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Machine Learning Assisted Intelligent Antenna Parameters Estimation Using EOLRKC and SFIS Algorithms

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ABSTRACT: In this research, the optimization of antenna parameters for the Vivaldi antenna, Inverted F antenna, and Probe Feed Microstrip Patch antenna was carried out using EOLRKC and the Sugeno Fuzzy Inference System (SFIS) machine learning techniques. The research explores numerical and conventional antenna design methods to understand the necessary concepts comprehensively. After a thorough analysis, an intelligent model for antenna selection recommends the best antenna based on various performance metrics evaluated with the Enhanced Logistic Regression Kernel Classifier. Additionally, the geometric properties of the antenna are discussed, and the SFIS is developed by integrating five primary learners to maximize the potential of each learner type. The EOLRK Classifier classifies antennas into three groups: Vivaldi, Inverted F, and Probe Feed Microstrip Patch, while SFIS determines the optimal parameters for antenna size. The accuracy of the EOLRK Classifier is assessed, while the performance of the Sugeno FIS is evaluated using MSE and MAPE. The proposed methodology achieves an MAPE below 4% and an accuracy exceeding 99%, demonstrating exceptional performance in parameter prediction and antenna classification. Implementing these methods has the potential to enhance innovative antenna design practices significantly.

1. INTRODUCTION

Antenna design and analysis are essential elements of wireless communication technology. The Vivaldi antenna provides exceptional impedance matching and wideband performance, while the Inverted F antenna offers compact, efficient performance for mobile and wireless applications. The low-profile, versatile Probe Feed Microstrip Patch antenna is commonly used in communication and GPS systems. The EOLRK Classifier categorizes antennas into three types: Vivaldi, Inverted F, and Probe Feed Microstrip Patch, whereas SFIS identifies the optimal parameters for antenna dimensions. It combines an Enhanced Optimized Logistic Regression Kernel Classifier (EOLRKC) with a SFIS. This approach predicts antenna parameters more quickly and accurately while achieving high classification accuracy. The SFIS correctly predicts crucial parameters including taper dimensions, patch size, and feed line modifications. At the same time, the EOLRKC classifier efficiently detects antenna types, outperforming current models in terms of accuracy and computing economy. This article focuses on enhancing the beam width, directionality, and impedance matching of the Microstrip feed line to the slot line through a parametric study and the design of Vivaldi, Inverted F, and Probe Feed Microstrip Patch antennas. The computer-aided design of the Vivaldi Antenna is utilized to analyze the impact of factors like the exponential slot opening rate and circular slot diameter on the antenna's performance. The study emphasizes the key elements influencing side lobes, beam width, directionality, and VSWR. The experimental antenna achieved a gain of around 7 dBi within the frequency range of 1 GHz to 13 GHz, while the simulated antenna showed a peak gain exceeding 9 dBi. The prototype antenna tested displayed linear polarization and a total radiation efficiency of over 90%. Alavi and Mirzavand introduced the Improved Ensemble-Based Machine Learning (IEBML) algorithm to improve the precision of the computed far-field [1]. Jaiswal et al. developed machine learning algorithms like Classification and Regression Trees (CART), Random Forest (RF), and Principal Component Analysis (PCA) to effectively determine the geometrical parameters of the Vivaldi antenna, reducing computational time [2]. Patel et al. designed smart antennas for 5G applications using the Enhanced Tree-Based Machine Learning (ETRBML) method, which requires less computational time than the current method [3]. Ramasamy and Bennet recommended an optimizable K-Nearest Neighbors (KNNs) algorithm for antenna classification. They devised the Adaptive Neuro-Fuzzy Inference System (ANFIS) method for accurate estimation of antenna parameters, offering low Mean Absolute Percentage Error (MAPE), minimal testing error, and high accuracy with reduced computational time [4]. Alnas et al. introduced the Dynamic Hybrid Binary Particle Swarm Optimization (DHBPSO) algorithm to enhance the bandwidth of inverted F antennas, resulting in improved gain, bandwidth, and efficiency suitable for 5G applications [5]. Gao et al. suggested a Gaussian Process (GP) and Support Vector Machine (SVM) model for estimating microstrip antenna design parameters, offering high accuracy and reduced computation time [6]. Verma and Srivastava introduced a particle swarm optimization (PSO) technique to opti-

