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ARTICLE

Physics-Informed and Uncertainty-Aware FT-Transformer for Accurate Electromagnetic Modeling and S_{11} Prediction of Slotted 2.4 GHz Microstrip Patch Antennas

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ABSTRACT: To enhance the speed of electromagnetic design optimization and avoid repeated full-wave simulations, the accurate prediction of the antenna reflection characteristics is necessary. The relationship between antenna design, operating frequency, and impedance matching, however, is highly non-linear, making it hard for conventional machine learning models to predict accurately. The proposed Physics-Informed Uncertainty-Aware FT-Transformer (PI-UA-FTTransformer) framework accurately predicts the S_{11} response of slotted microstrip patch antennas in the 2.4 GHz industrial, scientific, and medical (ISM) band, accounting for uncertainties. The proposed framework first constructs electromagnetically meaningful physics-informed features based on the antenna's geometry and operating frequency, then tokenizes and embeds them for transformer learning. The embedded features are then passed through a multi-head self-attention and a residual dense representation to learn complex non-linear feature relationships, and an ensemble-based uncertainty estimation module is used to produce S_{11} predictions and confidence intervals in an integrated regression framework. Electromagnetically meaningful descriptors, including electrical patch dimensions and wavelength-normalized geometric ratios, are incorporated to improve feature representation and learning stability. The proposed framework was evaluated using a publicly available CST-generated dataset containing 55,053 simulated antenna samples and benchmarked against representative regression models, including support vector regression (SVR), Random Forest, LSBoost, convolutional neural networks (CNNs), Standard Transformer, TabTransformer, and FT-Transformer. The proposed PI-UA-FTTransformer achieved an RMSE of 0.4007 dB, an MAE of 0.1215 dB, and an R^2 value of 0.9870, while the uncertainty-aware ensemble achieved a prediction interval coverage probability of 93.75%, demonstrating reliable confidence estimation. Unlike existing deterministic antenna prediction models, the proposed framework unifies physics-informed feature engineering, transformer-based global feature interaction learning, and uncertainty-aware prediction within a single architecture, thereby improving prediction reliability, model interpretability, and confidence-aware electromagnetic modeling for intelligent antenna design.

KEYWORDS: Microstrip patch antenna; S_{11} prediction; physics-informed learning; uncertainty-aware prediction; antenna modeling; transformer networks; electromagnetic modeling

1 Introduction

Microstrip patch antennas have become one of the most widely adopted radiating structures in modern wireless communication systems owing to their low profile, lightweight construction, ease of fabrication, and compatibility with printed circuit technology. They are used extensively in wireless local area networks

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(WLAN), Internet of Things (IoT) devices, fifth-generation (5G) communication systems, satellite communications, and industrial, scientific, and medical (ISM) band applications, fostering continual development to improve the performance of antennas to minimize development time and design cost. However, the electromagnetic properties of microstrip antennas are characterized by extremely non-linear relationships among geometric dimensions, substrate parameters, operating frequency, and slot shape. For this reason, antenna design continues to rely heavily on iterative full-wave electromagnetic simulation, which requires considerable engineering skills and computational power.

Artificial Intelligence (AI) has enabled novel opportunities to leverage data-driven surrogate modeling for antenna analysis and design, thereby accelerating the process. The use of Artificial Intelligence (AI) has opened new avenues for accelerating antenna analysis and design through data-driven surrogate modeling. Previous studies by Akinsolu et al. [1] have revealed the increasing adoption of machine learning methods in antenna design, demonstrating that intelligent algorithms can significantly reduce computational workload while preserving design accuracy. Similarly, Rashmitha et al. [2] studied microstrip patch antennas for fixed mobile and satellite communication systems in 5G wireless communication, emphasizing the growing demand for an efficient antenna-optimization technique that meets stringent electromagnetic performance requirements. Recently, Sarker et al. [3] conducted a comprehensive review of machine learning and deep learning applications in antenna design, optimization, and selection, and stated that antenna design and optimization problems using AI-assisted techniques have gained greater significance in solving complex electromagnetic optimization problems across a variety of antenna structures. However, these works mainly focus on extensive reviews or general ideas and do not present predictive analyses that incorporate all knowledge of the electromagnetic field, uncertainty estimation, and the prediction of antenna response using advanced transformer-based learning.

Inspired by these advances, machine learning algorithms for optimizing antenna parameters have attracted significant research interest. Tiwari et al. [4] demonstrated that microstrip antenna parameters can be predicted using machine learning, thereby reducing the need for repeated optimization during microstrip antenna synthesis. Yusuf et al. [5] then used machine learning techniques to design a compact microstrip patch antenna that can be frequency reconfigured, demonstrating that intelligent optimization can aid rapid selection of a frequency configuration. Similarly, Pusuluri et al. [6] introduced a decision-tree-based technique for optimizing a 5G sub-band antenna for wireless broadband applications of WiMAX and WLAN, demonstrating the potential of traditional machine learning algorithms for real-world antenna design. While these methods were effective in reducing computational complexity, they were mostly shallow learning methods with limited potential for modeling highly non-linear interactions among many electromagnetic design variables, typically failed to provide any measure of confidence when making predictions, and were primarily deterministic.

More recent studies have looked into the intelligent optimization of increasingly complex antenna structures. Raveendra [7] studied the optimization of microstrip antenna arrays using machine learning techniques for sub-3.5 GHz 5G networks and reported improved antenna performance through data-driven optimization. Similarly, Shah et al. [8] used machine learning methods to design and optimize a patch antenna, demonstrating that intelligent regression models can reduce the number of design iterations required. In addition, Liu et al. [9] summarized recent developments in the application of artificial intelligence to antenna engineering. They stated that the optimization of antennas using artificial intelligence has become an important part of future antenna design methodologies. Despite these promising advances, most current research still uses an optimization-based workflow in which machine learning selects the optimal antenna size. There is comparatively less work on building strong, high-fidelity surrogate models

that explicitly incorporate physical knowledge and the reliability of predictions into the learning process and accurately predict the full electromagnetic response.

However, the non-linear relationship between antenna geometry and electromagnetic characteristics becomes increasingly complex as the antenna structure becomes more complex, and traditional machine learning algorithms are prone to inaccuracy in modeling such relationships. In recent times, efforts have focused on developing antenna models using deep learning techniques to enhance prediction accuracy and design efficiency. Yaminisasi et al. [10] showed that machine learning can be used to successfully optimize compact fractal monopole antennas for multiband applications without significantly increasing the time required to search for optimal radiation performance, while ensuring acceptable radiation performance. Likewise, Jain et al. [11] presented a machine-learning-based antenna design paradigm for next-generation Internet of Things (IoT) applications, noting that data-driven optimization offers a promising approach to expedite the antenna synthesis process. Building on this, Priya et al. [12] developed an integrated machine learning approach for scalable series-fed microstrip patch antenna arrays, emphasizing the promise of intelligent algorithms for dealing with increasingly complex antenna configurations. Despite these achievements, the reported studies are mostly focused on optimizing geometry and selecting design parameters, rather than on learning a surrogate model that is accurate across a wide design space to predict electromagnetic responses. Moreover, the model's predictive uncertainty was not precisely quantified, which hinders its use in a practical context for antenna designs requiring high reliability.

Some recent studies have investigated predicting electromagnetic responses using supervised learning models rather than optimizing antenna geometry. In an artificial intelligence-based framework for predicting S_{11} characteristics of a compact microstrip patch antenna, Mersani et al. [13] demonstrated that significant reductions in reliance on repeated full-wave electromagnetic simulations are achieved by using data-driven regression models. Similarly, Qin Hua et al. [14] presented a dual neural network design for a rectangular microstrip patch antenna, demonstrating that deep neural networks can learn highly non-linear relationships between antenna parameters and electromagnetic characteristics. Surrogate learning has also been shown to be useful for fitting up-sampling scattering parameters of a circularly polarized ultra-wideband MIMO antenna using machine learning, as reported by Gupta et al. [15] more recently. Yang et al. [16] later introduced an intelligent surrogate modeling method based on a one-dimensional GP-HetCNN architecture to enhance the efficiency of antenna modeling and optimization. These studies successfully predict the problem, but they typically use deterministic regression approaches that provide only a single prediction, without any measure of confidence or incorporation of electromagnetic-domain knowledge to learn the problem.

