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Artificial neural network-based optimisation of a modified star fractal antenna

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ABSTRACT

In antenna engineering, artificial neural networks (ANNs) are increasingly used to improve critical performance metrics. An ANN-based method is used to improve the reflection coefficient of a modified star fractal antenna operating between 5.6 GHz and 8.4 GHz. This model takes as inputs various geometric characteristics, including the radius of the central circular slot, the width of the feedline, and the radius of the adjacent smaller circular slots. The ANN produces the complex components of the reflection response, which are subsequently employed as optimisation objectives. A dataset for training and validation was generated using computer simulation technology (CST) Microwave Studio simulations. Our built ANN model has produced remarkably accurate forecasts and successfully assigned highly optimised return-loss characteristics within a brief timeframe. The developed ANN model achieved accurate predictions and successfully identified antenna configurations with improved return loss. Notably, the proposed approach significantly reduces the computational burden of repeated full-wave electromagnetic simulations while retaining high prediction accuracy. The results reveal that ANN-based surrogate modeling effectively enhances the return-loss performance of modified star fractal antennas.

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1. INTRODUCTION

Fractal antennas have attracted considerable attention because their self-similar geometries can provide compact radiating structures with multiple resonant frequencies. Different fractal configurations, including Sierpinski, Koch, Minkowski, Apollonian, Hilbert, and star fractals, have been investigated for multiband antenna applications [1]-[6]. Recent studies have also demonstrated that the integration of fractal antennas using metasurfaces and defective ground structures (DGS) can enhance antenna properties like gain, bandwidth, and impedance matching [1], [6]. Fractal antennas are appealing for contemporary wireless communication systems that need to be small and multiband because of these characteristics.

The design and optimization of fractal antennas remain challenging because their electromagnetic behavior depends nonlinearly on several geometrical and electromagnetic parameters. Conventional optimization generally requires numerous full-wave simulations using electromagnetic solvers such as computer simulation

technology (CST) Microwave Studio or high-frequency structure simulator (HFSS). Although these simulations provide accurate results, their computational cost increases significantly when a large multidimensional design space is explored [7]-[9]. Consequently, efficient surrogate and data-driven approaches have become increasingly important for reducing the number of required electromagnetic simulations.

An efficient method for speeding up antenna analysis and optimization is artificial intelligence (AI), especially machine learning (ML) and artificial neural networks (ANNs). Without running a full-wave simulation for each design iteration, ANN models can learn nonlinear correlations between antenna design parameters and electromagnetic responses and then produce quick predictions [7], [8], [10]-[12]. Recent studies have applied ANN and ML techniques to multiband antenna synthesis [13]-[15], antenna optimization [9], [16]-[18] and inverse antenna design [19]. These approaches demonstrate the potential of data-driven models to reduce computational effort while maintaining accurate prediction of antenna characteristics.

The combination of ANN and fractal antenna technology is particularly promising. Recent investigations have applied ML to compact fractal monopole antennas [2], Apollonian gasket fractal antennas [3], Minkowski fractal antennas [5], and other fractal configurations [4], [20]-[24]. ANN-based approaches have also been employed for multiband fractal antenna design and optimization [14], [25], [26]. However, relatively limited attention has been given to the systematic development of an ANN model for predicting multiple electromagnetic responses of a star fractal antenna over a broad range of geometrical configurations and operating frequencies. This constraint drives the creation of an effective data-driven framework that may reduce the computing load associated with repeated full-wave simulations while accurately simulating the electromagnetic behavior of star fractal antennas.

In this work, an ANN-based optimization framework is proposed for the design of a multiband star fractal antenna. A dataset containing 120,000 samples is generated from CST Microwave Studio simulations by varying the principal geometrical parameters and operating frequency. The ANN uses four input parameters: frequency, feedline width, patch width, and the radii of the central and secondary circular elements. It predicts five electromagnetic responses, namely the reflection coefficient S_{11}, magnitude, phase, real part, and imaginary part. The network is trained using the Adam optimizer with mean squared error (MSE) as the loss function. It has two hidden layers with 128 and 64 neurons, respectively, and uses rectified linear unit (ReLU) activation in the hidden levels and a linear output layer. The dataset is split into 20% testing and 80% training, which includes 20% validation inside the training subset.