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mize microstrip patch antennas, achieving an optimal antenna bandwidth of 48.68% [7]. Zhang et al. demonstrated a compact ultra-wideband (UWB) dual-polarized Vivaldi antenna that reduces radar cross-section (RCS). At the same time, Rajesh et al. recommended a modified Vivaldi antenna design that decreases RCS by 10 dB and operates between 4 and 12 GHz. The proposed approach focuses on reducing the RCS of the Vivaldi antenna by altering its structure, such as removing a portion of the metal radiator and adding holes along its edges [8, 9]. This study presents a wideband Vivaldi antenna that is flush-mounted and dual-polarized. Properly matched Vivaldi elements with an all-metal cavity can operate without resonance over a 4 : 1 frequency range, featuring a larger aperture and identical characteristics. Expanding the operation bandwidth may lead to the degradation of some patterns [10]. Jia et al. proposed a Low-RCS Vivaldi antenna that utilizes Characteristic Mode Analysis to achieve multiband frequency coverage. The main objective of this antenna is to minimize broadband RCS [11]. Kumar and and Shaby developed a metaheuristic optimization approach to address microstrip antenna gain and restricted bandwidth challenges. This approach is specifically designed for C-band systems [12]. Machine learning algorithms, such as regression, can be employed to optimize Vivaldi, inverted F, and probe feed patch antennas. These algorithms establish the relationship between input parameters and antenna performance measures by defining dimensions, material characteristics, and operating frequencies and collecting performance data through simulations or testing. Linear regression, support vector regression, decision trees, and neural networks can be utilized to forecast and enhance antenna parameters such as frequency response, impedance matching, and radiation pattern. Through iterative model training, evaluation, and optimization, antenna performance and functionality can be improved by meeting design goals and constraints. However, it should be noted that existing algorithms can be computationally expensive when dealing with large-scale antenna systems. The detailed literature survey reveals that while many researchers have proposed machine learning models for efficient and accurate classification of antenna types, only a few have attempted to estimate antenna parameters following classification. Additionally, there is scope for improvement in both the computational time and parameter estimation accuracy. The proposed (EOLRKC+SFIS) method efficiently classifies three types of antennas — Vivaldi, Inverted F, and Probe Feed Microstrip Patch antennas — using the EOLRK classifier while also predicting antenna parameters through SFIS with high accuracy and reduced computational time.

2. SYSTEM DESCRIPTION

Figure 1 illustrates a robust framework for antenna design. The system comprises the SFIS model and intricate EOLRK classification module. The system determines the suitable antenna type in the initial classification phase by inputting electromagnetic signals like gain, S_{11}, bandwidth, and resonant frequency into a trained EOLRK classification model. The datasets were created using HFSS and Matlab tools to train and test our proposed approach, ensuring data specificity for the problem domain. An 80% training and 20% testing split were chosen as it is a widely accepted practice in machine learning. It provides a balanced trade-off between having sufficient data for practical model training and retaining enough data for unbiased performance evaluation. A simulation technique was used to build the dataset for the antenna research study. Initially, HFSS was used to model and simulate various antenna designs, such as probe-fed patch antennas, Vivaldi, and Inverted-F antennas. Various frequencies were used to test essential performance metrics, including radiation patterns, gain, bandwidth, and return loss (S_{11}).