However, machine learning has also shown great promise in other microwave and radio-frequency system design tasks outside of antenna modeling. In the context of high-frequency component optimization, Passos et al. [17] introduced a machine-learning-based passive component synthesis framework, namely PACOSYT, demonstrating the potential of surrogate modeling to accelerate high-frequency component synthesis. Likewise, Ali Karahan et al. [18] reviewed recent developments in deep learning-based RF integrated circuit and antenna design and introduced the use of attention-based neural architectures for intelligent electromagnetic engineering. The developments here show that transformer-based learning strategies can have significant potential to learn complex feature interactions from high-dimensional engineering data. However, the majority of previous work focuses primarily on design automation and optimization problems, and relatively little effort has been devoted to designing surrogate models that combine electromagnetic physics, global feature dependencies, and uncertainty-aware predictions, which are readily applicable to practical engineering decision-making.

The proliferation of transformer architectures and physics-informed learning has further broadened the application of AI to scientific and engineering challenges. Arslan et al. [19] showed that transformer-based deep learning models not only outperform several conventional machine learning models for complex non-linear regression tasks, but also excel at capturing long-range feature dependencies by the self-attention mechanisms. Its study, even when applied to the forecasting of renewable energy, validated the superior representational power of transformer architectures for high-dimensional regression. Héliot et al. [20] studied the stochastic behavior of exposure to radio-frequency electromagnetic fields in massive multiple-input multiple-output (MIMO) systems. They highlighted the need for accurate modeling of the complex electromagnetic interactions. To build upon this idea, Bilson et al. [21] developed a physics-informed machine learning approach to modeling an RF electromagnetic field. They showed that incorporating physical knowledge into the learning phase enhances the model's consistency and generalizability. However, the above studies were designed for electromagnetic exposure assessment rather than antenna surrogate modeling, did not include transformer-based regression, and did not account for uncertainty in electromagnetic response estimation.

Recent advances have also shown that artificial intelligence is emerging as a valuable aid in the intelligent design of electromagnetic components, beyond traditional microstrip antennas. The need for intelligent optimization of emerging electromagnetic devices is widely recognized, as demonstrated by Kiani et al. [22] with a graphene-based reconfigurable substrate-integrated waveguide filter in the terahertz band. Likewise, Haque et al. [23] used machine learning algorithms to optimize a terahertz MIMO antenna for a future 6G communication system, reinforcing the growing importance of data-driven approaches for next-generation wireless devices. At the same time, Koziel et al. [24] showed that low-dimensional models, which can be viewed as surrogate models, can be used to accelerate antenna optimization while maintaining model accuracy. To efficiently handle computationally intensive antenna design problems, Li et al. [25] also proposed surrogate-assisted learning and multi-objective evolutionary optimization. Overall, these studies demonstrate that surrogate modeling is an effective approach for reducing computational cost in antenna optimization. Most current methods, however, are optimization-based and assume deterministic prediction, so they do not provide any information about prediction confidence or model reliability during the actual engineering design process.

Furthermore, with the emergence of large-scale electromagnetic data, data-driven antenna modeling has gained significant momentum. To facilitate comparison of AI-based S_{11} prediction performance, Mersani et al. [26] presented a comprehensive parametric simulation database for slotted 2.4 GHz microstrip patch antennas. Recently, Akinsolu et al. [27] demonstrated that artificial intelligence can be effectively used to design wideband digitally coded microstrip array antennas, suggesting that intelligent learning algorithms are increasingly being incorporated into antenna design. Such open data sources and new smart design theories have made tremendous progress in the field of antennas. Still, most research focuses on the predictive accuracy of deterministic models or on optimization efficiency. To the authors' best knowledge, a single framework that combines physics-informed feature engineering, transformer-based global feature interaction learning, residual representation learning, and uncertainty-aware electromagnetic prediction for accurate S_{11} modeling of slotted microstrip patch antennas has not been reported.

From the literature reviewed above, it is worth noting the common limitations across the existing studies. Firstly, the reported machine learning solutions primarily optimize antenna parameters rather than accurately model electromagnetic responses. Second, conventional regression models typically treat antenna parameters as purely numerical variables and fail to account for the underlying electromagnetic relationships among them explicitly. Third, while deep learning has achieved higher prediction accuracy, deterministic neural networks can only provide point predictions without quantifiable prediction uncertainty, making

them less useful for engineering decisions. Fourth, previous research on transformer design for antenna engineering is still at a relatively early stage, and previous applications have mainly focused on architecture exploration or optimization. In contrast, the physics-informed transformer structure for confidence-aware S_{11} prediction has received little attention. Last but not least, there is limited literature that jointly investigates physics-informed learning, uncertainty estimation, and the contributions of components through systematic ablation analysis.

To speed up the antenna development process and avoid excessive computation in full-wave electromagnetic simulations, the antenna's reflection coefficient (S_{11}) must be accurately predicted. Currently available surrogate modeling approaches, however, have difficulty achieving high prediction accuracy while remaining physically consistent and quantifying prediction uncertainty, as they either neglect to incorporate existing electromagnetic domain knowledge or rely on deterministic learning architectures, which are unable to quantify prediction uncertainty. Furthermore, current transformer-based antenna studies have not yet fully leveraged attention-based global feature learning, physics-informed feature engineering, and uncertainty-aware regression within a unified modeling framework. There is, therefore, a knowledge gap regarding the creation of an intelligent electromagnetic surrogate model that can provide accurate, reliable S_{11} predictions necessary for practical antenna design.

To overcome these problems, an accurate modeling and S_{11} prediction framework based on the Physics-Informed Uncertainty-Aware FT-Transformer (PI-UA-FTTransformer) for slotted 2.4 GHz microstrip patch antennas is proposed in this paper. The proposed framework differs from traditional regression models by first adding electromagnetically relevant descriptors, such as wavelength-normalized geometric parameters and electrical patch dimensions, to embed physical knowledge into the learning process. The obtained physics-informed features are then processed by an FT-Transformer architecture that learns complex global interactions among the antennas' design variables via multi-head self-attention. An ensemble-based uncertainty estimation strategy provides prediction confidence in addition to S_{11} estimates, and dense residual feature learning enhances representation. The proposed framework therefore aims to provide a physically more consistent surrogate modeling solution for intelligent antenna analysis and optimization, thereby improving reliability.

This work makes the following main contributions:

- A novel Physics-Informed Uncertainty-Aware FT-Transformer (PI-UA-FTTransformer) framework is proposed to accurately predict the S_{11} of slotted 2.4 GHz microstrip patch antennas, combining electromagnetic feature engineering, transformer learning, and uncertainty estimation within a unified regression architecture.
- By incorporating wavelength-normalized geometric descriptors and electrical antenna parameters into the development of physics-informed feature encoding, the learning model is better equipped to capture the underlying electromagnetic relationships between antenna geometry and reflection characteristics.
- A new uncertainty-aware ensemble prediction technique is proposed to not only estimate the antenna S_{11} response but also its prediction confidence, thereby enhancing the reliability and usefulness of data-driven Electromagnetic Compatibility (EMC) modeling for engineering decisions.
- The proposed framework is extensively benchmarked against representative machine learning and deep learning models and systematically ablated, using a freely available dataset of 55,053 CST-generated antenna samples to fully validate the framework and test the individual contributions of physics-informed learning, residual feature representation, and uncertainty-aware prediction.

2 Materials and Methods

2.1 Dataset Description and Preprocessing

This study employed a publicly available parametric simulation dataset of a slotted microstrip patch antenna designed to operate in the vicinity of the 2.4 GHz Industrial, Scientific, and Medical (ISM) band. The dataset comprises 55,053 CST Microwave Studio simulation samples generated through extensive parametric sweeps of antenna geometrical variables. Each sample represents a unique antenna configuration characterized by multiple structural parameters together with its corresponding reflection coefficient (S_{11}).

The antenna dimensions relate to the substrate dimensions, slot dimensions, feedline parameters, and the radiating patch characteristics. The target variable is the return loss S_{11} in dB (decibels), which is useful to assess the performance of impedance matching and the characteristics of the antenna resonance.

The full dataset was split into training, validation, and test sets at 70:15:15. Feature normalization, using z-score standardization, was used to improve convergence stability and optimize the neural network.

