Machine Learning Prediction of X-Band Microwave Absorption Using KNN Regression for Single-Slot Pyramidal Microwave Absorbers

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Abstract. This paper presents a machine learning modelling approach for predicting microwave absorption performance of single-slot pyramidal microwave absorbers operating in the X band frequency range (8–12 GHz). The absorbers were fabricated using biomass derived carbon coating material as part of a sustainable microwave absorber design and configured with three slot sizes, namely small, medium, and big. Experimental absorption data were obtained from multiple frequency measurements and used as the dataset for modelling. Prior to modelling, the experimental data were preprocessed using interquartile range (IQR) outlier removal followed by Min Max normalization to ensure consistent scaling of the input and output variables. The modelling process was carried out using the k Nearest Neighbour (KNN) regression algorithm to predict the absorption performance based on normalized frequency and slot size. The dataset was divided into 70% training data and 30% testing data using the holdout method. Different values of k were tested to determine the optimal number of neighbours for the KNN model. The model performance was evaluated using coefficient of determination (R^2) and root mean square error (RMSE). The results show that the proposed KNN model achieved high prediction accuracy with R^2 values greater than 0.97 and RMSE values below 0.05 for the X-band dataset. The comparison between slot sizes indicates that the absorption behaviour can be predicted consistently using the trained model. The study demonstrates that KNN-based machine learning modelling is suitable for predicting microwave absorption performance of sustainable pyramidal microwave absorbers using experimental data and can reduce the need for extensive measurements in absorber design..

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1 Introduction

Microwave absorbing materials have been widely studied due to their important role in electromagnetic interference (EMI) reduction, radar cross-section (RCS) control, and radio frequency (RF) measurement applications. In recent years, the development of sustainable microwave absorbers using biomass-derived carbon materials has received increasing attention because of their low cost, lightweight structure, and environmentally friendly characteristics [1]–[3]. Pyramidal microwave absorbers are commonly used in anechoic chambers and RF testing environments due to their wideband absorption capability and stable performance over different frequency ranges [4], [5].

The absorption performance of pyramidal microwave absorbers is influenced by several design parameters, including material properties, absorber geometry, coating thickness, and structural modification such as slot configuration. The introduction of slots on the absorber surface has been reported to improve impedance matching and enhance absorption performance at specific frequency bands [6], [7]. However, the absorption behaviour of slotted pyramidal absorbers may vary depending on the slot size and operating frequency, making the analysis more complex when experimental data are collected from multiple configurations.

In experimental studies, a large amount of measurement data is usually required to evaluate the performance of microwave absorbers across different frequencies. Repeated measurements for different absorber configurations can be time-consuming and costly, especially when the absorber design involves multiple slot sizes and wideband frequency testing. Therefore, data-driven modelling approaches have been increasingly used to predict electromagnetic behaviour based on experimental datasets, allowing the performance to be estimated without performing extensive measurements [8], [9].

Machine learning techniques have recently been applied in microwave absorber research to model reflection loss, absorption performance, and electromagnetic properties. Various algorithms such as artificial neural networks, support vector regression, random forest, gradient boosting, and regression-based machine learning models have been used to predict absorber performance with good accuracy [10]–[12]. Recent studies have also demonstrated the increasing use of data-driven modelling approaches for electromagnetic absorber optimization and microwave material characterization using experimental datasets [13]–[16]. Among these methods, the k-Nearest Neighbour (KNN) algorithm is a simple yet effective distance-based learning technique that can provide accurate prediction results without requiring complex training procedures [17], [18]. KNN regression is particularly suitable for experimental datasets because it relies on similarity between data points rather than predefined mathematical equations.

Most previous studies focused on simulation-based modelling or single-configuration absorber analysis, while limited work has been reported on machine learning prediction using experimental data obtained from pyramidal microwave absorbers with different slot sizes. In addition, modelling of X-band absorption behaviour using experimental datasets for sustainable pyramidal absorbers is still not widely discussed in the literature [15], [16].

Therefore, this study proposes a machine learning modelling approach using KNN regression to predict the microwave absorption performance of single-slot pyramidal microwave absorbers operating in the X-band frequency range (8–12 GHz). The absorbers were fabricated using biomass-derived carbon coating material and tested with three different slot sizes, namely small, medium, and big. Experimental data were preprocessed using interquartile range (IQR) outlier removal and Min–Max normalization before being used for model development. The objective of this work is to evaluate the capability of the KNN regression model to predict absorption performance based on normalized frequency and slot configuration using experimental data.Please note that the first paragraph of a section or subsection is not indented. The first paragraphs that follows a table, figure, equation etc. does not have an indent, either.