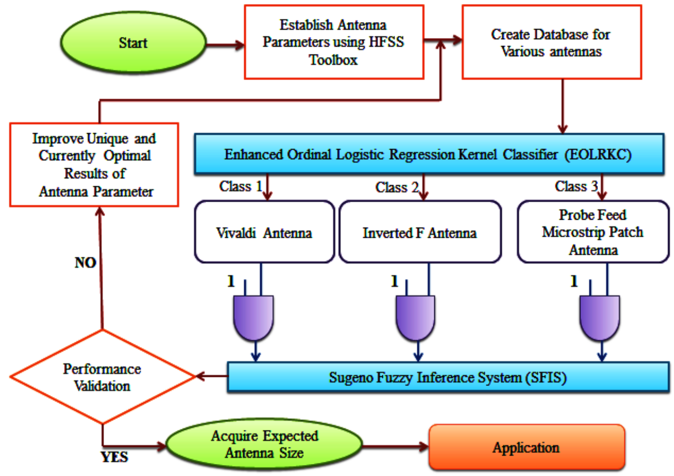

FIGURE 1. Overview of the proposed intelligent antenna synthesis system.

The gathered data was organized, cleansed, and examined to yield valuable performance assessment and optimization insights. The robustness and reproducibility of the dataset are guaranteed by thorough process documentation. The knowledge acquired by EOLRKC is represented either as a set of predetermined rules or as a modified ordinal logistic regression model. The modified ordinal logistic regression is employed when the dependent variable is ordered. The dependent variable categorizes and organizes two or more levels or categories. When the SFIS accurately predicts the various parameters of the antennas, the output for that particular class is assigned a value of one. In contrast, the output for the other courses is assigned a value of zero. The production of EOLRKC is then directed to an AND gate, which activates the SFIS only when the two inputs are identical. The Sugeno fuzzy inference systems store datasets that contain the optimal parameters for antenna size associated with the input design parameters, such as S_{11}, resonant frequency, bandwidth, and gain. The optimal antenna size parameters can be determined by evaluating the SFIS with a specific design parameter and comparing it to the stored datasets. The primary advantages of the EOLRK classifier include its adaptability to a wide range of feature subsets, simplicity, interoperability, ease of use, and the presence of decision rules at different stages of the classification process. The SFIS can be utilized to construct a model that predicts the occurrence of Vivaldi antennas, inverted F antennas, and probe feed patch antennas. Numerous models have been developed by researchers

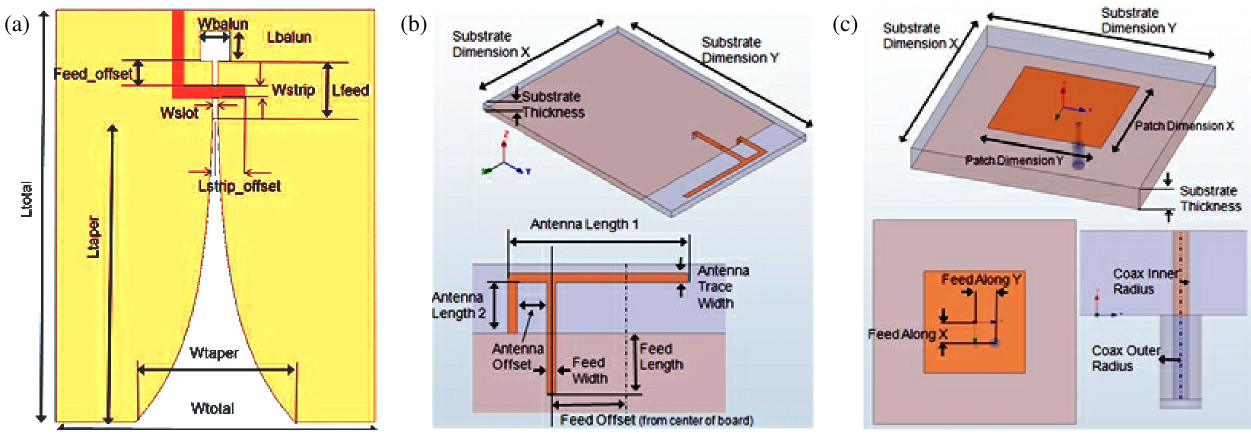

FIGURE 2. (a) Vivaldi antenna. (b) Inverted F antenna. (c) Patch antenna.

using SFIS as a foundation. These models can accurately anticipate the linear polarization and cross-polarization radiation patterns and the return-loss characteristics of Vivaldi antennas.