The goal of the suggested approach is to reduce the number of computationally demanding full-wave simulations needed for antenna optimization while still offering precise electromagnetic prediction. For contemporary wireless communication applications, it thus offers an effective framework for the quick construction and optimization of multiband star fractal antennas. This is how the rest of the paper is structured. The theoretical framework is presented in section 2. The ANN-based optimization framework is explained in section 3. The results and comments are presented in section 4, and the paper is concluded in section 5.

2. THEORETICAL FRAMEWORK

2.1. Fractal antenna design

Fractal antennas exploit self-similar geometries to obtain compact radiating structures with multiple resonant frequencies. Various fractal configurations, including Sierpinski, Koch, Minkowski, Hilbert, Apollonian, and star-shaped geometries, have been investigated for multiband and miniaturized antenna applications [1], [3]-[6], [20], [24], [27], [28]. Recent studies have also demonstrated that combining fractal geometries with defected ground structures [29] and metasurfaces can improve antenna features like gain, bandwidth, and impedance matching [1], [6].

The suggested altered star fractal antenna is made up of a center six-pointed star surrounded by five smaller star-shaped elements with circular slots. The main geometrical parameters are the central circular slot radius R_1, the secondary circular slot radius R_2, the feedline width W_f, and the patch width W_p. Figure 1 illustrates the proposed geometry, while the corresponding parameter ranges are summarized in Table 1.

2.2. Electromagnetic performance parameters

The suggested antenna's electromagnetic response is evaluated from the reflection coefficient S_{11} obtained from CST Microwave Studio. The ANN predicts the magnitude, phase, real part, and imaginary part of the complex reflection coefficient. These quantities are subsequently used to evaluate the prediction accuracy and the optimized antenna response.

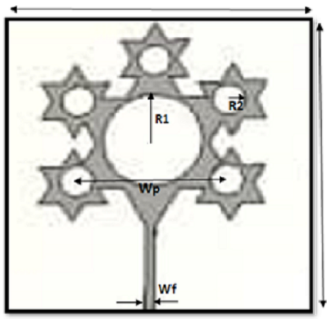


Figure 1. Proposed antenna structure

Table 1. Range of parameters

Criteria	Initial value	Final value	Count
freq	4 Ghz	9 Ghz	200
Wf	0.5 mm	3 mm	6
Wp	10.14 mm	10.14 mm	N/A
R1	1 mm	3.16 mm	10
R2	0.1 mm	1.14 mm	10
Wg	20 mm	20 mm	N/A
Lg	20 mm	20 mm	N/A

3. ANN-BASED OPTIMIZATION FRAMEWORK

3.1. Dataset generation and preprocessing

600 full-wave electromagnetic simulations conducted in CST Microwave Studio spanning the frequency range of 4–9 GHz produced a dataset with 120,000 samples. While changing the chosen antenna parameters, 200 frequency points were taken into account for each simulation. An Excel database was created by extracting and organizing the resulting S_{11} replies together with their respective real and imaginary components. The operating frequency f, feedline width W_f, surrounding circular slot radius R_2, and central circular slot radius R_1 were the input variables. S_{11}, its magnitude, phase, real portion, and imaginary part, were the ANN outputs. Eighty percent of the entire dataset was utilized for training, twenty percent was used for independent testing, and twenty percent was used for validation. The proposed ANN workflow is illustrated in Figure 2.

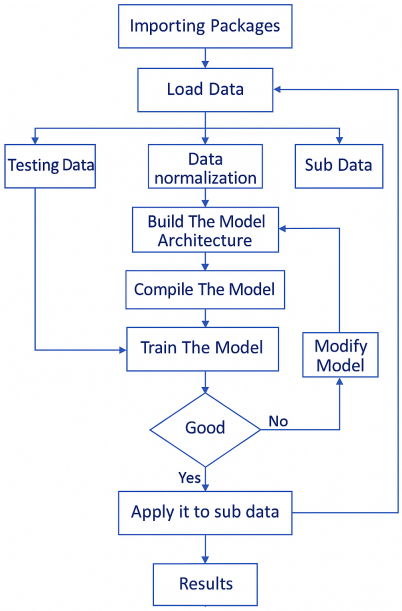


Figure 2. Flowchart of the proposed ANN model

3.2. ANN architecture and training

A feed-forward ANN was developed to model the nonlinear relationship between the antenna parameters and electromagnetic responses. The final architecture consists of five input neurons, two hidden layers containing 128 and 64 neurons, respectively, and five output neurons, corresponding to:

$$4 \rightarrow 128 \rightarrow 64 \rightarrow 5 \quad (1)$$

The output layer for continuous regression used a linear activation function, whereas the hidden layers

used the ReLU activation function. The Adam optimizer was used to train the network, and the loss function was MSE. The 128–64 architecture was chosen as the final configuration after a number of network configurations were assessed during model development. The definition of the ReLU function is:

$$f(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases} \tag{2}$$

The prediction performance was evaluated using MSE, root mean squared error (RMSE), and mean absolute error (MAE), defined respectively as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{3}$$

$$RMSE = \sqrt{MSE} \tag{4}$$

and

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{5}$$

For the output layer, a linear activation function was selected because it is particularly suitable for regression tasks involving continuous output prediction. The combination of ReLU in the hidden layers and linear activation in the output layer enables accurate modeling of the relationship between antenna geometrical parameters and electromagnetic response characteristics. The proposed ANN architecture is illustrated in Figure 3.

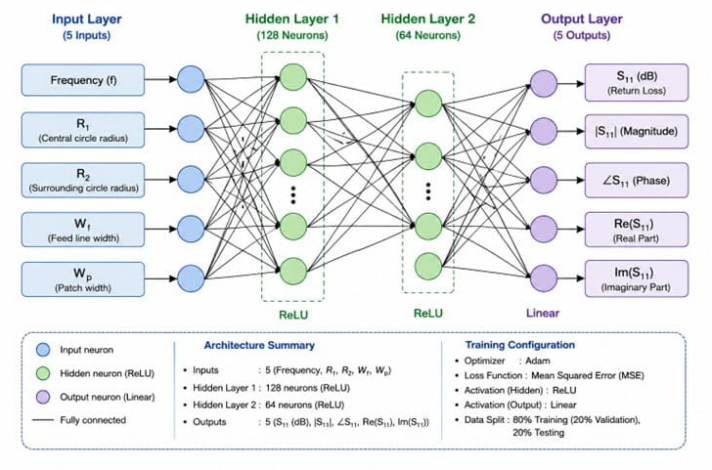


Figure 3. Architecture of the proposed ANN model

3.3. ANN-based optimization

After training, the ANN was used as a surrogate model to rapidly evaluate candidate antenna configurations. The optimization objective was to minimize the predicted reflection coefficient S_{11} within the parameter ranges given in Table 1. The optimization problem can be expressed as:

$$\min J = S_{11}(f, R1, R2, Wf) \tag{6}$$

subject to:

$$R_{1,\min} \leq R_1 \leq R_{1,\max} \tag{7}$$

$$R_{2,\min} \leq R_2 \leq R_{2,\max} \tag{8}$$

$$W_{f,\min} \leq W_f \leq W_{f,\max} \tag{9}$$

and

$$f_{\min} \leq f \leq f_{\max} \tag{10}$$

The trained ANN therefore replaces repeated full-wave simulations during the optimization stage, allowing candidate configurations to be evaluated with substantially lower computational cost. The resulting optimized configuration is subsequently verified using CST Microwave Studio pedance matching and more efficient power transmission. The ANN model directly predicts the electromagnetic response from antenna geometrical parameters, enabling rapid evaluation of candidate antenna configurations.