2 Methodology

2.1 Absorber Design and Data Collection

In this study, single-slot pyramidal microwave absorbers were designed and fabricated using biomass-derived carbon coating material as part of a sustainable microwave absorber structure. The slot dimensions used in this study were 3 cm × 6 cm for the small slot, 6 cm × 12 cm for the medium slot, and 9 cm × 18 cm for the big slot. These slot configurations were designed to represent progressive geometric variations on the absorber surface to investigate their influence on microwave absorption performance within the X-band frequency range. All absorbers were fabricated using the same pyramidal structure and biomass-derived carbon coating material to ensure consistent experimental conditions during the measurement process.

The absorption measurements were conducted using a microwave measurement system covering the X-band frequency range from 8 GHz to 12 GHz. For each slot configuration, multiple frequency points were measured to obtain the absorption value in decibel (dB). The collected data from all slot sizes were combined to form the experimental dataset used for machine learning modelling. Experimental measurement-based datasets are preferred in absorber studies because they represent the actual behaviour of the absorber compared to simulation-only results [8], [9]..

2.2 Statistical Preprocessing Using IQR Outlier Removal

Experimental microwave absorption data may contain inconsistent values caused by measurement noise, material variation, or environmental interference. Therefore, statistical preprocessing was applied to ensure that the dataset used for modelling was consistent and suitable for machine learning analysis. Outlier detection was performed using the interquartile range (IQR) method, which is widely used in experimental data analysis due to its robustness against extreme values [19], [20]. The IQR is defined as equation (1).

$$IQR = Q3 - Q1 \tag{1}$$

where Q1 is the first quartile and Q3 is the third quartile of the dataset. A data point is considered an outlier if it lies outside the range as equation (2).

$$Q1 - 1.5\left(IQR\right) \le x \le Q3 + 1.5\left(IQR\right) \tag{2}$$

The 1.5Q criterion was used in this study to remove abnormal absorption values before the modelling process. This method helps to improve the stability of machine learning prediction by eliminating inconsistent data points [21]..

2.3 Min–Max Normalization

After outlier removal, Min–Max normalization was applied to scale the input and output variables into the range between 0 and 1. Normalization is important in distance-based machine learning algorithms such as KNN because variables with different scales may affect the distance calculation [22]. The Min–Max normalization is defined as equation (3).

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{3}$$

where x is the original value, xmin is the minimum value, and xmax is the maximum value of the dataset. In this study, the frequency and absorption values were normalized before being used as input for the KNN regression model.

2.4 K-Nearest Neighbour Regression Model

The machine learning modelling process was carried out using the k-Nearest Neighbour (KNN) regression algorithm. KNN is a non-parametric method that predicts the output value based on the similarity between the input data and the nearest neighbours in the training dataset [17], [18]. The Euclidean distance was used to determine the similarity between data points equation (4).

$$d = \sqrt{\sum_{i=1}^{n}\left(x_i - y_i\right)^2} \tag{4}$$

where d is the Euclidean distance between two data points, while xi and yi represent the corresponding feature values used in the distance calculation.

The dataset was divided into 70% training data and 30% testing data using the holdout method. Several values of k were tested to determine the optimal number of neighbours for the prediction model. The input variables consisted of normalized frequency and slot size, while the output variable was the normalized absorption value.

The slot size variable was encoded numerically as Small = 1, Medium = 2, and Big = 3 prior to the modelling process. This ordinal encoding was selected to represent the progressive variation in slot dimensions while maintaining compatibility with the Euclidean distance calculation used in the KNN regression algorithm. Since the slot configurations follow an increasing physical size relationship, the numerical encoding remains meaningful for neighbourhood-based prediction.

One-hot encoding was not used because the slot configurations represent ordered geometric variations rather than independent categorical classes. KNN regression is suitable for experimental microwave absorber datasets because it does not require a predefined mathematical model and can adapt to nonlinear behaviour in the data [17].

2.5 Performance Evaluation

The performance of the KNN regression model was evaluated using the coefficient of determination (R^2) and root mean square error (RMSE). These metrics are commonly used in machine learning regression analysis to measure prediction accuracy [8]. The coefficient of determination is defined as equation (5).

$$R^2 = 1 - \left(\frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \hat{y})^2} \right) \tag{5}$$

The RMSE is calculated as equation (6).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - y_i)^2} \tag{6}$$

where yi is the measured value and is the predicted value. A high R^2 value and low RMSE indicate good agreement between measured and predicted absorption values. These metrics were used to evaluate the accuracy of the proposed KNN model for predicting microwave absorption performance in the X-band.