3. METHODS DESCRIPTION

This section examines inverted-F antennas, Vivaldi antennas and probe-fed patch antennas. Wide bandwidth, high gain, and excellent impedance matching make the Vivaldi antenna — known for its tapered slot design — ideal for satellite communications, wireless networks, and radar systems. The inverted-F and probe-fed patch antennas are commonly employed in wireless communication systems because of their compact size, ease of integration, and applicability for various applications, including biomedical systems and Internet of Things (IoT) devices.

3.1. Vivaldi Antenna

Figure 2(a) illustrates the planned structure of the Vivaldi antenna. This antenna, named after the esteemed composer Antonio Vivaldi, is a wideband and directional antenna extensively employed in radio frequency and microwave applications. The length of the taper directly impacts the antenna's bandwidth and radiation parameters. In our proposed methodology for building Vivaldi antennas, the estimated parameters include the length and width of the taper. To calculate the taper width at any point along the antenna, the following formula can be utilized:

$$W(x) = W\,\text{max} - x\tan(\theta) \tag{1}$$

In Equation (1), W max is the taper's maximum width, usually selected to meet the intended impedance, and x is the distance from the feed point along the taper. The taper angle is θ.

3.2. Inverted F Antenna

The illustration in Figure 2(b) showcases the structure of the proposed Planar Inverted-F Antenna (PIFA). PIFA is a popular design choice for wireless communication devices such as mobile phones, and it is known for its compact design. Positioned above a ground plane, typically the main circuit board of the device, this planar antenna features a flat metal element that is often shaped like an inverted "F" or a rectangular patch with a shorting pin. A resonant structure is created when a shorting pin connects the patch element and ground plane. PIFAs are valued for their small size and versatility, allowing them to be integrated into devices with limited space and operate across multiple bands or broadband frequencies.

3.3. Probe Feed Patch Antenna

The structure of the proposed Probe Feed Patch antenna is illustrated in Figure 2(c). Microstrip patch antennas are widely used in wireless communication systems and are known for their planar design. These antennas consist of a dielectric substrate with a ground plane on one side and a radiating patch on the other. The patch, typically made of a conductive material like copper, can be designed in various shapes, such as rectangle, circle, or ellipse, depending on the specific application and desired characteristics.

4. DISCUSSION OF RESULTS

The Vivaldi tapered slot antenna is characterized by its wide gain range and directed emission pattern. It is widely employed in wireless devices due to its small size and decent performance. In contrast, probe feed patch antennas, which are small and rectangular, are highly recommended for integration into small devices and systems because of their superior design. The expected performance indicators for the antennas are outlined in Table 1.

4.1. Principle of Enhanced Ordinal Logistic Regression Kernel Classifier

EOLRKC is one of the most commonly used techniques for modeling classifiers, allowing users to infer information from data even without specialized knowledge. This method involves a straightforward modified ordinal logistic regression categorization model. The development of modified ordinal logistic regression classification models was an early and well-known approach to constructing discriminatory models. The fields of machine learning and statistics independently developed this method.

TABLE 1. Antenna performance parameters.

Parameters	Vivaldi Antenna	Probe Feed Patch Antenna	Inverted F Antenna
S_{11} (dB)	-12.7 dB to -24.17 dB	-10.13 dB to -10.48 dB	-10.24 dB to -27.06 dB
Fr (GHz)	8 GHz to 13 GHz	5 GHz to 15 GHz	1 GHz to 5 GHz
Gain (dB)	5.1 dB to 10.9 dB	0.2 dB to 7.16 dB	0.11 dB to 4 dB
BW (GHz)	3.5 GHz to 7 GHz	0.12 GHz to 0.426 GHz	0.1 GHz to 0.31 GHz

