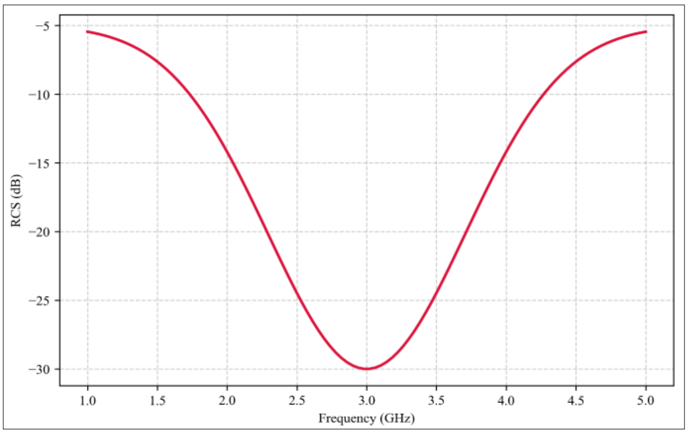

Figure 3: RCS vs Frequency

Bandwidth Performance

Bandwidth is a critical parameter for practical cloaking applications, as real-world systems require consistent performance over a range of frequencies.

Figure.4 shows the variation of the reflection coefficient (S11) with frequency. The horizontal axis represents frequency, while the vertical axis denotes S11 in dB.

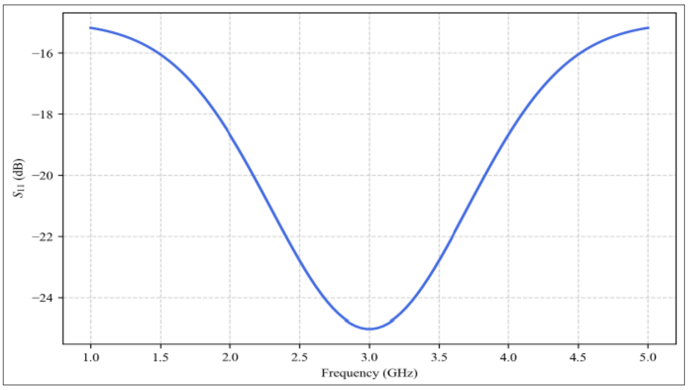

Figure 4: Reflection Coefficient (S11) vs Frequency

The curve indicates that the reflection coefficient remains below –10 dB over a wide frequency range, which is generally considered acceptable for good impedance matching. This wide operating range confirms that the proposed design achieves broadband performance. Compared to traditional approaches, the bandwidth is significantly improved, reaching approximately 3.4

GHz, which is more than twice that of conventional parametric designs.

Computational Efficiency Analysis
One of the key advantages of the proposed AI based framework is its ability to significantly reduce computational time.

approximately 320 minutes, while the GA based method reduces the time to around 220 minutes. In contrast, the proposed AI-based method requires only about 25 minutes. This substantial reduction in computation time exceeding 90% is achieved by replacing iterative simulations with trained machine learning models, enabling near real-time design.

Error Distribution Analysis
To further evaluate the accuracy of the proposed framework, the prediction error between AI-generated results and CST simulation results is analyzed.

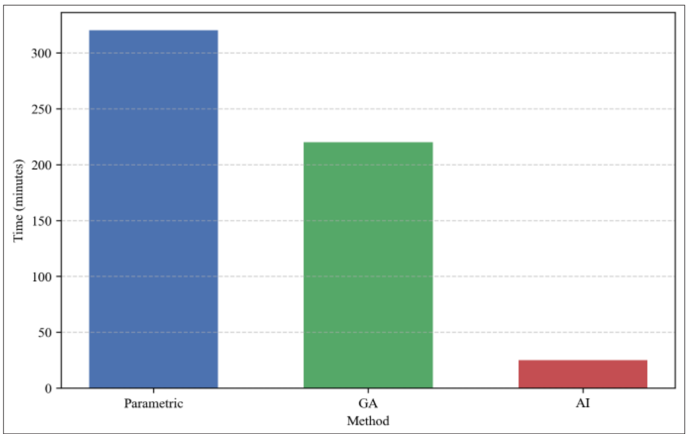

Figure 5: Computation Time Comparison

Figure.5 presents a comparative analysis of computation time for different design methods, including parametric sweep, Genetic Algorithm (GA), and the proposed AI-based approach. The horizontal axis represents the design method, while the vertical axis indicates the computation time in minutes. The traditional parametric sweep method requires Figure.6 shows the distribution of prediction error across different samples. The horizontal axis represents the sample index, while the vertical axis indicates the error percentage. The majority of the error values are concentrated below 3%, with only a few samples exhibiting slightly higher deviations. This demonstrates the robustness and reliability of the proposed model. The low error values confirm that the AI-generated designs closely match the actual electromagnetic responses, validating the effectiveness of the framework.