3 Results and Discussion

3.1 Statistical Analysis of X-Band Absorption Data

The statistical distribution of the X-band absorption data for the big, medium, and small slot configurations is summarized in Table 1. Each slot size contains 201 data points obtained from the experimental measurement system. The absorption values show a wide variation, indicating that the slot size has a significant influence on the microwave absorption behaviour. The minimum absorption values were recorded as −36.462 dB, −35.76 dB, and −40.871 dB for the big, medium, and small slots respectively, while the maximum values were around −9 dB for all slot sizes. The quartile values also show that the data distribution is not uniform, which suggests the presence of extreme values in the dataset. These variations indicate that preprocessing is required before the data can be used for modelling.

Table 1. Statistical Summary of X-Band Absorption Data Before Outlier Removal.

No	Parameter	Big Slot	Medium Slot	Small Slot
1	Number of Data Points	201	201	201
2	Min	-36.462	-35.76	-40.871
3	Max	-9.413	-9.486	-13.96
4	Q1 (25th percentile)	-16.509	-21.264	-27.02
5	Q2 (Median)	-12.16	-17.347	-20.926
6	Q3 (75th percentile)	-10.156	-13.899	-18.097

Table 2. Statistical Summary of X-Band Absorption Data After Outlier Removal

No	Parameter	Big Slot	Medium Slot	Small Slot
1	Number of Data Points	194	197	200
2	Min	-25.1990	-31.0643	-38.9198
3	Max	-9.4127	-9.4855	-13.9602
4	Q1 (25th percentile)	-16.0306	-21.2344	-26.9965
5	Q2 (Median)	-11.8094	-20.9237	-20.9237
6	Q3 (75th percentile)	-10.1292	-18.0911	-18.0911

After applying the interquartile range (IQR) outlier removal method, the number of data points was reduced to 194, 197, and 200 for the big, medium, and small slots respectively as shown in Table 2. The removal of outliers reduced the data range and improved the consistency of the dataset. The minimum values became less extreme compared to the original dataset, indicating that abnormal measurements were successfully removed. The quartile values also became closer to each other, which shows that the data distribution is more stable after preprocessing. This step is important to ensure that the machine learning model is trained using reliable experimental data.

The boxplot results before and after outlier removal are shown in Fig. 1(a) and Fig. 1(b). The boxplot before preprocessing shows several extreme points outside the whisker range, while the boxplot after preprocessing shows a more compact distribution. This confirms that the IQR method with the 1.5Q criterion is suitable for removing abnormal values in microwave absorption datasets