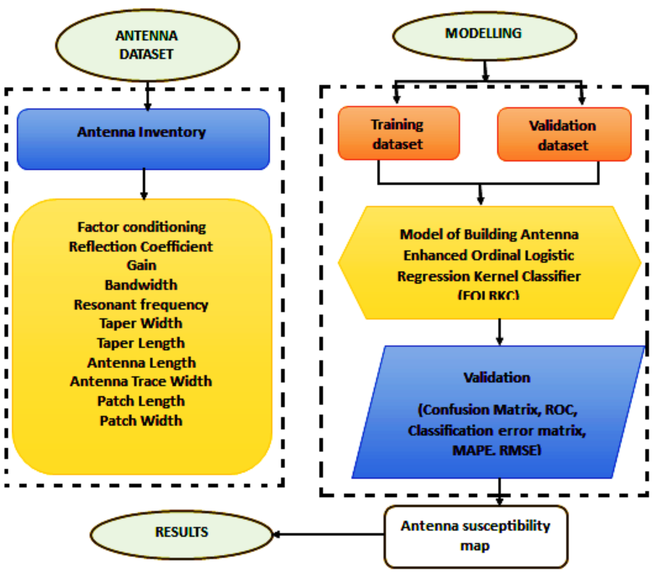

FIGURE 3. Flowchart for enhanced optimized logistic regression kernel classifier.

The susceptibility map of the Vivaldi antenna within the research area, as illustrated in Figure 3, is developed through a systematic five-step process. First, data is collected using HFSS software to create parameter maps specific to the Vivaldi antenna design. These parameter maps are sampled with antenna inventories to extract the data required for further analysis. Second, the dataset is prepared by randomly splitting the data into two groups: 80% for training and 20% for validation. The training data is used to build models and maps, while the validation data ensures the accuracy and reliability of the developed models. Four different models — Fine Tree, Optimizable KNN, Optimizable SVM, and Direct Torque Control (DTC) — are developed in the third step. Using these models, the EOL-RKC is designed based on training data and several parameters, including gain, resonance frequency, patch size, taper width, taper length, antenna length, antenna trace width, patch length, and patch width. The fourth step involves validating the accuracy of the antenna susceptibility models using techniques such as the confusion matrix, ROC analysis, AUC values, and classification error metrics. Finally, the fifth step generates antenna susceptibility maps using multiple susceptibility indices derived during model-building. These maps were utilized to evaluate the vulnerability of antennas. Antennas can be classified into three distinct categories: Vivaldi antenna, inverted F antenna, and probe feed patch antenna.

This classification will demonstrate ordinal logistic regression, which aims to analyze the relationship between antenna characteristics (represented by predictor variables X) and performance metrics (represented by ordinal outcome variable Y). The three categories are labelled as 1, 2, and 3. We employ enhanced ordinal logistic regression and kernel methods to optimize the Vivaldi, inverted F, and probe feed patch antennas. The mathematical representation of this regression model involves the utilization of cumulative logits for outcome categories. In mathematical terms, this representation can be expressed as:

$$\text{Logit} = \text{logit}\left(P\left(Y \le k|X\right)\right) = \alpha k + \beta TX \tag{2}$$

In Equation (2), where $(P(Y \le k \mid X)$ is the cumulative probability of the outcome less than or equal to category k; αk are intercepted parameters specific to each category; β is the vector of coefficients; and X represents the predictor variables. Kernel approaches use a kernel function K to translate input data into a higher-dimensional space for nonlinear modeling. Translating input properties X into a higher-dimensional space $\ddot{\Upsilon}(X)$ may facilitate linear separation for antenna design. The kernel approach lets computations in this higher-dimensional space be done implicitly without constructing modified feature vectors. To optimize antenna design using enhanced ordinal kernel approaches, apply the kernel trick to predictor variables X in ordinal logistic regression. Replace the linear term X in the logistic regression equation with the kernel function applied to the predictor variables to create a nonlinear decision boundary in the feature space. Mathematically, this can be represented as:

$$\text{logit}\left(P\left(Y \le k|X\right)\right) = \alpha k + \beta T\phi\left(X\right) \tag{3}$$

In Equation (3), kernel approaches improve antenna design. The kernel trick is implemented on predictor variables X in ordinal logistic regression. By substituting the linear term X in the logistic regression equation with the kernel function applied to the predictor variables, a nonlinear decision boundary is created within the feature space.