4. RESULTS AND DISCUSSION

4.1. Return loss

The electromagnetic characteristics of the proposed modified star fractal antenna was evaluated using full-wave simulations conducted in CST Microwave Studio over the frequency range of 4–9 GHz. The simulation was performed to investigate the influence of antenna geometrical parameters on the reflection coefficient and overall antenna behavior. The obtained results demonstrate that the proposed antenna exhibits stable electromagnetic performance within the investigated frequency range. The reflection coefficient (S11) was analyzed to evaluate impedance matching and identify the resonant operating regions. Lower values of S11 indicate improved power transfer and reduced reflected energy. Several antenna configurations generated by varying the geometrical parameters, including the feed-line width (Wf), central circular slot radius (R1), surrounding circular slot radius (R2), and patch width (Wp), were simulated to analyze their impact on antenna performance. The simulation results revealed that these parameters significantly influence resonance behavior and return-loss characteristics. Representative simulation results, including S11 curves and antenna response characteristics, are presented in the following figures. These results serve as the reference dataset for training and validating the proposed ANN model. The obtained CST simulation results confirm the suitability of the modified star fractal antenna structure for optimization using the proposed ANN-based framework. Figure 4 presents the simulated reflection coefficient (S11) of the proposed modified star fractal antenna obtained using CST Microwave Studio. The results reveal two resonant frequencies located approximately at 5.8 GHz and 8.2 GHz. In both cases, the reflection coefficient remains below -10 dB, indicating acceptable impedance matching and return-loss characteristics. The observed resonance behavior demonstrates that the proposed antenna geometry provides stable electromagnetic performance within the investigated frequency range. The obtained simulation data were subsequently used to generate the dataset employed for training and validating the proposed ANN model.

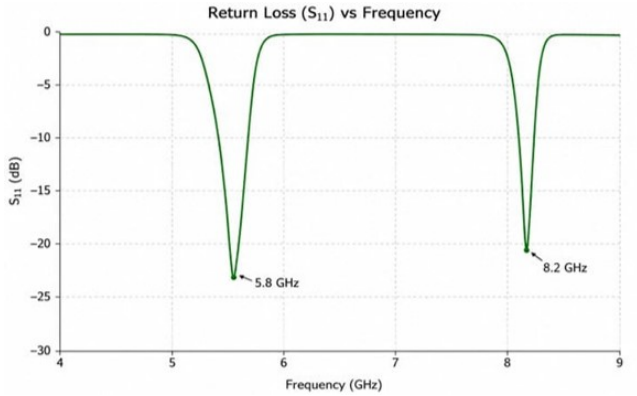


Figure 4. Simulated reflection coefficient (S11) of the proposed modified star fractal antenna obtained using CST Microwave Studio

4.2. ANN prediction performance

The predictive capability of the proposed ANN model was evaluated by comparing predicted electromagnetic responses with corresponding CST simulation results. Figure 5 presents the training and validation

loss as a function of the number of epochs during the training of the proposed ANN model. Figures 6–10 present the comparison between the ANN outputs and the reference CST data for different antenna response parameters. The close agreement between the predicted and simulated curves demonstrates that the developed ANN model successfully captured the nonlinear relationship between antenna geometrical parameters and electromagnetic behavior. The obtained results confirm the effectiveness of the proposed surrogate model in reducing computational effort while maintaining satisfactory prediction accuracy.

The training loss decreases sharply during the initial epochs and rapidly approaches a value close to zero. Similarly, the validation loss remains very low throughout the training process and closely follows the training loss. The small difference between the training and validation losses indicates a consistent learning behavior and suggests that the model does not exhibit significant overfitting. The rapid convergence of both loss curves demonstrates the effectiveness of the adopted training procedure and the ability of the proposed ANN model to learn the underlying relationship between the antenna geometrical parameters and its electromagnetic responses.

Figure 6 presents a comparison between the real part of the reflection coefficient predicted by the proposed ANN model and the corresponding values obtained from CST simulations. As shown in the figure, the predicted values exhibit a strong agreement with the reference CST data, with the data points closely distributed along the ideal diagonal trend. This close correspondence demonstrates that the proposed ANN model is capable of accurately reproducing the real component of the antenna response over the investigated range. The results therefore confirm the effectiveness of the developed surrogate model in capturing the nonlinear relationship between the antenna geometrical parameters and its electromagnetic behavior.

