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K-nearest neighbor prediction of multiband absorption in single-slot hollow pyramidal microwave absorbers

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ABSTRACT

This study develops a k-nearest neighbor (KNN) prediction model to estimate the absorption performance of single-slot hollow pyramidal microwave absorbers operating in the L-, S-, C-, and X-bands. Experimental absorption data were collected for three slot configurations: small, medium, and large. The dataset was preprocessed using interquartile range outlier removal and min-max normalization to improve data consistency. The KNN regression model employed frequency and slot configuration as input variables, while absorption performance served as the output variable. The optimal number of neighbors was identified by evaluating the root mean square error for k values from 1 to 20. The results show that k = 2 yielded the lowest prediction error across all frequency bands. The developed model achieved coefficient of determination values above 0.97, demonstrating excellent agreement between predicted and measured absorption performance. Residual analysis confirmed that prediction errors were randomly distributed without systematic bias. Unlike conventional approaches that rely on complex electromagnetic formulations and computationally intensive simulations, the proposed method offers a simple, accurate, data-driven alternative for rapid performance estimation. The findings demonstrate the potential of KNN regression as an efficient tool for the design and evaluation of multiband microwave absorbers.

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1. INTRODUCTION

Microwave absorbers are widely used in radio frequency (RF) and electromagnetic compatibility (EMC) applications, particularly in anechoic chambers, antenna measurements, and electromagnetic interference reduction systems [1]–[3]. Among various absorber structures, pyramidal microwave absorbers are commonly employed for their wideband absorption and stable performance across multiple frequency bands [4], [5]. However, the absorption performance is influenced by multiple parameters, including geometry, material properties, slot configuration, and operating frequency, resulting in highly nonlinear behavior that cannot be effectively captured using conventional analytical or empirical models [6]–[8].

Traditionally, the performance of microwave absorbers is evaluated using electromagnetic simulation techniques such as the finite element method (FEM) and finite-difference time-domain (FDTD) [9], [10]. Although these approaches provide accurate results, they require high computational cost and extensive parameter tuning, especially when multiple configurations and wide frequency ranges are considered. Experimental measurements, on the other hand, are time-consuming and require complex setups, particularly for optimization and multiband analysis [11], [12]. Therefore, data-driven modelling approaches have emerged as attractive alternatives for rapid performance prediction and design evaluation [13]–[15]. Recent studies have demonstrated the effectiveness of machine learning techniques, including artificial neural networks (ANN), support vector machines (SVM), and regression-based models, for microwave absorber modelling and RF material characterization [16]–[18]. In particular, studies have shown that KNN-based and data-driven regression models are effective for nonlinear engineering prediction problems [19]–[22].

Despite these developments, most existing studies focus on simulation-based modelling, limited absorber configurations, or single-band analysis [23]–[25]. The use of experimentally measured multiband datasets for hollow pyramidal microwave absorbers with different slot configurations remains limited in the literature. Furthermore, the application of KNN regression for predicting multiband absorption performance using experimental data has not been sufficiently investigated. Therefore, there is a need for a computationally efficient prediction model that estimates absorber performance across multiple frequency bands using experimentally measured data.

This study proposes a data-driven KNN regression model to predict the absorption performance of single-slot hollow pyramidal microwave absorbers operating across the L-band, S-band, C-band, and X-band. The model is developed using experimentally measured multiband absorption data, with frequency and slot-configuration encoding as input features. Data preprocessing techniques, including interquartile range (IQR) outlier removal and min-max normalization, are applied to improve data quality before modelling. The main contributions of this study are summarized as follows: i) development of a KNN regression model for predicting the multiband absorption performance of single-slot hollow pyramidal microwave absorbers across the L-band, S-band, C-band, and X-band frequency ranges, ii) integration of experimentally measured multiband absorption data and slot-size encoding from multiple slot configurations, providing a practical data-driven alternative to conventional simulation-based prediction approaches, iii) comprehensive evaluation of model performance using root mean square error (RMSE), mean absolute error (MAE), coefficient of determination (R^2), and residual error analysis to assess prediction accuracy and robustness and iv) demonstration of high prediction accuracy across all investigated frequency bands, with R^2 values exceeding 0.97, confirming the suitability of KNN regression for microwave absorber performance prediction and design support. The proposed model offers a simple, computationally efficient alternative to repeated electromagnetic simulations and extensive experimental evaluations, thereby supporting future microwave absorber design and optimization studies.