The normalized input feature vector is given by Eq. (1):

$$x_i^{norm} = \frac{x_i - \mu_x}{\sigma_x} \tag{1}$$

where x_i^{norm} denotes the normalized feature, μ_x represents the feature mean, and σ_x denotes the standard deviation.

Similarly, the target S_{11} values were normalized according to Eq. (2):

$$y_i^{norm} = \frac{y_i - \mu_y}{\sigma_y} \tag{2}$$

where y_i represents the original S_{11} value.

The antenna design used in this work is intended for use near the ISM band frequency of 2.4 GHz. Initially, the baseline microstrip patch antenna was designed according to conventional antenna design criteria for the operating frequency. Then the key geometrical parameters, such as patch dimensions, slot dimensions, feedline dimensions, substrate dimensions, and substrate thickness, were systematically parameterized over feasible ranges reported in the published antenna design literature and in previous design experience. Several extensive parametric sweeps were then performed in CST Microwave Studio to generate 55,053 physically realizable antenna configurations, along with their corresponding simulated S_{11} responses. This methodology enabled wide, yet physically meaningful, sampling of the antenna design space with realistic electromagnetic properties for machine-learning surrogate modeling.

The data set is for a small rectangular-slot-fed microstrip patch antenna for use at 2.4 GHz in the ISM band. The antenna geometry consists of a dielectric substrate, a radiating patch, a rectangular slot, and a microstrip feed line. These dimensions of the substrate, patch, slot, feedline, and thickness of the substrate were systematically varied within practical design ranges to create a physically realizable antenna configuration space of 55,053 different configurations with realistic electromagnetic behavior for surrogate modeling using machine learning.

In this study, the main variables in the datasets are summarized in Table 1.

Fig. 1 shows the overall flow of the proposed physics-informed, uncertainty-aware FT-Transformer framework for improving accuracy. S_{11} prediction of slotted 2.4 GHz microstrip patch antennas.

Table 1: Principal antenna parameters used for S_{11} prediction.

Parameter	Symbol	Description	Unit
Patch length	Lp	Length of radiating patch	mm
Patch width	Wp	Width of radiating patch	mm
Slot length	Ls	Length of slot	mm
Slot width	Ws	Width of slot	mm
Feed width	Wf	Width of microstrip feed line	mm
Feed length	Lf	Length of microstrip feed line	mm
Substrate length	L	Substrate length	mm
Substrate width	W	Substrate width	mm
Substrate height	h	Thickness of substrate	mm
Frequency	f	Operating frequency	GHz
Reflection coefficient	S_{11}	Return loss	dB

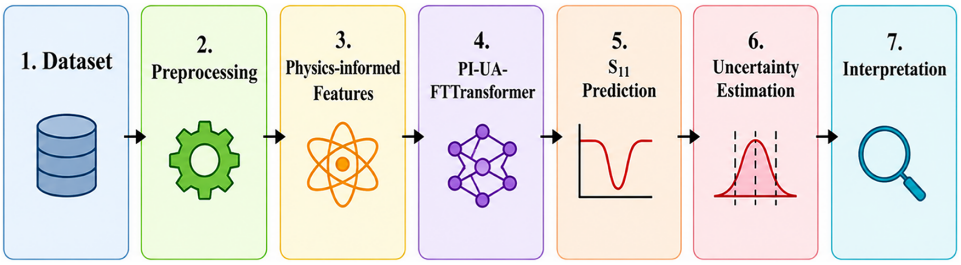


Figure 1: Overall workflow of the proposed PI-UA-FTTransformer framework for S_{11} prediction of slotted 2.4 GHz patch antennas.

2.2 Physics-Aware Feature Encoding

The coupled relationships among antenna geometry, operating frequency, and effective wavelength play a fundamental role in determining the electromagnetic behavior of practical antenna systems. To enhance the transformer model's learning ability, additional features derived from the original antenna parameters were extracted.

The free-space wavelength is calculated as given in Eq. (3):

$$\lambda_0 = \frac{c}{f} \tag{3}$$

where c denotes the speed of light and f represents the operating frequency.

The effective dielectric constant is approximated as shown in Eq. (4):

$$\varepsilon_{\text{eff}} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2}\left(1 + \frac{12h}{W}\right)^{-1/2} \tag{4}$$

where ε_r is the substrate relative permittivity.

The effective wavelength inside the dielectric substrate is then expressed as given in Eq. (5):

$$\lambda_{eff} = \frac{\lambda_0}{\sqrt{\varepsilon_{eff}}} \tag{5}$$

Several dimensionless physics-aware descriptors were subsequently generated, including electrical patch length, slot-to-patch ratio, feed-width ratio, and normalized substrate dimensions. For example, the electrical patch length was calculated as shown in Eq. (6):

$$L_{elec} = \frac{L_p}{\lambda_{eff}} \tag{6}$$

These engineered parameters provide physically meaningful representations that enhance the attention mechanism's ability to capture antenna resonance behavior and impedance-matching characteristics.

2.3 Proposed PI-UA-FTTransformer Architecture

The proposed model integrates feature-tokenized transformer learning with residual dense representation and ensemble prediction with uncertainty. The proposed framework explicitly models global interactions among the antenna geometrical parameters and allows for the use of self-attention mechanisms, unlike the conventional multilayer perceptron. The detailed architecture of the proposed PI-UA-FTTransformer framework, designed for accurate S_{11} prediction of slotted microstrip patch antennas is shown in Fig. 2. The proposed architecture begins with the input antenna's geometrical and frequency-related parameters and subsequently proceeds to physics-informed feature engineering that generates electromagnetically meaningful descriptors, including electrical patch dimensions and wavelength-normalized geometric ratios. The feature vector is then linearly projected back to embedded feature tokens, combined with position encoding. These tokens are processed by stacked transformer blocks with multi-head self-attention, residual connections, layer normalization, and feed-forward networks, which can encode complex global relationships among antenna parameters. All the learned representations are then aggregated to produce the predicted S_{11} response using global average pooling and dense regression layers. Lastly, the ensemble-based uncertainty estimation module integrates predictions from multiple transformer models, providing mean predictions and uncertainty information in a confidence-aware manner, thereby enhancing the reliability and interpretability of the proposed antenna modeling framework.

In the proposed framework, the original antenna parameters are first transformed into electromagnetically meaningful descriptors, which contrasts with a traditional FT-Transformer, where the raw numerical features are directly tokenized. These physics-informed features are based on antenna geometry, wavelength scaling, and dielectric effects prior to tokenization, allowing the self-attention mechanism to learn physically relevant global relations among antenna parameters.

The self-attention mechanism learns pairwise dependencies among antenna parameters according to the following Eq. (7), as given below:

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{7}$$

where Q, K, and V denote query, key, and value matrices, respectively, while d_k represents the attention scaling factor.

To improve representation stability, residual skip connections were incorporated after each attention block as shown in Eq. (8):

$$H_{l+1} = H_l + F(H_l) \tag{8}$$

where H_l denotes the intermediate hidden representation and $F(\cdot)$ represents the non-linear transformation learned by the residual block.

The final regression output for S_{11} prediction is given by Eq. (9) as given below:

$$\hat{y} = f_{PI-UA-FT}(X) \tag{9}$$

where $f_{PI-UA-FT}(\cdot)$ represents the proposed physics-informed uncertainty-aware FT-Transformer model.