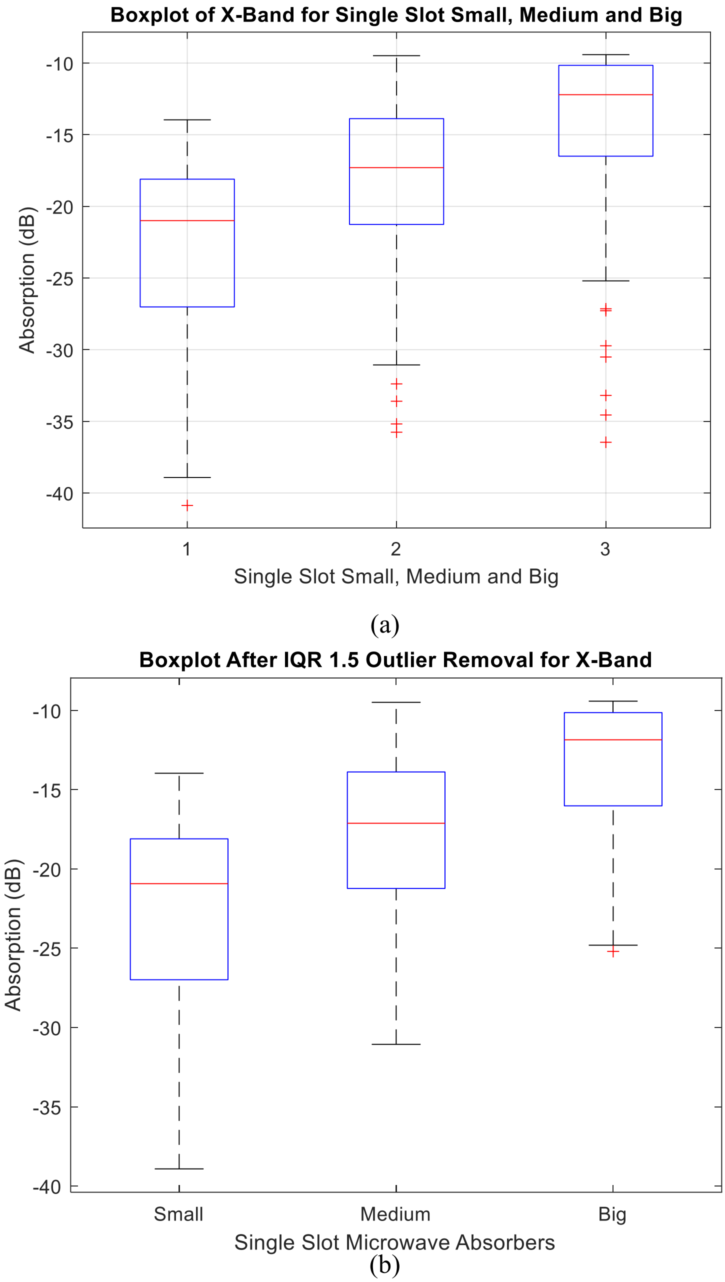


Fig. 1. Boxplot Results (a) before and (b) after outlier removal.

3.2 Linear Regression Analysis of Normalized Data

After outlier removal, the absorption data were normalized and linear regression analysis was performed to observe the relationship between normalized frequency and normalized absorption for each slot size. The regression results are summarized in Table 3. The regression equations show that the absorption behaviour does not follow a strong linear relationship, as indicated by the relatively low R^2 values of 0.3470 for the big and medium slots, and 0.4381 for the small slot.

Table 3. Linear Regression Analysis of X-Band Absorption Data After Outlier Removal

No	Parameter	Big Slot	Medium Slot	Small Slot
1	Regression Equation (y)	y=0.9593 -0.1931x	y=0.8882 -0.3374x	y=0.7754 -0.4454x
2	p-Value (Slope)	6.7778 x 10-10	8.6505 x 10-20	1.3895 x 10-26
3	R-squared (R^2)	0.1803	0.3470	0.4381
4	Root Mean Squared Error	0.1170	0.1351	0.1473
5	Sample Size (n)	194	197	200

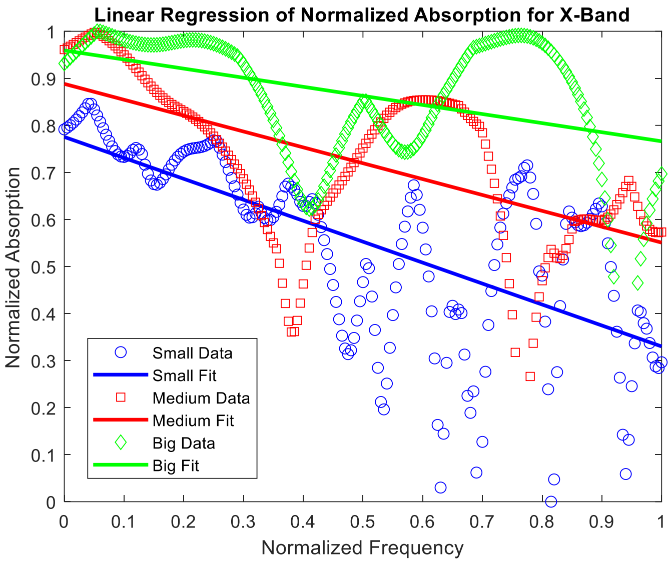


Fig. 2. Linear Regression Plot of Normalized Absorption Versus Normalized Frequency.

The p-values of the slope are extremely small, which indicates that the regression relationship is statistically significant, but the moderate R^2 values suggest that the absorption behaviour cannot be accurately represented using a simple linear model. This result confirms that a nonlinear modelling approach is required to predict the absorption performance more accurately. Fig. 2 shows the linear regression plot of normalized absorption versus normalized frequency for the three slot sizes. The scatter distribution does not follow a straight line, which further supports the need for machine learning modelling instead of conventional regression.

3.3 Development of KNN Regression Model for Slot Combination

To demonstrate the development of the machine learning model, one slot combination consisting of small, medium, and big slots (SMB) was selected as a representative dataset. The combined dataset contains 591 data points after preprocessing. The dataset was divided into 70% training data and 30% testing data, resulting in 414 training samples and 177 testing samples. The KNN regression model was developed using normalized frequency and slot group as input variables, while the normalized absorption value was used as the output. The Euclidean distance was used to determine the similarity between data points, and different values of k from 1 to 20 were tested to determine the optimal number of neighbours.