2. METHOD

The prediction model was developed using the KNN regression algorithm to estimate the normalized absorption performance of the single-slot hollow pyramidal microwave absorber. The KNN method was selected due to its simplicity and its capability to model nonlinear relationships without requiring an explicit mathematical formulation [18]. KNN regression has been successfully applied in electromagnetic material prediction and modelling tasks in previous studies [20], [21]. In this study, two input features were used in the prediction model, namely normalized frequency and slot configuration. The slot configuration represents the three slot sizes used in the absorber design and was numerically encoded as 1 for the small slot, 2 for the medium slot, and 3 for the big slot. The output variable corresponds to the normalized absorption value obtained after the data preprocessing stage.

2.1. Experimental dataset and absorber configuration

The experimental dataset was obtained from single-slot hollow pyramidal microwave absorbers coated with biomass-derived carbon material. Three slot configurations were investigated: small (3 × 6 cm), medium (6 × 12 cm), and big (9 × 18 cm). All samples used the same pyramidal structure and coating material to ensure measurement consistency.

Absorption measurements were collected across the $L-, S-, C-$, and X-band frequency ranges. For each slot configuration, 29, 57, 114, and 201 data points were recorded for the L-, S-, C-, and X-bands, respectively, with the X-band covering 8–12 GHz. The measured absorption values, expressed in decibels (dB), formed a multiband dataset used for machine learning modelling. Measurements were performed using the NRL arch free-space method. The absorber was positioned at the center of the NRL arch, where

transmitting and receiving horn antennas measured the reflected microwave signal at normal incidence. The pyramidal structure was fabricated from cardboard and coated with biomass-derived activated carbon mixed with water. The same measurement setup and absorber orientation were maintained for all slot configurations to ensure a consistent experimental dataset.

2.2. Data preprocessing

Before model development, the experimental absorption data were preprocessed using IQR-based outlier removal followed by min–max normalization. The IQR method was applied to identify abnormal measurements that may occur due to measurement noise, fabrication variation, or temporary experimental disturbance. The IQR was calculated as the difference between the third quartile and the first quartile, where IQR = Q3−Q1. Data points below Q1−1.5 × IQR or above Q3 + 1.5 × IQR were considered outliers and removed from the dataset. The 1.5 × IQR threshold was selected because it is widely used for moderate outlier detection and provides a balance between preserving natural data variation and removing extreme observations.

After outlier removal, min–max normalization was applied to scale the frequency, slot configuration, and absorption values into the range of 0 to 1. This normalization step is important for KNN regression because the algorithm calculates distance between samples, and variables with larger numerical ranges may dominate the prediction process. The normalized value was calculated as $xnorm = (x - xmin)/(xmax - xmin)$, where x is the original value, xmin is the minimum value, and $xmax$ is the maximum value of the dataset. The cleaned and normalized dataset was then used for KNN model development. The dataset was divided into training and testing subsets using the hold-out validation method, with 70% of the data used for training and the remaining 30% for testing. The partitioning process was performed using a controlled random seed to ensure reproducibility of the results. The holdout approach is widely used for evaluating regression models when the dataset size is moderate [20].

In addition to the holdout validation approach, k-fold cross-validation was considered to assess model robustness. Although cross-validation reduces dependence on a single data partition, the moderate dataset size and consistent holdout results indicated that holdout validation was sufficient for this study. The use of multiple random seeds further ensured that model performance was independent of a specific data split, with stability analysis demonstrating consistent results across different training-testing partitions. The optimal number of neighbors, k, was determined through hyperparameter tuning by evaluating RMSE for k values ranging from 1 to 20. The value producing the lowest RMSE was selected as the optimal parameter. To verify robustness, the holdout validation was repeated using multiple random seeds for each frequency band. Although the optimal k varied slightly across partitions, it consistently remained within a narrow range, indicating stable model performance. Prediction accuracy was evaluated using RMSE, MAE, and R^2, which are widely used regression metrics [20]. The RMSE is defined in (1).