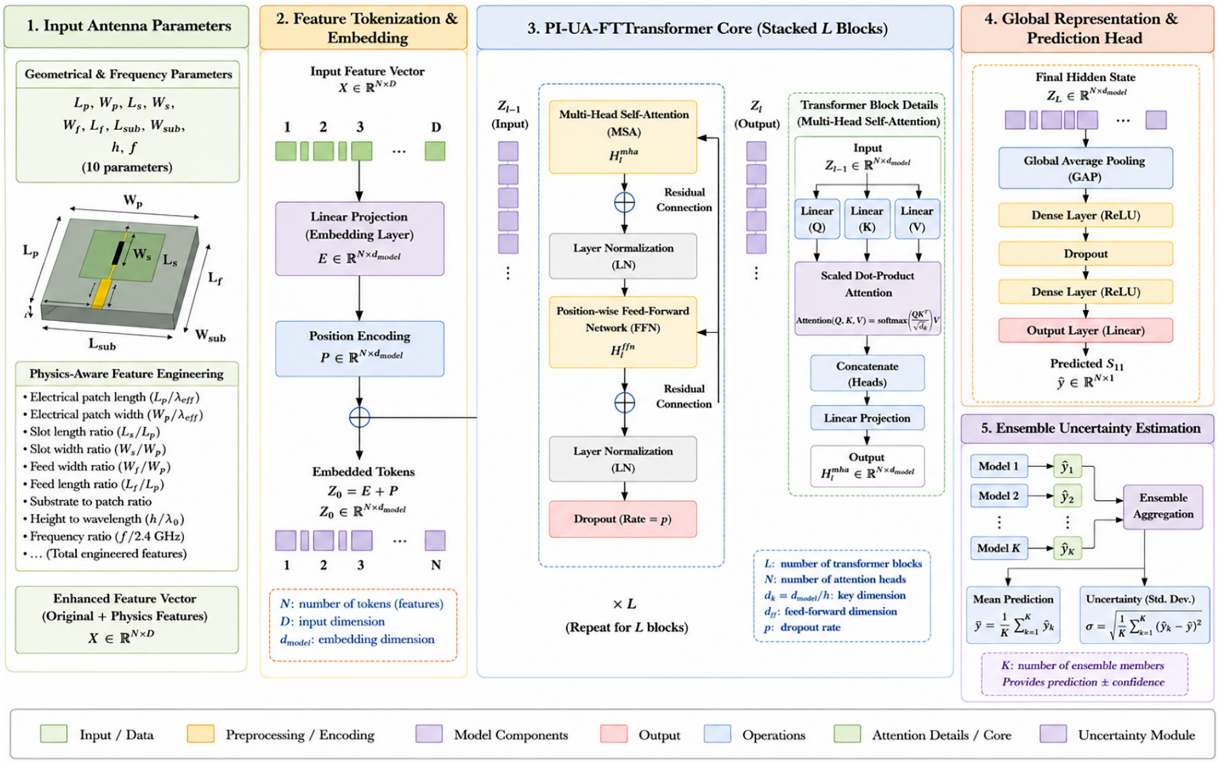


Figure 2: Block diagram of the proposed PI-UA-FTTransformer architecture.

Table 2 summarizes the principal hyperparameters of the proposed framework.

Table 2: Main hyperparameters of the proposed PI-UA-FTTransformer model.

Parameter	Value
Transformer embedding dimension	128
Number of attention heads	8
Feed-forward dimension	256
Dropout rate	0.03
Batch size	128
Maximum epochs	250
Optimizer	Adam
Initial learning rate	3×10^{-4}
Ensemble members	5

As shown in Table 2, relatively low dropout regularization was employed to preserve information flow while minimizing overfitting in structured antenna regression tasks.

2.4 Uncertainty-Aware Ensemble Prediction

To improve prediction reliability, ensemble-based uncertainty estimation was incorporated into the proposed framework. Multiple independently initialized transformer models were trained, and the final prediction was obtained by averaging across them.

The ensemble prediction is expressed as given in Eq. (10):

$$\bar{y} = \frac{1}{N}\sum_{i=1}^{N}\hat{y}_i \tag{10}$$

where N represents the number of ensemble models.

Prediction uncertainty was estimated using the ensemble variance as shown in Eq. (11):

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - \bar{y})^2 \tag{11}$$

This uncertainty-aware formulation enables confidence-guided RF modeling and provides additional reliability information during antenna optimization and design-space exploration.

3 Results and Discussion

3.1 Dataset Characteristics and Physics-Aware Feature Analysis

The proposed framework has been applied to 55,053 antenna simulation samples of various slotted microstrip patch antenna designs for the ISM band around 2.4 GHz. The regression problem is highly non-linear with a wide range of reflection coefficients.

The dataset has been analyzed statistically and physically, and the results obtained are shown in Fig. 3.

As shown in Fig. 3a, the histogram indicates that most S_{11} values are close to 0 dB, and deeper-resonance values are infrequent. This distribution count is a moderately unbalanced regression problem, with many fewer antennas exhibiting strong resonance. So, it is very interesting to calculate the low S_{11} region for practical use in antenna design.

The correlation matrix of the original features and the physics-based features is shown in Fig. 3b. Interdependencies between several engineered parameters, such as electrical length, substrate scaling, and feed geometry, are substantial. These are structured relationships, and feature interaction learning with a transformer can be used here, as it is better suited to modeling features at a global level (which is difficult for local learning models).

The importance of electrical patch length and operating frequency in predicting S_{11} is further highlighted by the feature importance shown in Fig. 3c. This is in accordance with the theory of Microstrip Antennas, which states that the electrical size of the radiating structure strongly influences the resonant characteristics. Other parameters, such as the substrate size and slot geometry, also play a role in the impedance-matching properties, but to a lesser degree.

The raw patch length and patch width have lower individual importance scores, but this does not necessarily contradict classical microstrip antenna theory. While they remain relevant for determining antenna resonance and matching, the proposed physics-informed descriptors provide most of these predictive parameters, especially the electrical patch length and the geometrical ratios normalized by wavelength. These engineered features combine the effects of geometry, operating frequency, and substrate properties to provide a more meaningful representation for the learning algorithm in an electromagnetic sense. Moreover, the design variables for many antennas are highly coupled, as they strongly influence the antenna's resonant behavior. The predictive contribution is therefore naturally spread over several correlated features,

not only individual geometrical parameters. The comparatively lower standalone importance of the raw patch dimensions is attributed to the combined effect of feature correlation and physics-informed feature engineering, rather than solely to the proposed PI-UA-FTTransformer.

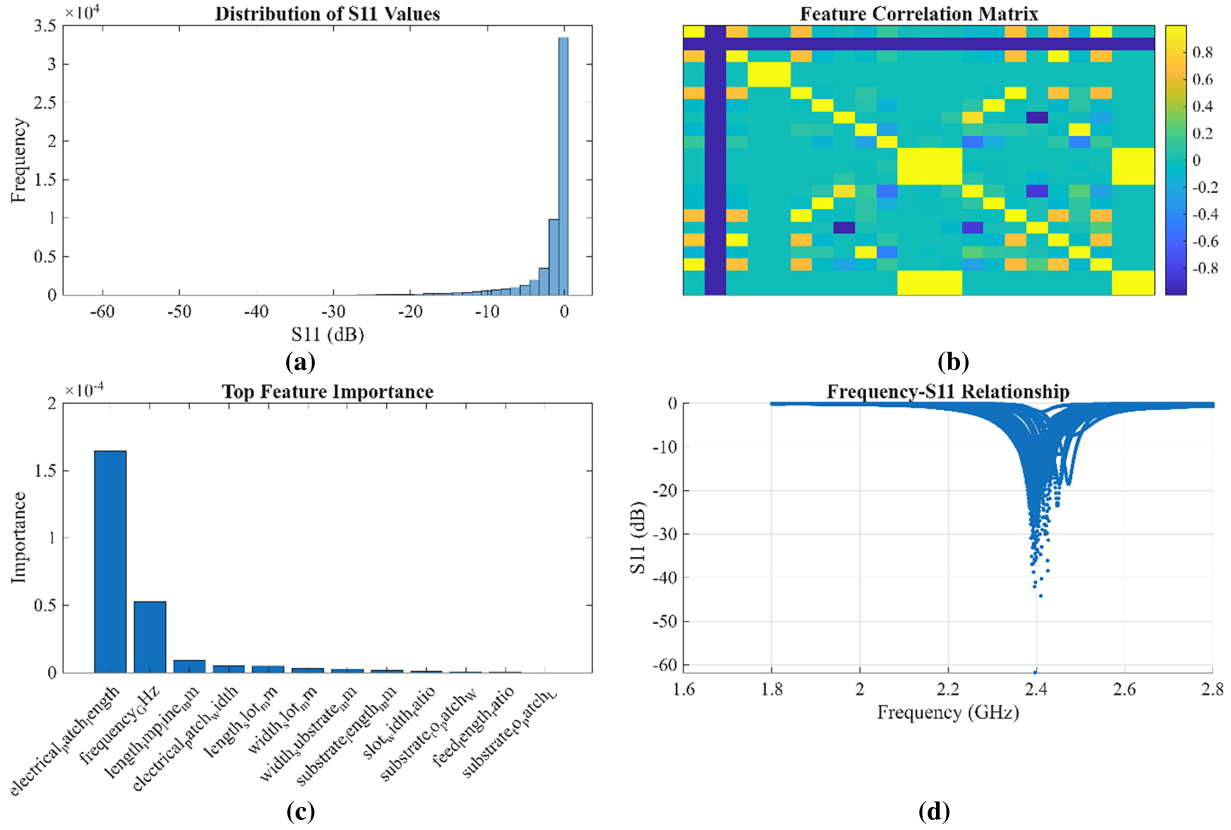


Figure 3: Dataset characteristics and physics-aware feature analysis: (**a**) Distribution of S_{11} values, (**b**) Feature correlation matrix, (**c**) Feature importance analysis, and (**d**) Frequency vs. S_{11} relationship.