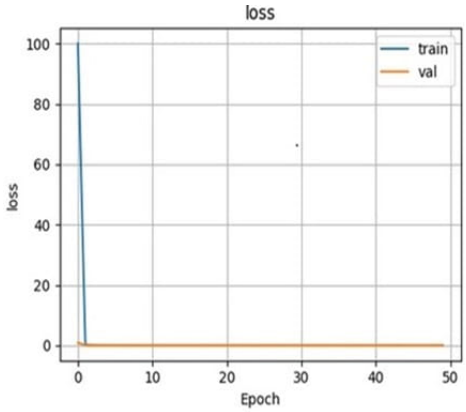


Figure 5. Loss during training and validation across epochs

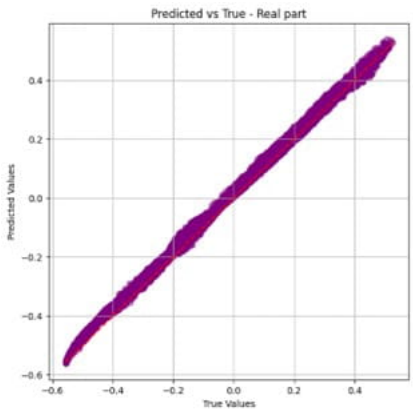


Figure 6. Actual Re of CST vs Predicted Re of ANN model

Figure 7 presents a comparison between the magnitude predicted by the proposed ANN model and the corresponding magnitude obtained from CST simulations. The predicted values show a strong agreement with the reference CST data, as evidenced by their close distribution along the ideal diagonal line. The small deviations observed at certain points remain limited over the investigated range. This close correspondence indicates that the proposed ANN model accurately reproduces the magnitude response of the antenna and demonstrates its ability to capture the nonlinear relationship between the antenna parameters and the corresponding electromagnetic response.

Figure 8 presents a comparison between the imaginary part of the reflection coefficient predicted by the proposed ANN model and the corresponding values obtained from CST simulations. The predicted values are closely distributed around the ideal diagonal relationship, demonstrating a strong agreement with the reference CST data. Only small deviations can be observed, particularly in some regions of the investigated range. This close correspondence confirms the ability of the proposed ANN model to accurately reproduce the imaginary component of the antenna electromagnetic response. The results further demonstrate the effectiveness of the ANN-based surrogate model in capturing the nonlinear relationship between the antenna geometrical parameters and its electromagnetic behavior.

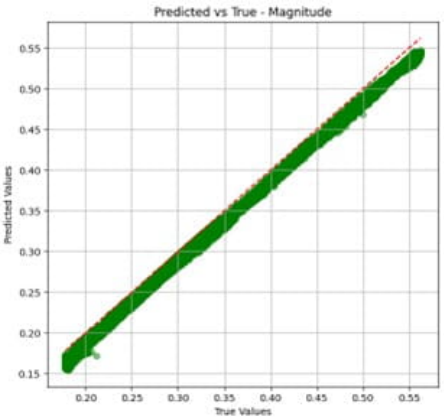


Figure 7. Predicted magnitude VS actual magnitude of CST

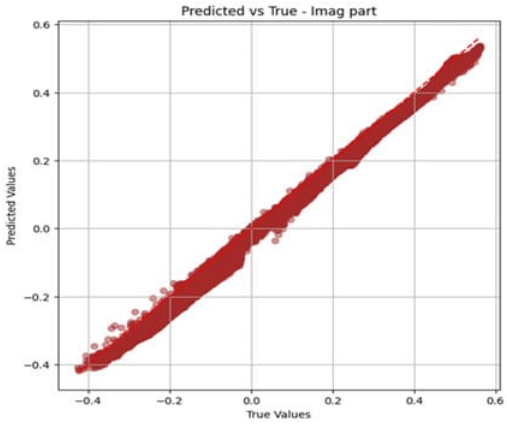


Figure 8. Predicted Im of ANN model VS actual Im of CST

Figure 9 presents a comparison between the phase predicted by the proposed ANN model and the corresponding phase values obtained from CST simulations. The predicted values exhibit an almost perfect linear correspondence with the reference CST data, with the data points closely following the ideal diagonal relationship. This strong agreement indicates that the proposed ANN model accurately reproduces the phase response of the antenna over the investigated range. The very small deviations observed between the predicted and simulated values further confirm the high prediction capability of the developed ANN model and its effectiveness as a surrogate model for electromagnetic analysis.

Figure 10 presents a comparison between the optimized return loss obtained using the proposed ANN model and the corresponding CST simulation results. The two curves exhibit similar resonance behavior, with resonant frequencies occurring at approximately 5.8 GHz and 8.2 GHz. A close agreement can be observed between the ANN-predicted and CST-simulated responses over the investigated frequency range, particularly around the resonant regions. The optimized ANN response successfully reproduces the main characteristics of the simulated return loss, including the locations and depths of the resonance minima. These results demonstrate the capability of the proposed ANN-based optimization framework to predict suitable antenna configurations while maintaining electromagnetic performance consistent with full-wave CST simulations.