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

Where yi is the measured value, $\hat{y}i$ is the predicted value, and n is the number of samples. The MAE is defined as (2).

$$MAE = \frac{1}{n}\sum|y_i - \hat{y}_i| \tag{2}$$

The R^2 is defined as (3).

$$R^2 = 1 - \left(\frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}\right) \tag{3}$$

Where $\bar{y}$ represents the mean of the measured values.

In addition, residual error analysis was performed to evaluate the stability of the prediction model. The residual is defined as the difference between the measured value and the predicted value. Statistical indicators such as the mean residual, standard deviation, and the minimum and maximum residual values were used to assess whether the model exhibits systematic bias. A residual distribution that is randomly scattered around zero indicates that the developed KNN model provides stable and accurate predictions. Furthermore, residual plots and measured-versus-predicted plots were generated for each frequency band to visually assess the model's predictive performance. All modelling and analysis were performed using the MATLAB environment.

3. RESULTS AND DISCUSSION

The performance of the proposed KNN regression model was evaluated using normalized absorption data from the single-slot pyramidal microwave absorber across four frequency bands: L-band, S-band, C-band, and X-band. The analysis focuses on selecting the optimal number of neighbors, prediction accuracy, residual behavior, and the stability of the developed model. The optimal number of neighbors was determined by evaluating the RMSE for k values ranging from 1 to 20. The agreement between measured and predicted absorption values was examined to assess the model's predictive capability across all frequency bands. Residual error analysis was conducted to evaluate prediction errors and identify potential systematic patterns. In addition, the model's performance was assessed using RMSE, MAE, and R^2. Stability analysis using multiple random seeds was also performed to examine the consistency of the model across different data partitions. Finally, different distance metrics were compared to investigate their influence on prediction accuracy.

3.1. Selection of optimal k value

The optimal number of neighbors was determined by evaluating RMSE across k values from 1 to 20 for each frequency band. Figure 1 shows the variation of RMSE with respect to k for L-band, S-band, C-band, and X-band, while Table 1 summarizes the RMSE values obtained for all tested k values. From the results, the minimum RMSE for all frequency bands occurs at small k values.

The optimal value of k = 2 was selected for all bands since it produced the lowest RMSE. As k increases, the RMSE gradually increases, indicating that a larger neighborhood size leads to excessive smoothing and reduces the model's ability to follow the actual data pattern. This result shows that the absorption behavior of the microwave absorber can be accurately predicted using a small number of nearest neighbors, indicating that the normalized dataset exhibits a consistent pattern across different slot configurations. The selection of the neighborhood size is an important consideration in KNN modelling because predictions depend on the nearest samples and the selected value of k [20].

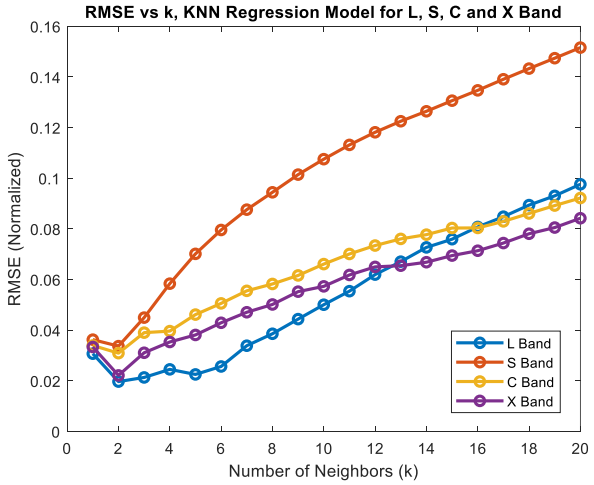


Figure 1. RMSE vs. k for KNN regression model for L-band, S-band, C-band and X-band

3.2. Measured vs predicted absorption

To evaluate the predictive capability of the KNN model, measured-versus-predicted plots were generated for all frequency bands, as shown in Figure 2. The figure compares the measured normalized absorption with the predicted values obtained using the KNN regression model. Overall, the predicted values closely match the measured data across all frequency bands, indicating good predictive performance. Figure 2(a) shows the L-band results, which exhibit the closest agreement between measured and predicted values. Figure 2(b) presents the S-band results, where slightly larger deviations are observed. Figures 2(c) and 2(d) show the C-band and X-band results, respectively, with greater variations due to the more complex absorption patterns. Nevertheless, the model demonstrates good overall prediction accuracy across all frequency bands. Previous studies have also investigated machine learning approaches for predicting and optimizing microwave absorber performance, highlighting the potential of data-driven methods for electromagnetic applications [13], [16], [17].