The kernel that can be optimized for Naive Bayes techniques is a collection of supervised learning algorithms that utilize Bayes' theorem while assuming that every pair of features is conditionally independent, given the value of the class variable [13]. The Bayes theorem provides the following relationship: When evaluating the class variable b and independent feature vectors a_1 through a_n,

$$\text{P}(b|a_1, \ldots\ \ldots\ \ldots, a_n) = \frac{P\left(b\right)P(a_1, \ldots\ \ldots\ \ldots, a_n|b)}{P(a_1, \ldots\ \ldots\ \ldots, a_n)} \tag{4}$$

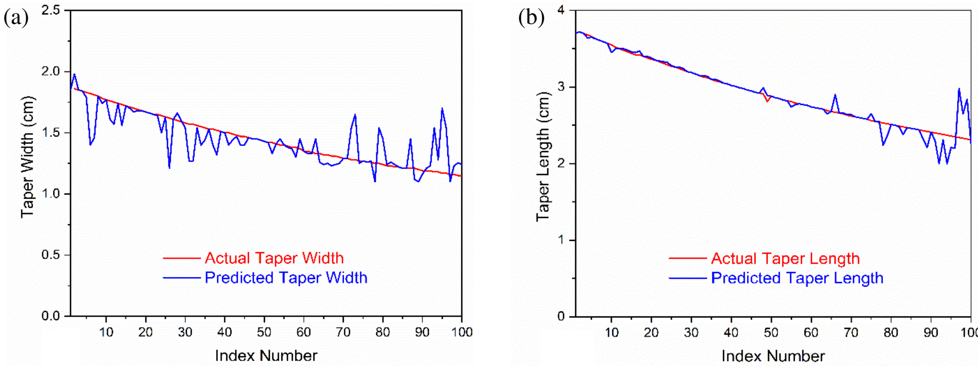

FIGURE 4. (a) Comparative analysis of the anticipated and observed values of the Vivaldi antenna's taper width(cm). (b) Comparison of the expected and actual values of the taper length(cm) for the Vivaldi antenna.

TABLE 2. Result analysis of Sugeno fuzzy inference System.

	Vivaldi Antenna		Probe Feed Patch Antenna		Inverted F Antenna	
	Taper Length (cm)	Taper Width (cm)	Patch Dimension X (cm)	Patch Dimension Y (cm)	Antenna Length 1 (cm)	Antenna Length 2 (cm)
MAPE	5.42%	1.43%	3.04%	3.94%	1.34%	5.41%
RMSE	14.06%	11.89%	8.74%	11.36%	7.23%	10.58%
MAPE (Average)	3.425%		3.49%		3.375%	

Equation (4) uses the optimal naive conditional independence assumption, in which

$$\mathrm{P}(a_i|b, a_1 \ldots \ldots, a_{i-1}, a_{i+1}, \ldots, a_n) = P(a_i|y), \quad (5)$$

For every i, Equation (5) relationship is simplified to

$$P(b|a_1, \ldots \ldots \ldots, a_n) = \frac{P(b) \prod_{i=1}^{n} P(a_i|b)}{P(a_1, \ldots \ldots \ldots, a_n)} \quad (6)$$

In Equation (6) $(a_1, \ldots, a_n)$ is constant with the input, and we may apply the following categorization rule:

$$P(b|a_1, \ldots \ldots \ldots, a_n) \propto P(b) \prod\nolimits_{i=1}^{n} P(a_i|b) \quad (7)$$

$$\hat{y} = \arg\max_b P(b) \prod\nolimits_{i=1}^{n} P(a_i|b) \quad (8)$$

Equations (7) and (8) utilize conditional probability approximations for $P(b)$ and $(P(a_i|b))$ through Maximum A Posteriori (MAP) estimation. The frequency of class b in the training set is illustrated in the preceding Figure 3. The assumptions concerning the distribution of $(a_i|b)$ differ significantly among naive Bayes classifiers. Despite their apparent simplicity, these classifiers have demonstrated their effectiveness in numerous practical scenarios, such as spam detection and document categorization. They require only a small amount of training data to predict the essential parameters.