In the considered design space, the antenna with a slot is primarily used to refine impedance matching and perturb the current distribution, while the resonant frequency is still primarily determined by the effective electrical size of the radiating patch. That means the slot parameters receive lower scores than the electrical patch descriptors.

The operating frequency vs. S_{11} is shown in Fig. 3d. A clear resonance is observed at 2.4 GHz, with some antenna designs exhibiting sharp minima in return loss of −40 dB or lower. The non-linear nature of the phenomenon in Fig. 3d and its strong localization make the prediction task highly complex and motivate the use of more advanced architectures for non-linear regression.

3.2 Comparative Performance Analysis

The proposed PI-UA-FTTransformer framework was tested against several classical machine learning regression methods, and their performances were analyzed. A number of classical machine learning regression models were chosen as benchmark methods to compare the performance of the proposed PI-UA-FTTransformer framework. The comparison is made among CNN (Convolutional Neural Networks), LSBoost (Least Squares Boosting), RF (Random Forests), and SVR (Support Vector Regression). The same independent test set was used for training and testing all models to make a fair comparison. The quantitative

performance parameters are summarized in Table 3, and Fig. 4 shows a graphical comparison of the RMSE and R^2 values.

Table 3: Comparative performance analysis of baseline and proposed models.

Model	RMSE (dB)	MAE (dB)	R^2	NRMSE	RPD
CNN	0.6138	0.1705	0.9694	0.0146	5.7145
LSBoost	0.5603	0.1484	0.9745	0.0133	6.2599
Random Forest	0.4382	0.0962	0.9844	0.0104	8.0037
SVR	1.5975	0.4335	0.7925	0.0380	2.1956
Proposed PI-UA-FTTransformer	**0.4007**	**0.1215**	**0.9870**	**0.0095**	**8.7533**

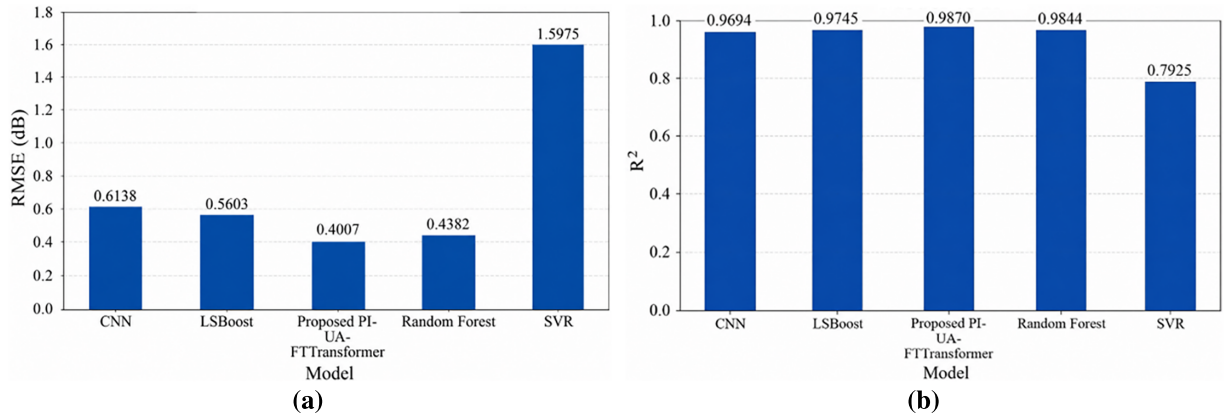


Figure 4: Comparative performance of baseline and proposed models: (**a**) RMSE comparison and (**b**) R^2 comparison.

As shown in Table 3, the proposed PI-UA-FTTransformer achieved the lowest RMSE (0.4007 dB), the highest coefficient of determination (R^2 = 0.9870), the lowest normalized RMSE (NRMSE = 0.0095), and the highest residual prediction deviation (RPD = 8.7533) among all evaluated models. These results indicate that the proposed framework provides the most accurate overall approximation of the non-linear electromagnetic relationship between antenna geometry and the corresponding S_{11} response over the entire design space.

It is noteworthy that the Random Forest model achieved the lowest MAE (0.0962 dB), which is slightly lower than the 0.1215 dB obtained by the proposed PI-UA-FTTransformer. Random Forest constructs an ensemble of decision trees that partitions the feature space into localized regions. Such localized, piecewise predictions often reduce the average absolute error because many samples are accurately predicted within their respective regions. However, the resulting piecewise-constant approximation may lead to larger prediction errors near sharp electromagnetic resonance transitions, where the antenna response changes rapidly and continuously. Since RMSE penalizes larger errors more heavily than MAE, these relatively few high-magnitude deviations increase the overall RMSE despite the lower average absolute error.

In contrast, the proposed PI-UA-FT Transformer learns global representations via multi-head self-attention while incorporating physics-informed electromagnetic descriptors and uncertainty-aware ensemble prediction. Rather than partitioning the feature space into independent regions, the transformer learns continuous long-range interactions among antenna geometry and operating frequency, enabling smoother approximation of the non-linear electromagnetic response. Even though Random Forest yields a

slightly worse MAE, the proposed framework achieves lower MAE, higher R^2, and more accurate overall generalization across the entire antenna design space by reducing large prediction errors.

The CNN and LS Boost models achieved similar accuracy in the prediction task but were less effective than the proposed framework in the overall regression task. The CNN mainly learns local feature patterns via convolutional operations and thus struggles to model long-range interactions among antenna parameters. Likewise, LS Boost sequentially reduces the residual error to enhance prediction, but it is limited when the modeling relationship between the electromagnetic field is highly non-linear. The model with the most errors of prediction, however, was the SVR model, which showed less ability to capture the complex non-linear relationships between antenna geometry and reflection characteristics.

These observations are consistent with the comparative results shown in Fig. 4. The proposed PI-UA-FT Transformer yielded the best RMSE among all the methods considered, as shown in Fig. 4a, and the highest R^2, as shown in Fig. 4b, indicating an excellent overall regression function for predicting the S_{11} response of slotted microstrip patch antennas. The results show that while Random Forest has the lowest average absolute error, the proposed PI-UA-FTTransformer offers better overall predictive performance, stronger global-level generalization, and greater robustness across the entire electromagnetic response.

3.3 Prediction Accuracy and Error Distribution

To test the predictive power of the proposed framework, scatter and residual plots of the relationship between actual and predicted values are shown. S_{11} values have been analyzed further. Finally, in Fig. 5, the regression fit and the distribution of residual errors are displayed, with the proposed PI-UA-FTTransformer used. Fig. 5a demonstrates a strong linear agreement between the predicted and reference. S_{11} values. Most prediction samples are close to the ideal 45° regression line that is observed throughout the entire range of operation. The proposed framework did not show any significant change in prediction behavior in the lower resonance regions with lower-level values (below −20 dB). As shown in the residual distribution in Fig. 5b, the prediction errors are sufficiently localized around zero. The range of most residual values is also relatively small around the origin, suggesting that there is no significant systematic bias in the proposed framework. A few outliers were found for very deep resonance situations, and these were very difficult to model due to their highly non-linear resonance response. The acquired residual behavior shows that the proposed model exhibits good generalization in both shallow and deep resonance regions and stable prediction performance.

3.4 Uncertainty-Aware Prediction Analysis

One of the major features of the proposed framework is the use of uncertainty-aware ensemble prediction. Unlike the deterministic regression models, the proposed method offers both values of S_{11} and confidence intervals of the values.

The uncertainty estimation performance was assessed by prediction interval coverage probability (PICP), mean prediction interval width (MPIW), and negative log-likelihood (NLL). The proposed framework achieved a PICP of 93.75%, indicating satisfactory results, with the generated CI enclosing the actual target values for most test samples.