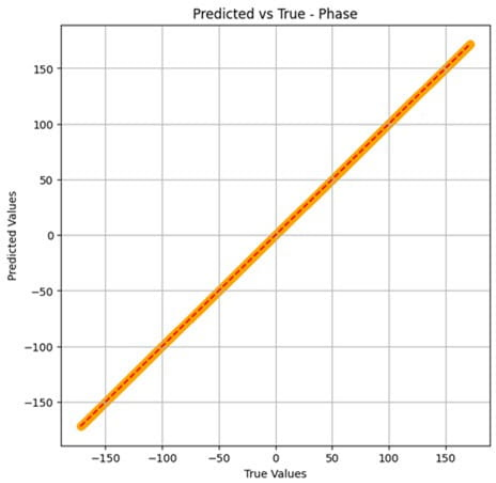


Figure 9. Phase of the ANN model and CST simulation data

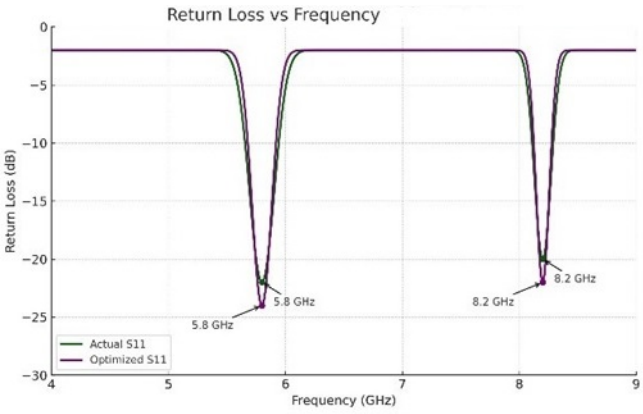


Figure 10. ANN-predicted and CST-simulated return loss

4.3. Quantitative comparison and validation:

Table 2 summarizes selected ANN-based antenna studies and their reported prediction errors. The comparison provides a reference for evaluating the performance of the proposed ANN approach. The prediction accuracy of the proposed ANN model was evaluated using the MSE, RMSE, and MAE. The obtained results are presented in Table 3.

Table 2. Comparison with reported work in literature

Ref	Hidden layers	Test errors (%)
[17]	GRNN	0.41
[18]	RBF-ANN	25
[26]	8 Sigmoid	2.40

Table 3. ANN performance indicators

Metric	Value (%)
MSE	0.0504
RMSE	0.2245
MAE	0.0999

5. CONCLUSION

This paper presents an ANN-based optimization framework to improve the electromagnetic performance of a modified star fractal antenna operating in the 5.6–8.4 GHz frequency range. The proposed methodology combined full-wave electromagnetic simulations in CST Microwave Studio with ML to develop an efficient predictive model for antenna optimization. A dataset containing 120,000 samples was generated by varying the antenna geometrical parameters and extracting the corresponding electromagnetic responses. The developed ANN architecture employed two hidden layers with 128 and 64 neurons, respectively, and used the ReLU activation function and the Adam optimization algorithm to model the nonlinear relationship between antenna geometry and return-loss characteristics. The results demonstrated that the proposed model accurately predicted antenna behavior and successfully identified optimized antenna configurations, while reducing the computational effort required for repeated full-wave simulations. Quantitative evaluation showed satisfactory predictive performance with a test MSE of 0.2245, RMSE of 0.0504, and MAE of 0.0999. Comparison with previously reported studies demonstrated the effectiveness of the proposed ANN-based surrogate modeling approach for the optimization of modified star fractal antennas. The developed methodology provides an efficient alternative to conventional simulation-driven optimization procedures. It may be extended in future work to support more complex antenna geometries and advanced deep learning optimization techniques.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Amina Bendaoudi		✓			✓	✓	✓	✓	✓	✓	✓			
Mahdjoub Zoubir	✓		✓	✓	✓		✓	✓	✓		✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal Analysis
I : **I**nvestigation
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.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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