Table 1. RMSE vs k for KNN regression model for L-band, S-band, C-band, and X-band

k value	RMSE (L band)	RMSE (S band)	RMSE (C band)	RMSE (X band)
1	0.030727	0.036276	0.033971	0.033377
2	**0.019704**	**0.033707**	**0.030939**	**0.022145**
3	0.021345	0.044975	0.039035	0.031094
4	0.024536	0.058383	0.039641	0.035345
5	0.022536	0.070149	0.046167	0.038129
6	0.025676	0.07958	0.050596	0.042935
7	0.033877	0.087606	0.055548	0.047088
8	0.038596	0.094456	0.058259	0.050159
9	0.044377	0.10145	0.061628	0.055221
10	0.050065	0.10754	0.066106	0.057313
11	0.055415	0.11318	0.070108	0.061823
12	0.061956	0.11816	0.073432	0.065009
13	0.067069	0.12252	0.076059	0.065477
14	0.072702	0.12645	0.077741	0.066849
15	0.075941	0.13065	0.080358	0.069469
16	0.080772	0.13472	0.080388	0.071389
17	0.084835	0.1391	0.082974	0.074418
18	0.089408	0.14331	0.08609	0.078085
19	0.093058	0.14742	0.089228	0.080539
20	0.097632	0.1516	0.092196	0.084211