The prediction intervals obtained from the proposed framework are shown in Fig. 6, along with the associated uncertainty levels.

The prediction intervals remain narrow for most test samples, indicating high confidence in the estimates. S_{11} responses (as shown in Fig. 6). A slight enlargement of the uncertainty regions is observed at resonances whose transitions vary rapidly, which is physically reasonable, as these zones exhibit greater non-linear sensitivity to changes in antenna geometry.

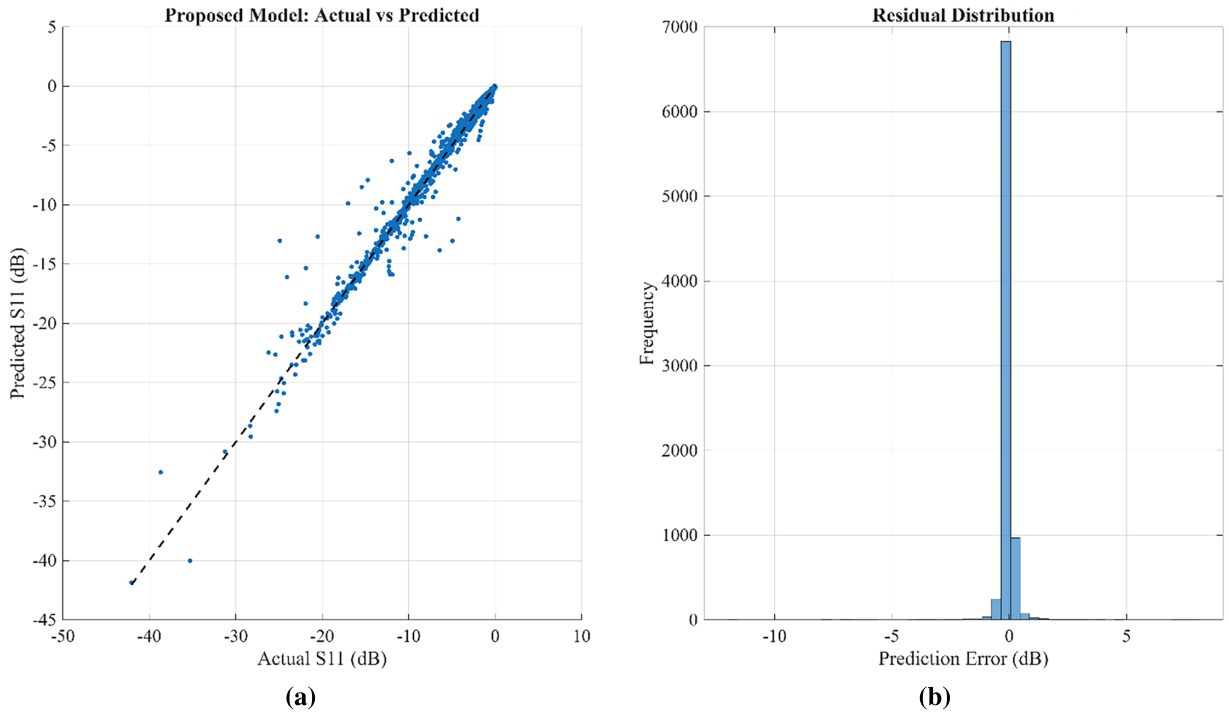


Figure 5: Prediction accuracy analysis of the proposed PI-UA-FTTransformer: (**a**) Actual vs. predicted S_{11} values and (**b**) Residual error distribution.

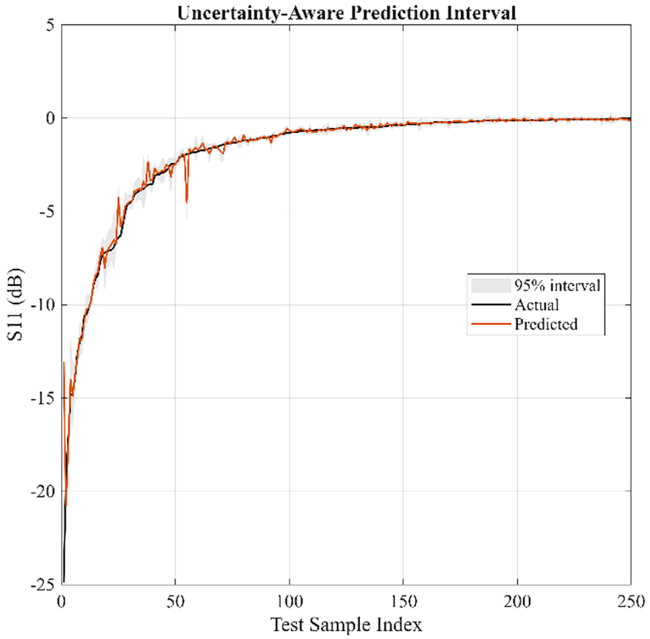


Figure 6: Uncertainty-aware prediction intervals generated by the proposed framework.

The uncertainty-aware capability of the proposed framework provides an additional reliability mechanism that can be helpful when collaborating with an antenna designer in automated design optimization and parameter exploration. The proposed model can not only generate deterministic output but also indicate the confidence region in which the prediction is relatively lower.

Current validation is limited to a single family of slotted microstrip patch antennas operating in the 2.4 GHz ISM band. Although the proposed PI-UA-FTTransformer is designed as a general surrogate learning framework, future work will evaluate its performance across multiple antenna families, including conventional microstrip patch, circular, fractal, slot, dielectric resonator, and millimeter-wave antennas, to further investigate its scalability and generalization capability.

3.5 Ablation Study

An ablation study was performed to determine the contribution of each key component of the proposed PI-UA-FTTransformer framework. We tested four variants: raw FT-Transformer, physics-informed encoding, residual FT-attention hybrid learning, and the last ensemble framework with uncertainty. The quantitative performance of all ablation variants is summarized in Table 4, which reports the complete evaluation metrics (RMSE, MAE, R^2, NRMSE, and RPD). The corresponding RMSE trend is shown in Fig. 7 to facilitate visual comparison of each component's contribution.

Table 4: Ablation study of the proposed PI-UA-FTTransformer framework.

Variant	RMSE (dB)	MAE (dB)	R^2	NRMSE	RPD
A0: Raw FT-Transformer	0.5755	0.2222	0.9731	0.0137	6.0951
A1: + Physics Encoding	0.4497	0.1352	0.9836	0.0107	7.7998
A2: + Residual FT-Attention Hybrid	0.4565	0.1411	0.9831	0.0109	7.6841
Proposed: + Ensemble Uncertainty	0.4007	0.1215	0.9870	0.0095	8.7533

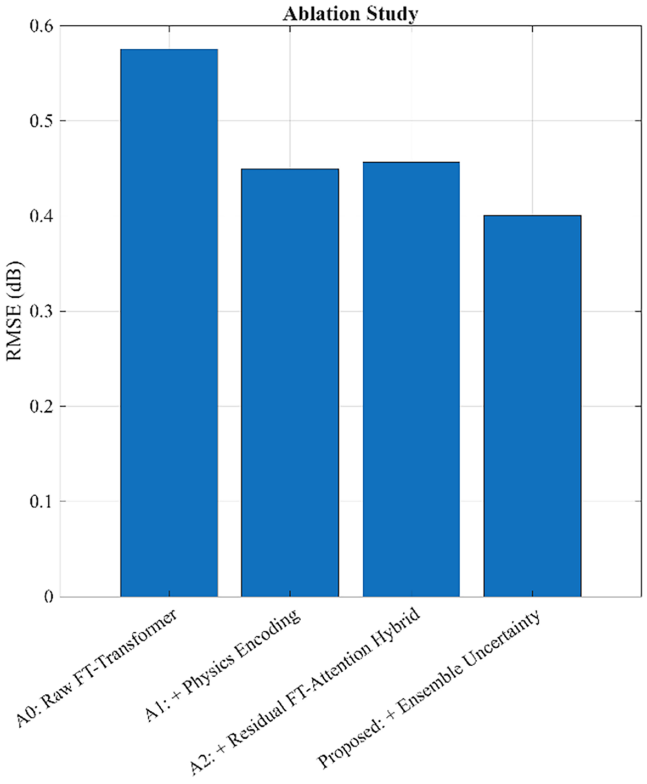


Figure 7: Visual comparison of RMSE across the ablation variants.