Table 4 shows the RMSE values obtained for different values of k. The minimum RMSE value within the evaluated range was obtained at k = 2 with an RMSE value of 0.0350. When k increased beyond 2, the RMSE gradually increased, indicating that using too many neighbours reduces the prediction accuracy. Therefore, k = 2 was selected as the optimal value for the KNN model. The RMSE vs k curve is shown in Fig. 3(b). The curve clearly shows that the error is lowest at k = 2, which confirms the selection of the optimal neighbour number. The selection of a small k value indicates that local neighbourhood information plays an important role in representing the nonlinear absorption behaviour of the microwave absorber dataset.

In this study, the testing dataset was initially used to observe the RMSE trend for different values of k due to the limited size of the experimental dataset. Although this approach provides a practical evaluation of model performance, the use of the testing dataset during hyperparameter selection may introduce optimistic prediction results. Future work may implement a separate validation dataset or k-fold cross-validation strategy to improve the robustness of hyperparameter optimization and model evaluation.

Table 4. RMSE values for different k

Number of k	RMSE values
1	0.0407
2	0.0350
3	0.0364
4	0.0436
5	0.0489
6	0.0525

7	0.0581
8	0.0634
9	0.0660
10	0.0701
11	0.0741
12	0.0771
13	0.0804
14	0.0827
15	0.0861
16	0.0875
17	0.0899
18	0.0919
19	0.0937
20	0.0958

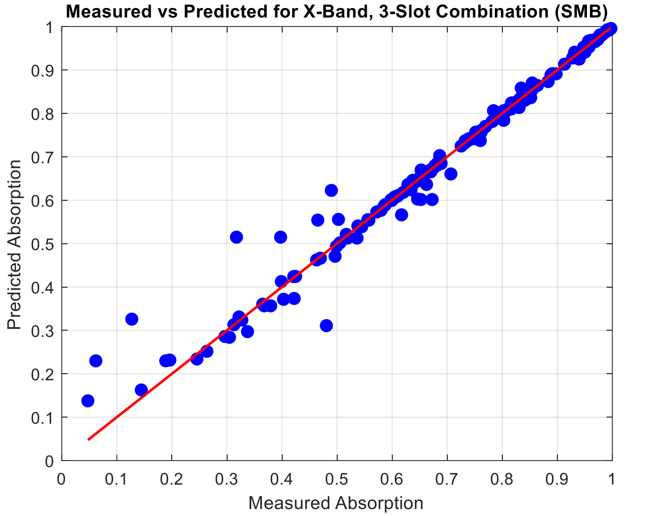
3.4 Performance Evaluation of the KNN Model

After selecting the optimal k value, the final KNN model was evaluated using the testing dataset. The model achieved an RMSE of 0.0350, MAE of 0.0135, and R^2 of 0.9749 in the normalized scale. Based on the original absorption range of the X-band dataset, the normalized RMSE and MAE correspond approximately to 1.10 dB and 0.42 dB, respectively. The high R^2 value indicates that the predicted absorption values are very close to the measured values, which shows that the KNN model can accurately represent the nonlinear behaviour of the microwave absorber. The prediction error of approximately 1.10 dB further demonstrates the practical capability of the proposed model for microwave absorber performance estimation.

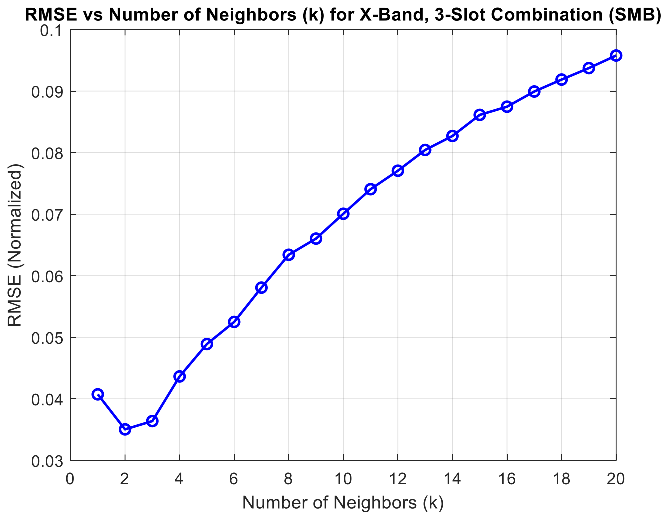
Fig. 3(a) shows the comparison between measured and predicted absorption values. Most of the data points lie close to the diagonal line, indicating good agreement between the experimental data and the model prediction. The residual error distribution is shown in Fig. 3(b). The residual values are distributed around zero without any clear pattern, which indicates that the prediction error is small and randomly distributed. This confirms that the model does not show systematic error.