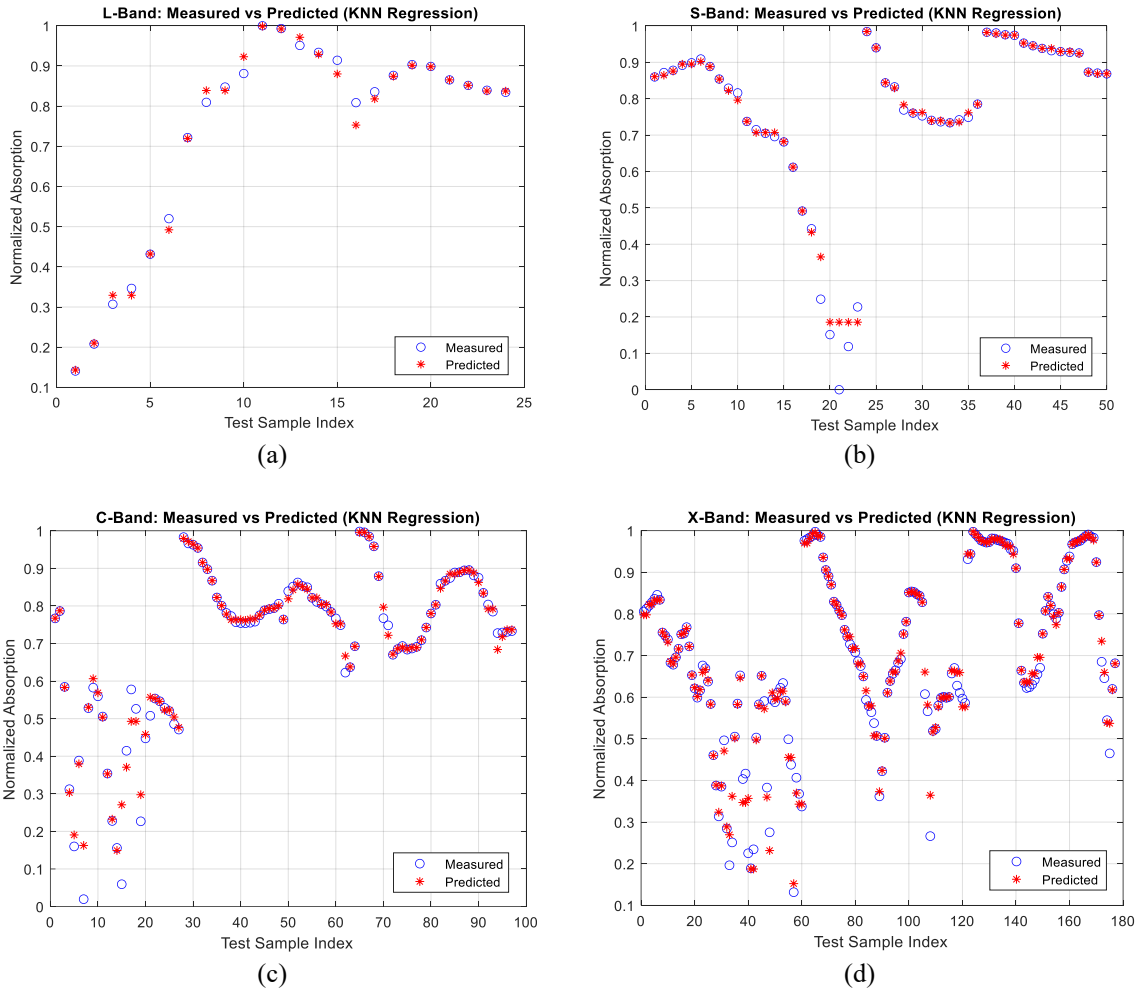


Figure 2. Measured vs. predicted (KNN regression) for (a) L-band, (b) S-band, (c) C-band, and (d) X-band

3.3. Residual error analysis

Residual error analysis was performed to evaluate the stability and reliability of the developed KNN regression model. The residual is defined as the difference between the measured absorption value and the

predicted value obtained from the model. A good regression model should produce residuals that are randomly distributed around zero, with no systematic pattern. Figure 3 presents the residual error distributions across all frequency bands. Figure 3(a) shows the residual distribution for the L-band, Figure 3(b) for the S-band, Figure 3(c) for the C-band, and Figure 3(d) for the X-band.

Across all frequency bands, the residual values are centered around zero and remain within a narrow range, indicating low prediction error and no systematic bias. The absence of clear trends or structured patterns in the residual plots confirms that the KNN model captures the relationship between frequency, slot configuration, and absorption performance with good accuracy. This behavior demonstrates that the selected input features are sufficient to represent the microwave absorber's absorption characteristics [8], [12].