The results showed that the best improvement in model performance over the raw FT-Transformer baseline is achieved through physics-aware feature encoding. In particular, by incorporating electromagnetic feature engineering, the RMSE reduced from 0.5755 to 0.4497 dB, resulting in a significant performance improvement.

The residual FT-attention hybrid architecture further enhanced representation learning by improving non-linear feature interaction modeling. Finally, the uncertainty-aware ensemble strategy outperformed the others in overall performance, with an RMSE of 0.4007 dB and well-founded confidence estimation properties.

As illustrated in Fig. 7, the RMSE decreases progressively as successive components are incorporated into the proposed PI-UA-FTTransformer framework. This visual trend is consistent with the quantitative results reported in Table 4, confirming that each proposed component improves overall predictive performance.

In general, the ablation study confirms the efficiency of adopting a unified antenna modeling framework that leverages physics-informed feature engineering, transformer-based attention learning, and uncertainty-aware ensemble prediction.

3.6 SHAP-Based Interpretability Analysis

To investigate the learned feature contributions and assess whether they are consistent with established electromagnetic principles, SHAP (SHapley Additive exPlanations) analysis was performed on the trained PI-UA-FTTransformer model. SHAP quantifies the contribution of each input feature to the predicted S_{11}, providing a transparent interpretation of the model's decision-making process.

The mean absolute SHAP values are displayed in Fig. 8a, where it can be observed that the most influential features are substrate height, patch height, feed-length ratio, and feedline length. Moreover, the physics-informed descriptors, such as electrical patch length, electrical patch width, wavelength-normalized height, and frequency-related parameters, all help predict, showing that the proposed framework can effectively leverage both raw geometric parameters and engineered electromagnetic features.

The SHAP summary plot in Fig. 8b shows a wide range of positive and negative SHAP values, with many features contributing in ways that are not straightforward. The model captures the highly complex, non-linear relationships between the features and the target variable, as demonstrated by the distribution of values in the SHAP summary plot. In Fig. 8c, the non-linear dependence of electrical patch length on the predicted S_{11} is also shown, as expected from microstrip antenna theory. Lastly, the feature interaction heatmap shown in Fig. 8d indicates strong interactions among the substrate dimensions, electrical patch parameters, wavelength-normalized features, and operating frequency. Overall, the SHAP analysis shows that the proposed PI-UA-FTTransformer learns physically consistent electromagnetic relationships while improving model interpretability.

3.7 Comparison with Published Literature

Over the last few years, machine learning has significantly accelerated the modeling of antennas and the development of electromagnetic surrogates, leveraging the fact that full-wave simulations are often time-consuming and complex. However, the majority of the work to date has focused on increasing prediction accuracy. Comparatively, little has been done on incorporating domain knowledge about electromagnetic objects, learning complex interactions between global features, or estimating prediction uncertainty. Table 5 compares the proposed PI-UA-FTTransformer framework with representative recent studies.

Mersani et al. [13] proposed an Artificial Intelligence framework for predicting the S_{11} response of a compact 2.4 GHz microstrip patch antenna using conventional machine learning algorithms. The model was able to predict deterministically, but it didn't incorporate electromagnetic knowledge into feature construction or provide a measure of prediction confidence. Likewise, Qin Hua et al. [14] used a dual neural network approach to model rectangular microstrip patch antennas and demonstrated improved predictive capability. However, the adopted neural architecture was purely data-driven and did not explicitly exploit the electromagnetic relations that govern antenna behavior.

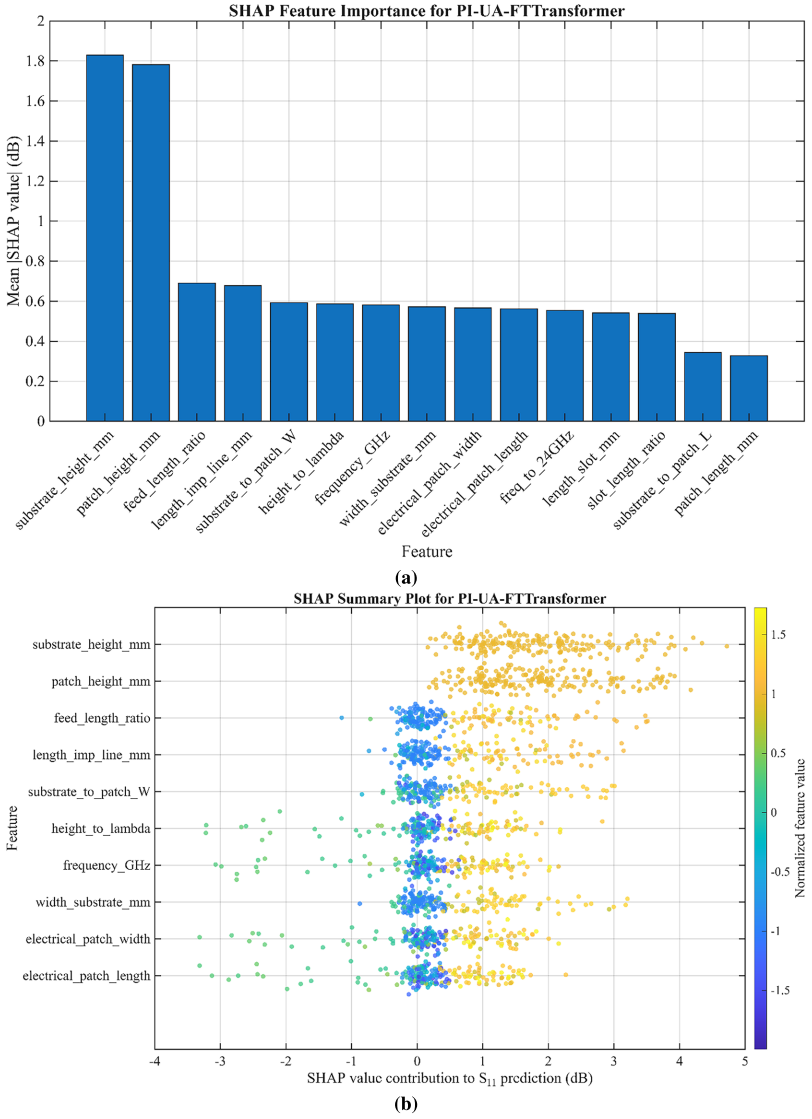
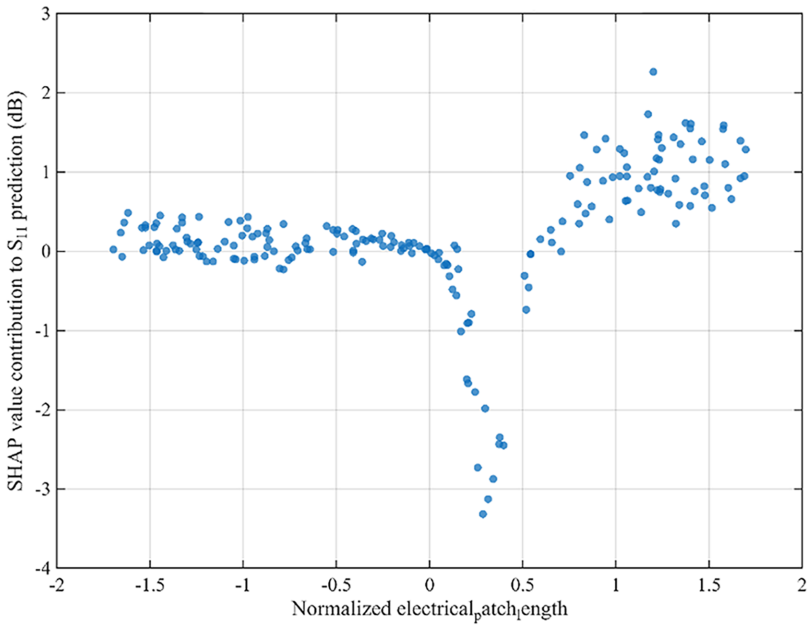
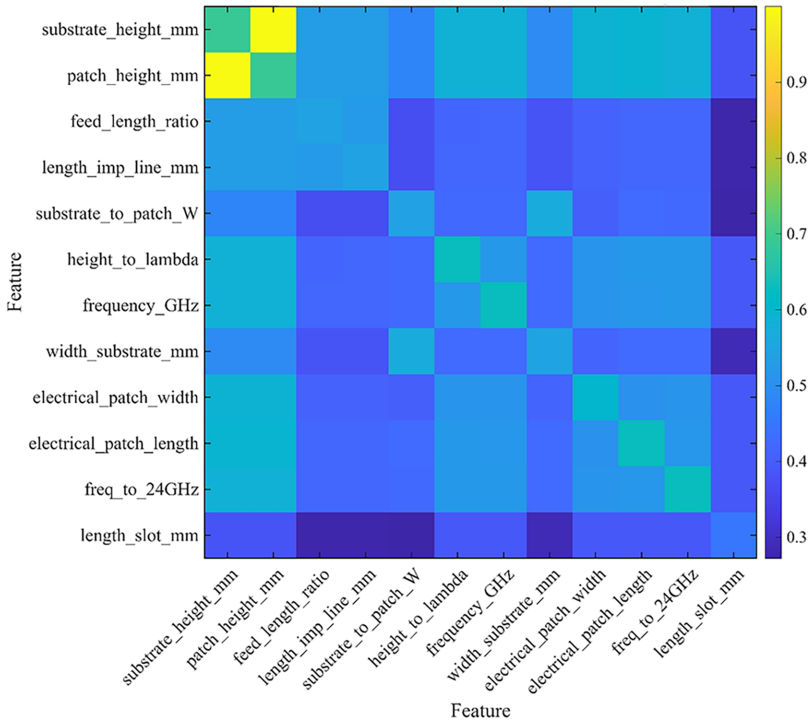