The developed KNN model was trained using three discrete slot configurations, namely small, medium, and big slots. Therefore, the current model is primarily applicable to the tested slot geometries within the measured X-band frequency range. Prediction performance for unseen slot dimensions, different absorber geometries, or other operating frequency bands may require additional experimental datasets and further model retraining to improve generalization capability.

Although various nonlinear machine learning models such as Support Vector Regression (SVR), Random Forest, and Gradient Boosting have been reported in microwave absorber prediction studies, this work focuses specifically on evaluating the capability of the KNN regression model using experimental X-band absorber data. The KNN approach was selected due to its simplicity, low computational complexity, and suitability for nonlinear experimental datasets without requiring complex model training. Comparative evaluation with other machine learning regressors will be considered in future work to further investigate model generalization and prediction performance.



(a)



(b)

Fig. 3. (a) Comparison between measured and predicted absorption values, (b) RMSE versus k values.

In addition, KNN regression provides interpretable neighbourhood-based prediction behaviour which is suitable for experimental microwave absorber datasets with limited sample sizes. Stability Analysis of the KNN Model to verify the stability of the KNN model, the modelling process was repeated using different random seeds for the train-test split shown in Table 5. The results show that the best k value remains equal to 2 for most of the trials, while a few trials produce $k = 3$ or $k = 4$. These results indicate that the model provides relatively stable prediction performance under different random train-test splits.

Although the holdout validation method was used in this study to evaluate the KNN model performance, the possibility of neighbouring frequency points from similar absorber configurations appearing in both the training and testing datasets may contribute to optimistic prediction performance due to the similarity between neighbouring frequency samples. Nevertheless, the holdout approach was selected due to the limited size of the experimental dataset and to maintain sufficient data for model training. Future work may consider more conservative validation strategies such as block-by-frequency splitting, leave-one-slot-out validation, or k-fold cross-validation to further evaluate the generalization capability of the proposed model.

Table 5. Stability Analysis of the KNN Model

Seed	Best k
1	2
2	3
3	3
4	3
5	2
6	3
7	1
8	2
9	2
10	3

4 Conclusion

This study presents the development of a machine learning model using the K-Nearest Neighbour (KNN) regression method to predict the microwave absorption performance of single-slot pyramidal microwave absorbers operating in the X-band frequency range. The absorbers were fabricated using biomass-derived carbon coating material as a sustainable microwave absorber design. Experimental data obtained from three slot sizes, namely small, medium, and big, were used as the dataset for modelling.

Prior to modelling, statistical preprocessing using boxplot analysis was applied to detect and remove outliers using the interquartile range (IQR) method. The cleaned dataset was then normalized using the Min–Max normalization technique to ensure consistent data scaling. Linear regression analysis showed that the relationship between frequency and absorption was not fully linear, indicating the need for a more flexible modelling approach.

The KNN model was developed using the combination of small, medium, and big slots as the representative dataset. The dataset was divided into 70% training data and 30% testing data, and different values of k from 1 to 20 were evaluated to determine the optimal number of neighbours. The results show that the best performance was obtained at k = 2 with RMSE = 0.0350, MAE = 0.0135, and R^2 = 0.9749. The high R^2 value indicates that the developed model can accurately predict the absorption performance.

The comparison between measured and predicted values shows good agreement, and the residual analysis confirms that the prediction error is randomly distributed without systematic deviation. Stability testing using different random seeds also shows that the optimal k value remains consistent, indicating that the proposed model provides relatively consistent prediction performance.

Overall, the results demonstrate that the KNN-based machine learning approach is suitable for predicting the microwave absorption performance of sustainable pyramidal absorbers using experimental data. The proposed method can reduce the need for repeated measurements and can assist in the design and optimization of microwave absorbers in future studies.

Future work may include comparative evaluation with other machine learning regression models such as SVR, Random Forest, and Gradient Boosting, as well as model extension toward different microwave frequency bands and absorber geometries. The integration of machine learning techniques with sustainable microwave absorber research is expected to become increasingly important for future RF and electromagnetic engineering applications.

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