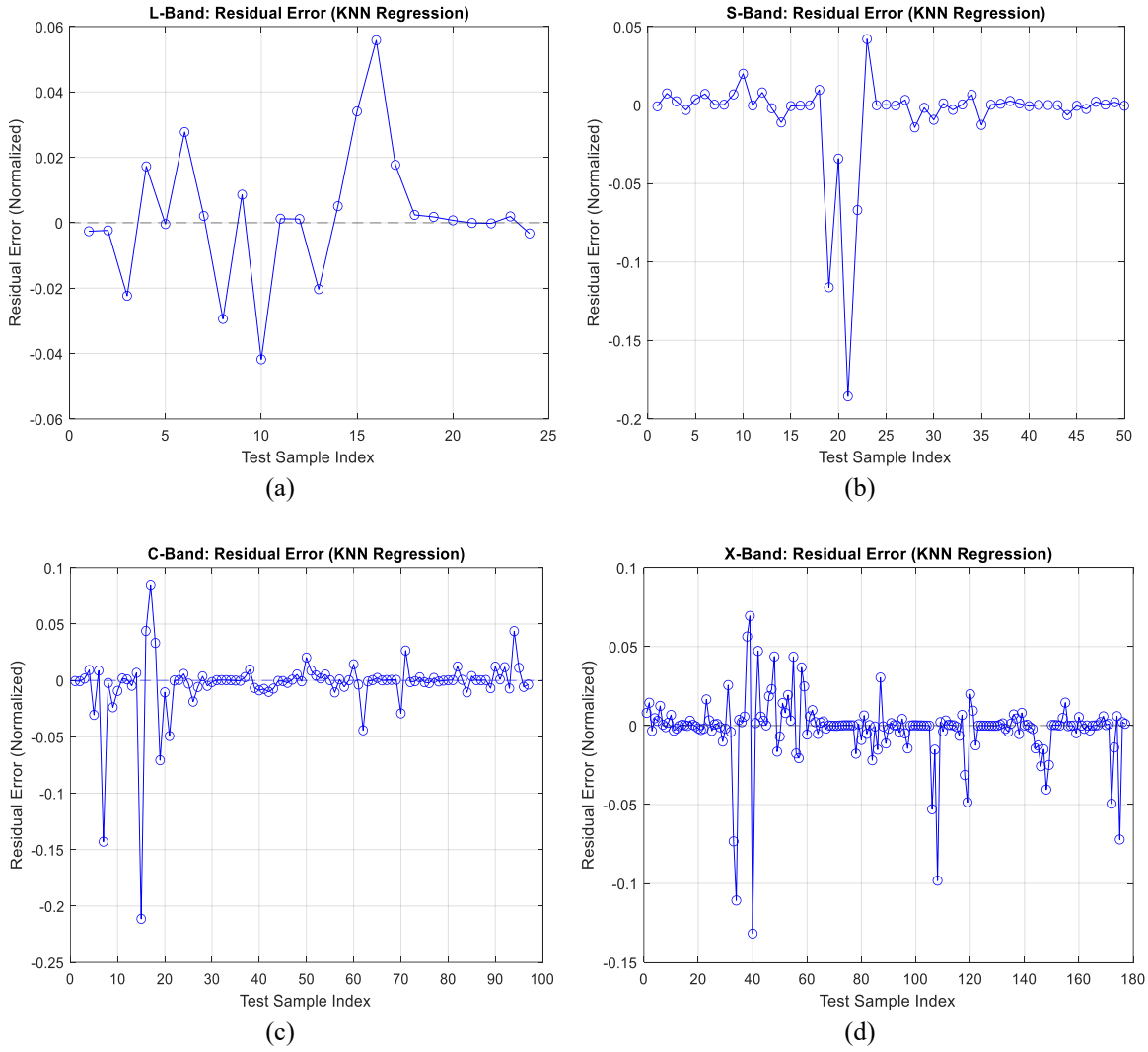


Figure 3. Residual error of KNN regression for (a) L-band, (b) S-band, (c) C-band, and (d) X-band

The L-band residual plot shows the smallest variation among the bands, indicating that the prediction error is minimal at lower frequencies. This result is consistent with the measured-versus-predicted analysis, in which the L-band showed the highest agreement between experimental and predicted data. The smaller residual variation suggests that the absorption behavior at lower frequencies is more stable and less sensitive to small structural variations in the absorber.

For the S- and C-bands, slightly larger residual fluctuations are observed. This behavior is expected because the absorption mechanism becomes more complex as the operating frequency increases. At higher frequencies, electromagnetic waves interact more strongly with the absorber geometry, slot configuration, and material properties, introducing nonlinear effects that are more difficult to model with simple regression

methods. Nevertheless, the residual values remain within an acceptable range, indicating that the KNN model continues to provide reliable predictions [12], [13], [16].

The X-band residual distribution shows wider scattering than the lower bands, but the values remain randomly distributed around zero with no systematic deviation. This confirms that the developed model remains stable even in higher-frequency bands, where the absorption behavior is more nonlinear. The ability of the KNN model to maintain small residual values across all bands demonstrates that the proposed data-driven approach is suitable for predicting multiband microwave absorbers [13], [16].

Overall, the residual error analysis confirms that the developed KNN regression model yields unbiased and stable predictions across all frequency bands. The random distribution of residual values confirms that the model does not overfit the training data and can generalize well for new input data. These results support the robustness of the proposed prediction model for practical microwave absorber design applications [8], [12].

3.4. Performance evaluation of the KNN model

The overall performance of the KNN regression model was evaluated using RMSE. The overall performance of the proposed KNN regression model was evaluated using RMSE, MAE, and R^2. These metrics are commonly used to assess the accuracy of regression models and to measure the agreement between measured and predicted values. The performance results for all frequency bands are summarized in Table 2.

Table 2. Performance evaluation of the KNN regression model for L-band, S-band, C-band, and X-band

Parameter	L-Band	S-Band	C-Band	X-Band
Best k	2	2	2	2
RMSE	0.019704	0.033707	0.030939	0.022145
MAE	0.012507	0.012027	0.012165	0.010240
R^2	0.993952	0.979610	0.978057	0.988438

The results show that the developed KNN model achieves high prediction accuracy for all frequency bands. The R^2 values are greater than 0.97 across all cases, indicating a strong correlation between the measured absorption data and the model-generated predictions. This result confirms that the normalized dataset has a consistent pattern that can be effectively learned using the KNN regression approach [8], [12]. Among the four frequency bands, the lowest RMSE is observed for the L-band, indicating that prediction error is minimal at lower frequencies. This behavior is consistent with the residual analysis and the measured-versus-predicted plots, in which the L-band exhibited the most stable absorption characteristics. The relatively simple absorption behavior at lower frequencies allows the distance-based KNN algorithm to find similar data points more easily, resulting in higher prediction accuracy [20].