Figure 8: (Continued)



(c)



(d)

Figure 8: Proposed PI-UA-FTTransformer: (**a**) Mean absolute SHAP feature importance, (**b**) SHAP summary plot, (**c**) SHAP dependence plot for electrical patch length, and (**d**) Feature interaction heatmap.

Table 5: Comparison of the proposed PI-UA-FTTransformer framework with representative recent studies.

Ref.	Year	Antenna/ Application	AI Method	Physics-Informed	Transformer	Uncertainty	Prediction Target	Performance	Main Limitation
Mersani et al. [13]	2025	Slotted 2.4 GHz Patch	ML Regression	No	No	No	S_{11}	Accurate S_{11} prediction	Deterministic prediction only
Qin Hua et al. [14]	2025	Rectangular Patch	Dual Neural Network	No	No	No	Antenna characteristics	High prediction accuracy	No uncertainty estimation
Gupta et al. [15]	2026	UWB MIMO	ML Regression	No	No	No	Scattering parameters	Accurate S-parameter prediction	No physics-informed learning
Yang et al. [16]	2026	General Antenna	GP-HetCNN Surrogate	Partial	No	No	Antenna modeling	Efficient surrogate modeling	No transformer architecture
Bilson et al. [21]	2024	RF Electromagnetic Modeling	Physics-informed ML	Yes	No	No	RF field prediction	Improved physical consistency	Not developed for an antenna S_{11} prediction
Koziel et al. [24]	2024	Antenna Optimization	ML Surrogate	No	No	No	Design optimization	Fast optimization	No electromagnetic response prediction
Li et al. [25]	2025	Multi-objective Antenna Design	Surrogate + Evolutionary	No	No	No	Optimization	Efficient optimization	Deterministic optimization only
Proposed	2026	Slotted 2.4 GHz Patch	Physics-Informed FT-Transformer	Yes	Yes	Yes	S_{11} prediction + Confidence Interval	RMSE = 0.4007 dB MAE = 0.1215 dB R^2 = 0.9870 PICP = 93.75%	Unified physics-informed, uncertainty-aware transformer framework

More recently, machine learning has been expanded to increasingly complex antenna configurations. The application of machine learning to predict the scattering parameters of circularly polarized UWB MIMO antennas was shown to be effective by Gupta et al. [15], and GP-HetCNN-based antenna modeling and optimization were proposed by Yang et al. [16]. Similarly, Koziel et al. [24] and Li et al. [25] developed surrogate-based optimization techniques that led to substantial savings in computational effort during antenna design. While both studies have employed AI to address issues in electromagnetic engineering, their main goal was still to replace optimization or prediction with surrogate simulation, not to address uncertainty estimation or even transformer-based global feature learning.

Previous studies also showed the feasibility of using standard machine learning to optimize antennas and predict their parameters. Tiwari et al. [4] used regression models to predict microstrip antenna parameters, while Yusuf et al. [5] and Pusuluri et al. [6] explored machine learning techniques for frequency-reconfigurable and 5G antenna optimization, respectively. Later, Raveendra [7], Shah et al. [8], Yaminisasi et al. [10], Jain et al. [11], and Priya et al. [12] further validated that machine learning can significantly reduce the number of design iterations and computational costs. However, in most of the resulting models, learning was shallow, or the models relied on conventional neural networks without dedicated mechanisms to account for long-range dependencies between antenna parameters.

The proposed PI-UA-FTTransformer presents a series of complementary advances in a single framework that complement these representative studies. First, the physics-informed feature engineering incorporates electromagnetically relevant descriptors, enabling the model to leverage prior knowledge of the problem space without relying solely on raw geometric variables. Secondly, the FT-Transformer architecture introduces a multi-head self-attention mechanism to learn complex global relationships among antenna parameters that are difficult to capture by traditional regression models. Third, ensemble-based uncertainty estimation produces calibrated confidence intervals alongside point predictions, thereby enhancing the reliability of predictions for real-world antenna design. Lastly, the proposed framework is subjected to comprehensive experimental assessment, and the results indicate that it achieves an RMSE of 0.4007 dB, an MAE of 0.1215 dB, and an R^2 value of 0.9870, with uncertainty quantified (PICP = 93.75%). The proposed framework possesses these attributes and is clearly distinct from some current deterministic antenna prediction models, thereby serving as a more reliable surrogate modeling tool for intelligent RF/Electromagnetic design.

4 Conclusions

For the accurate S_{11} prediction of slotted 2.4 GHz microstrip patch antennas, a Physics-Informed Uncertainty-Aware FT-Transformer (PI-UA-FTTransformer) framework was proposed in this study. The intended approach involves physics-informed feature engineering, self-attention-based learning with transformers, residual-dense representations, and ensemble-based uncertainty estimation within a single regression framework. To improve feature representation and better enable the model to learn the complex, non-linear relationship between antenna geometry and reflection characteristics, wavelength-normalized antenna dimensions and geometric ratios were added. It was tested on a large, publicly available data set generated by the CST, consisting of 55,053 samples, and compared against representative machine learning and deep learning models, including SVR, Random Forest, LSBoost, CNN, Standard Transformer, TabTransformer, and FT-Transformer. The proposed PI-UA-FTTransformer outperformed the other methods in terms of prediction accuracy, as evidenced by RMSE of 0.4007 dB, MAE of 0.1215 dB, and R2 of 0.9870. Moreover, the confidence levels of the predicted antenna responses were within a reliable range for practical engineering use, with a prediction interval coverage probability of 93.75% for the uncertainty-aware ensemble strategy, thereby enhancing the trustworthiness of the predictions. The ablation study also demonstrated that both

the physics-informed feature encoding and the ensemble-based uncertainty estimation strategies improved model robustness and prediction reliability relative to the baseline FT-Transformer model. In addition to its predictive power, the main contribution of this work is the development of a unified physics-informed, uncertainty-aware transformer framework for intelligent electromagnetic modeling. In contrast to traditional deterministic antenna prediction techniques, which focus mainly on regression accuracy, the proposed PI-UA-FTTransformer integrates domain knowledge of the electromagnetic field, global feature interaction learning via an attention mechanism, and confidence-based prediction within a unified architecture. The combination not only offers better prediction accuracy but also greater model reliability, interpretability, and applicability for surrogate electromagnetic modeling. Thus, the proposed framework offers an effective alternative to full-wave electromagnetic simulations, which are computationally intensive, and is a potentially viable direction for intelligent antenna design and next-generation data-driven RF design. The proposed framework has been validated using a large-scale CST Microwave Studio dataset; however, in the future, it will be further tested using HFSS, COMSOL, ADS, Lumerical, and experimental data from the antennas to assess its robustness, generalization capability, and applicability across different Electromagnetic modeling environments.

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