The Root Mean Square Error (RMSE) and Mean Absolute Percentage Error, which are the precise expressions of Equations (9) and (10), respectively, are used to assess the effectiveness of the tested model [14].

$$MAPE = \frac{100}{n} \sum\nolimits_{i=1}^{n} \left| \frac{X_i - Y_i}{Y_i} \right| \quad (9)$$

$$MSE = \frac{1}{n} \sum\nolimits_{i=1}^{n} (X_i - Y_i)^2 \quad (10)$$

Y_i is the value predicted by the suggested model, and X_i is the value discovered. Equations (9) and (10) are used to compute the performance parameters, such as MAPE and RMSE, of the inverted F, Vivaldi, and probe feed patch antennas. Table 2 shows that the MAPE of the inverted F antenna is 3.375%; the probe feed patch antenna is 3.49%; and the Vivaldi antenna is 3.425%. These incredibly low values suggest that the forecast made by the proposed model is more accurate.

Figures 4(a) and 4(b) display, respectively, the projected and actual values of the Vivaldi antenna taper width (cm) and length (cm) using the SFIS technology. The taper length (cm) projections have a 0.01046 cm mean and a 0 cm median. These values' variances, shown as error $\in$, span a range of -0.53 cm to 0.42 cm. The error values are the differences in antenna taper width between -0.64 cm and 0.39 cm, with a mean of -0.00139 cm and a median of 0 cm. Similarly, the probe-fed patch antenna and inverted F antenna's actual and expected values are evaluated.

Moreover, the trained model is used to evaluate the effectiveness of the proposed model following the procedure illustrated in Figure 1. It is imperative to formulate the Vivaldi an-

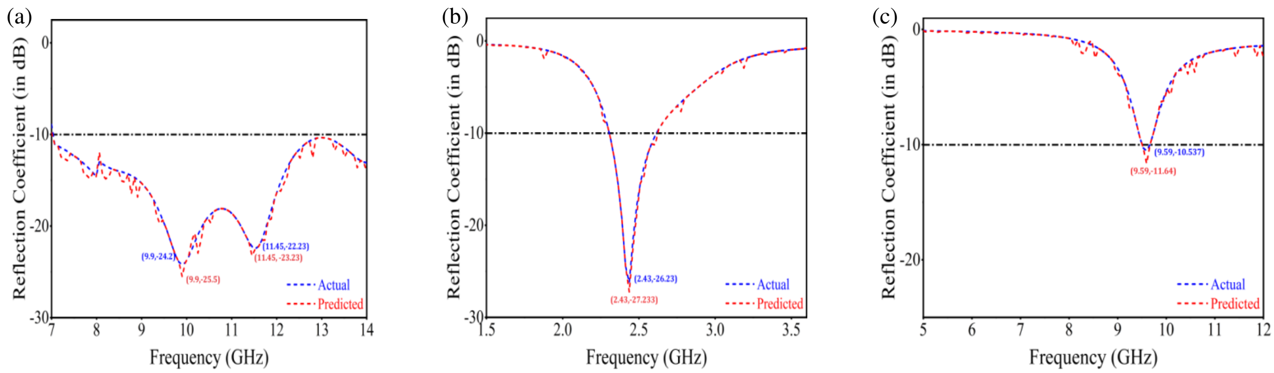

FIGURE 5. (a) Actual and predicted S_{11} for Vivaldi antenna. (b) Actual and predicted S_{11} for inverted F antenna. (c) Actual and predicted S_{11} for probe feed patch antenna.

TABLE 3. Expected performance compared with predicted result.