For the S-band and C-band, the RMSE values are slightly higher compared to the L-band. This increase in prediction error is expected because the absorption behavior becomes more complex as the operating frequency increases. At higher frequencies, the interaction between the electromagnetic wave and the pyramidal absorber structure yields more nonlinear responses, making the prediction task more challenging. Nevertheless, the RMSE and MAE remain small, indicating that the model continues to perform reliably [13], [16]. The X-band also shows high predictive accuracy, with R^2 values close to unity, demonstrating that the developed model can handle multiband data with varying absorption characteristics. The ability of the KNN model to maintain consistent performance across L, S, C, and X bands confirms that the proposed data-driven modelling approach is suitable for predicting microwave absorber performance over a wide frequency range [12], [13], [16]. Overall, the performance evaluation results verify that the KNN regression model provides accurate and stable predictions without requiring complex electromagnetic analytical equations. This demonstrates that machine learning-based modelling can be used as an efficient alternative to simulation and repeated experimental measurements in microwave absorber design [8], [12], [15].

3.5. Stability analysis using multiple random seeds

To verify the robustness of the developed KNN regression model, the holdout validation process was repeated using multiple random seeds. The purpose of this analysis is to evaluate the model's generalization performance across different data partitions and verify that the selected optimal k value is not dependent on any single data split. In machine learning modelling, different random splits of the dataset may yield slightly different results; stability analysis is required to confirm that the model delivers consistent performance [8], [15].

Table 3 shows the optimal k values obtained for L-band, S-band, C-band, and X-band when different random seeds are used in the data partitioning process. The results indicate that the optimal k varies slightly with the training-testing split, but the values remain within a narrow range of 1 to 3 in most cases. This small variation indicates consistent generalization performance and low sensitivity to dataset partitioning. For the L-band, the optimal k is typically 2, with occasional values of 1 or 3. Similar behavior can be observed for the S-band, C-band, and X-band, where the optimal k fluctuates slightly but remains within a narrow range. The most frequent value across all frequency bands is k=2, consistent with the RMSE analysis presented in the previous section. This result confirms that the selected parameter is reliable and suitable for modelling the microwave absorber's absorption behavior. The stability of the optimal k value indicates that the normalized dataset has a consistent structure, allowing the KNN algorithm to identify similar patterns even when the training data changes. This behavior demonstrates good generalization, enabling accurate prediction of unseen absorption data without significant degradation [8], [15].

Table 3. Optimal k values obtained using different random seeds for L-band, S-band, C-band, and X-band

k values	L Band	S Band	C Band	X Band
1	2	2	2	2
2	1	5	2	3
3	2	2	1	3
4	2	1	2	3
5	2	2	3	2
6	1	3	2	3
7	3	1	2	1
8	1	3	2	2
9	2	3	3	2
10	1	2	3	3

In addition, the stability analysis confirms that the proposed KNN regression model maintains consistent generalization performance across multiple frequency bands, even though the absorption characteristics differ by band. Despite the increased nonlinearity at higher frequencies, the model maintains consistent optimal parameter values, demonstrating that the data-driven approach is suitable for modelling microwave absorber performance across wide frequency ranges. Overall, the results of the multiple random seed tests indicate consistent model performance and low sensitivity to data partitioning. This confirms that the proposed prediction model can be confidently applied to estimating microwave absorber performance and evaluating design.

Although k-fold cross-validation is commonly employed to improve statistical reliability, the holdout validation approach adopted in this study is considered appropriate for the available dataset size. The stability analysis using multiple random seeds showed consistent model performance and a narrow range of optimal k values across all frequency bands. These results indicate that the developed KNN model is not highly sensitive to data partitioning and that the adopted validation strategy provides a reliable assessment of the model's generalization performance on the experimental dataset [8], [15].