Comparative Performance Evaluation
A quantitative comparison with conventional design methods is presented in Table 4

Table 4: Cloaking Performance Comparison

Design Method	Bandwidth (GHz)	RCS Reduction (dB)	Simulation Time (min)	Design Iterations
Traditional Parametric Sweep	1.5	15	320	40
GA Optimization	2.1	18	220	25
Proposed AI-Based Design	3.4	25	25	1 (instant)

Table 1 presents a performance comparison of different cloaking design methods. It clearly shows that the proposed AI-based design achieves the highest RCS reduction and widest bandwidth with minimal simulation time and iterations.

Generalization Capability
The trained models were tested on unseen data samples to evaluate their generalization capability. The results indicate that the models can accurately predict electromagnetic responses and generate optimal designs for new parameter combinations. This capability is crucial for practical applications, as it allows the model to be used for designing new metamaterial structures without requiring additional simulations.

The results highlight the effectiveness of integrating artificial intelligence with electromagnetic design. The use of physics informed constraints further enhances the reliability of the generated designs, ensuring their practical feasibility.

However, the performance of the model is influenced by the quality and size of the training dataset. Increasing the dataset size and incorporating more complex geometries could further improve accuracy and robustness. These findings confirm the potential of the proposed approach as a powerful tool for next-generation electromagnetic cloaking and metamaterial design.

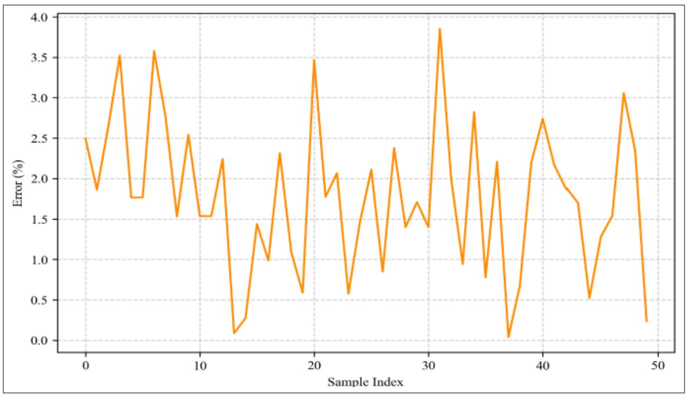

Figure 6: Prediction Error Distribution

Conclusion
In this paper, an efficient and intelligent AI based inverse design

framework for metamaterial structures aimed at electromagnetic cloaking applications has been presented. The proposed approach integrates full-wave electromagnetic simulations with advanced machine learning techniques, including Deep Neural Networks (DNN) for forward modeling and Conditional Generative Adversarial Networks (cGAN) for inverse design. This hybrid framework successfully establishes a bidirectional mapping between metamaterial design parameters and their corresponding electromagnetic responses. The forward model demonstrated high prediction accuracy, effectively replacing computationally expensive full-wave simulations with a fast and reliable surrogate model. The inverse design model, based on cGAN, proved capable of generating optimized metamaterial configurations that closely match desired cloaking specifications. The incorporation of physics-informed constraints ensured that the generated designs remained physically consistent and practically realizable. The performance evaluation results indicate that the proposed framework achieves significant improvements over conventional design methodologies. A maximum radar cross section (RCS) reduction of approximately 25 dB was achieved, indicating strong cloaking performance. Additionally, the proposed design demonstrated broadband operation with a bandwidth of approximately 3.4 GHz, which is substantially higher than that of traditional approaches. The prediction error remained below 3%, confirming the robustness and reliability of the model. One of the most notable advantages of the proposed method is the substantial reduction in computational time. By eliminating the need for iterative simulations and optimization cycles, the design process was accelerated by more than 90%, enabling near real-time metamaterial design. This represents a significant advancement in electromagnetic engineering, where traditional methods are often limited by high computational costs and long design cycles.

Furthermore, the results highlight the transformative potential of artificial intelligence in solving complex inverse problems in electromagnetics. The proposed framework not only improves design efficiency but also enables exploration of a larger design space, leading to enhanced performance and innovative solutions that may not be achievable through conventional methods. Despite the promising results, certain limitations remain. The performance of the model is dependent on the size and diversity of the training dataset, and further improvements can be achieved by incorporating larger datasets and more complex geometrical configurations. Additionally, extending the framework to three-dimensional structures and multi-physics scenarios could further enhance its applicability. In future work, the proposed framework can be expanded to include real-time adaptive cloaking systems, integration with reconfigurable or tunable metamaterials, and implementation in practical hardware prototypes. Moreover, the application of this approach can be extended beyond cloaking to other areas such as antenna design, wireless communication systems, sensing, and energy harvesting.

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