Antenna	Actual		Predicted	Error
Circular Disc Monopole Antenna	BW (GHz)	1.02	1.034	0.014
	Gain (dB)	8.03	7.14	0.89
	S_{11} (dB)	-34.92	-35.92	1.00
Vertical Trapezoidal Monopole Antenna	BW (GHz)	0.816	0.817	0.01
	Gain (dB)	2.34	2.28	0.06
	S_{11} (dB)	-21.39	-21.58	0.19
Wire Monopole Antenna	BW (GHz)	0.99	0.87	0.12
	Gain (dB)	1.79	1.81	0.02
	S_{11} (dB)	-16.21	-15.01	1.20

TABLE 4. Comparison with existing and proposed method.

Algorithms	Accuracy (Percentage)	MAPE	RMSE
Gaussian Process Regression [14]	93.77 %	-	6.98 %
Linear Regression [14]	79.57 %	-	11.36 %
Random Forest Regression [14]	84.53 %	-	10.28 %
Optimizable-KNN +ANFIS [6]	99.16 %	1.4514 %	-
DT+FIS [15]	99 %	3.28 %	17.771 %
Random Forest [16]	82 %	9.4 %	-
WKNN WOA [17]	98.93 %	-	-
FMN-GA [18]	94.74 %	-	-
Proposed Method (EOLRKC+SFIS)	99.3 %	3.375 %	7.23 %

tenna with specific performance criteria: S_{11} (-24.2 dB), gain (10.52 dB), bandwidth (22.08 GHz), and resonant frequency (9.9 GHz). The taper should be 3.02 cm in length and 1.51 cm in width. The proposed model offers the necessary geometric parameters: a taper length of 3.12 cm and a width of 1.52 cm. Subsequently, simulations are conducted using the target and synthetic geometric parameters to observe the characteristic parameters of each of the three antennas. Figure 5(a) exhibits the comparison of the S_{11} curves. Similarly, the system acquires inputs for the actual performance of the probe feed patch antenna, which include S_{11} (-10.537 dB), gain (3.09 dB), bandwidth (18.77 GHz), and resonant frequency (9.59 GHz). The geometric parameters for the patch should be 1.24 cm for dimension X and 0.95 cm for dimension Y. The anticipated geometric parameters for the patch are 0.94 cm for dimension Y and 1.26 cm for dimension X. The S_{11} curves generated by the simulation are shown in Figure 5(b). The desired performance characteristics for the inverted F antenna are S_{11} (-26.23 dB), gain (3.82 dB), bandwidth (0.78 GHz), and resonant frequency (2.43 GHz). The geometric parameters for antenna lengths 1 and 2 are 2.42 cm and 0.78 cm, respectively. However, for an inverted F antenna, it is recommended to use antenna lengths of 2.41 cm for the first and 0.787 cm for the second. Figure 5(c) illustrates the comparison of probe feed patch antenna S_{11} curves.

The findings demonstrate that the estimated S_{11} curves using the suggested geometric parameters closely resemble the real S_{11} curves. Table 3 compares the remaining distinctive parameters.

Table 4 contrasts the accuracy of different machine learning techniques, MAPE, and RMSE. The proposed approach (EOLRKC+SFIS) achieves a superior balance between low MAPE and moderate RMSE while delivering high accuracy.

5. CONCLUSION

In this study, an intelligent machine-learning model has been developed to predict geometric parameters and categorize antennas. The proposed model utilizes SFIS for antenna classification and achieves an accuracy of over 99%. In contrast, the geometric parameter estimation model using SFIS provides accuracy within 4%. The suggested method's training time and prediction speed are 4.5031 seconds and 3300 seconds, respectively, faster than existing approaches. The performance analysis of the antenna demonstrates its high gain and enhanced bandwidth, making it suitable for satellite communication. Satellite systems typically require a minimum gain of 7–10 dBi. Furthermore, alternative machine learning methods will examine the identical antenna design and account for additional characteristics. Implementing the proposed (EOLRKC+SFIS) model in real-time is recommended for precise antenna classification and geometric parameter prediction. Implementing the proposed (EOLRKC+SFIS) model in real-time is recommended for precise antenna classification and geometric parameter prediction. The suggested antennas can be enhanced using machine learning technology to optimize design parameters, making them suitable for satellite communication, IoT devices, and biomedical applications.

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