Despite its high prediction accuracy, the KNN algorithm has several limitations. The prediction performance of KNN can be sensitive to noisy data and outliers because predictions are based directly on neighboring samples. In addition, the computational cost increases with dataset size since distance calculations must be performed for all training samples during prediction. In this study, outlier removal and data normalization were applied to reduce noise effects and improve model stability. Future work may incorporate statistical tests such as the Shapiro-Wilk normality test and Ljung-Box autocorrelation test to provide a more rigorous assessment of residual behavior and model assumptions.

3.6. Effect of distance metrics

To further investigate the influence of distance metrics on the prediction performance of the KNN regression model, three distance measures, namely Euclidean, Manhattan, and cosine distances, were evaluated using the optimal neighbor value determined for each frequency band. Table 4 summarizes the obtained RMSE, MAE, and R^2 values for L-band, S-band, C-band, and X-band. The results indicate that Euclidean and Manhattan distances produced identical prediction performance across all investigated frequency bands. For L-band, both metrics achieved RMSE = 0.019704 and R^2 = 0.99395. Similar behavior was observed for S-band (RMSE = 0.033707, R^2 = 0.97961), C-band (RMSE = 0.030939, R^2 = 0.97806), and X-band (RMSE = 0.022145, R^2 = 0.98844). These results demonstrate that the developed KNN model is highly stable with respect to the selected distance metric [20].

In contrast, the cosine distance metric produced significantly poorer prediction performance for all frequency bands. The most substantial degradation was observed in the L-band, where the R^2 decreased to R^2 = -1.4269. Similar reductions in prediction accuracy were also observed in the C-band and X-band datasets. These findings indicate that cosine distance is not suitable for representing the relationship between normalized frequency, slot configuration, and absorption performance.

Table 4. Comparison of distance metrics for KNN regression across different frequency bands

Band	Distance metric	RMSE	MAE	R^2
L	Euclidean	0.019704	0.012507	0.99395
	Manhattan	0.019704	0.012507	0.99395
	Cosine	0.394710	0.317990	-1.42690
S	Euclidean	0.033707	0.012027	0.97961
	Manhattan	0.033707	0.012027	0.97961
	Cosine	0.058552	0.043304	0.93848
C	Euclidean	0.030939	0.012165	0.97806
	Manhattan	0.030939	0.012165	0.97806
	Cosine	0.195220	0.129290	0.12634
X	Euclidean	0.022145	0.010240	0.98844
	Manhattan	0.022145	0.010240	0.98844
	Cosine	0.139360	0.106150	0.54211

Based on the obtained results, Euclidean distance was selected as the final distance metric because it consistently achieved excellent prediction accuracy while remaining the most commonly adopted metric in KNN regression applications [20]. From an engineering perspective, the developed KNN model can be used during the preliminary design stage to rapidly estimate the absorption performance of different slot configurations across the investigated frequency bands. Instead of performing repeated full-wave electromagnetic simulations or experimental measurements for each candidate design, engineers can use the trained model to quickly predict absorber performance and identify promising configurations for further evaluation. This approach reduces computational effort, shortens the design cycle, and enables only the most promising absorber configurations to proceed to detailed electromagnetic simulation or experimental validation, thereby supporting efficient microwave absorber development. Such a prediction model may also support future microwave absorber design workflows by enabling rapid preliminary performance evaluation before detailed electromagnetic simulations, prototype fabrication, or experimental validation [12], [15].

4. CONCLUSION

This study developed a KNN regression model to predict the absorption performance of single-slot hollow pyramidal microwave absorbers across the L-, S-, C-, and X-bands. The optimal number of neighbors was k = 2, achieving R^2 values above 0.97 across all frequency bands. Residual and stability analyses confirmed the model's reliability and robustness. Among the evaluated distance metrics, Euclidean and Manhattan distances provided better prediction accuracy than cosine distance. Overall, the proposed KNN model offers an accurate and computationally efficient approach for predicting microwave absorber performance without requiring repeated electromagnetic simulations. However, the study was limited to experimental data from three slot configurations. Future work will investigate additional absorber geometries, multi-slot configurations, and materials, as well as comparative evaluations with other machine learning methods to improve generalization and support absorber design optimization.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The datasets used and analyzed during the current study are available from the corresponding author, [NI], upon reasonable request.

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