A Model for Image Segmentation under Noisy Conditions and Anomaly Detection in Medical MRI Images Using an RBF Neural Network and the PSO Metaheuristic Algorithm for Breast Cancer Detection

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Abstract

The aim of the present study was to develop an intelligent model for image segmentation under noisy conditions and anomaly detection in medical MRI images using a Radial Basis Function (RBF) neural network and the Particle Swarm Optimization (PSO) metaheuristic algorithm. In this model, the RBF neural network was responsible for learning and separating different image regions, while the PSO algorithm was employed for the automatic optimization of the network parameters, including centers, weights, and radii of the basis functions. The MRI images used in this study consisted of real data from the breast tissues of patients with and without cancer. Following the preprocessing stage, which included Gaussian and salt-and-pepper noise removal and pixel intensity normalization, the images were applied to the proposed model. The model output provided accurate segmentation of regions suspected of abnormalities from other tissues, and the results were compared with classical K-Means, FCM, and standalone RBF network methods. The findings demonstrated that the hybrid RBF–PSO model was able to increase segmentation accuracy under noisy conditions to an average of 96.4% and achieved a Dice overlap index of 0.92, representing a significant improvement compared to the other methods. Furthermore, the proposed model showed stable performance in preserving the actual tumor boundaries and eliminating noisy regions. Based on the obtained results, the RBF–PSO model can be considered an efficient tool for the early detection of breast cancer through the automated analysis of MRI images. It is recommended that future studies integrate this model with deep learning networks in order to improve its accuracy and generalizability in clinical datasets.

Keywords: *Radial Basis Function (RBF) Neural Network, Particle Swarm Optimization (PSO) Algorithm, Metaheuristic Algorithms, Hybrid Algorithm Design, MATLAB Simulation, Intelligent Segmentation*

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1. Introduction

Breast cancer remains one of the leading causes of mortality among women worldwide and represents a major challenge for healthcare systems because of its complex pathological characteristics and the importance of early diagnosis. Early identification of malignant tissues significantly improves treatment effectiveness and survival rates, making computer-aided diagnosis systems an increasingly important area of medical image analysis research. Recent developments in artificial intelligence, machine learning, and medical imaging technologies have enabled researchers to design automated systems capable of identifying suspicious lesions with high precision. Image segmentation, as one of the most critical stages of computer-aided diagnosis, plays a fundamental role in separating abnormal tissues from healthy structures and directly influences the accuracy of subsequent classification and diagnostic processes [1, 2]. In medical imaging modalities such as Magnetic Resonance Imaging (MRI), accurate segmentation is particularly important because MRI provides high soft-tissue contrast and detailed anatomical information, allowing physicians to identify breast abnormalities and tumor boundaries more effectively than several conventional imaging approaches. However, MRI images are frequently affected by different types of noise, intensity inhomogeneity, and structural complexity, which make precise segmentation difficult and motivate the development of intelligent and robust segmentation frameworks [3, 4].

Medical image segmentation methods have evolved from traditional threshold-based and clustering-based approaches toward advanced intelligent systems that integrate machine learning and optimization algorithms. Classical segmentation techniques such as K-Means and Fuzzy C-Means (FCM) clustering have been widely used because of their computational simplicity and ability to partition medical images into homogeneous regions. Nevertheless, these approaches are highly sensitive to noise, initialization parameters, and local minima, which often reduce segmentation quality in complex MRI datasets [5, 6]. Moreover, conventional clustering methods generally lack adaptive learning capability and cannot effectively preserve tumor boundaries under noisy conditions. These limitations have encouraged researchers to employ neural networks and deep learning architectures for medical image segmentation. Convolutional Neural Networks (CNNs), U-Net-based models, and fully convolutional networks have demonstrated remarkable performance in the segmentation of tumors and anatomical structures in MRI, CT, ultrasound, and dermoscopic images [7-9]. Deep learning models can automatically extract hierarchical features and learn complex spatial patterns from medical images, thereby improving segmentation accuracy and robustness. Despite these advantages, deep neural networks often require large annotated datasets, high computational power, and extensive training time, which may limit their application in clinical environments with restricted resources.

In response to these limitations, hybrid intelligent systems combining neural networks with metaheuristic optimization algorithms have gained considerable attention in recent years. Metaheuristic algorithms such as Particle Swarm Optimization (PSO), Grey Wolf Optimization, Genetic Algorithms, and Ant Colony Optimization provide powerful global search mechanisms that can optimize model parameters and avoid convergence to local optima. PSO, in particular, has emerged as one of the most effective optimization methods because of its simple structure, fast convergence speed, and strong global optimization capability. Inspired by the collective behavior of bird flocks and fish schools, PSO iteratively updates candidate solutions according to individual and global experiences in the search space. This capability makes PSO highly suitable for optimizing neural network parameters, including connection weights, activation spreads, and cluster centers [6, 10]. Recent studies have demonstrated that integrating PSO with machine learning and neural network architectures can significantly improve classification and segmentation performance in biomedical applications. For example, Soleimani et al. developed a hybrid Radial Basis Function (RBF) and PSO model for cancer classification using microRNA expression data and reported considerable improvements in predictive performance and optimization stability [10]. Similarly, Bilal et al. proposed a Support Vector Machine optimized through an Improved Quantum Inspired Grey Wolf Optimization algorithm for breast cancer diagnosis and achieved enhanced diagnostic accuracy compared to traditional methods [11]. These findings indicate that optimization-driven intelligent systems can effectively improve medical image analysis and cancer detection tasks.

The Radial Basis Function neural network is considered one of the most efficient neural network architectures for nonlinear classification and pattern recognition tasks because of its fast learning capability, simple topology, and strong approximation performance. Unlike multilayer perceptrons, RBF networks use radial basis activation functions in the hidden layer to map input data into high-dimensional feature spaces, allowing complex nonlinear relationships to be modeled more effectively. The performance of an RBF network largely depends on the selection of centers, spreads, and output weights. Improper parameter selection can significantly reduce classification and segmentation accuracy, especially in noisy datasets. Therefore, optimization algorithms such as PSO can play a critical role in enhancing the performance of RBF networks by automatically determining optimal parameters [6, 10]. In medical image processing applications, hybrid RBF-based systems have demonstrated promising results because they combine efficient nonlinear learning capability with robust optimization strategies. These systems are particularly useful in MRI segmentation, where image intensities and tissue boundaries exhibit nonlinear variations and are affected by noise and imaging artifacts.

The role of noise reduction and preprocessing in medical image segmentation is also of substantial importance. MRI images often contain Gaussian noise, salt-and-pepper noise, and intensity distortions that negatively influence segmentation accuracy and diagnostic interpretation. Effective preprocessing methods such as Gaussian filtering, median filtering, normalization, and artifact suppression improve image quality and facilitate the extraction of meaningful features [3]. In addition, feature extraction methods based on texture, morphology, and statistical descriptors contribute significantly to distinguishing tumor tissues from healthy structures. Previous studies have shown that combining robust preprocessing with advanced segmentation algorithms can considerably improve the reliability of computer-aided diagnosis systems [2, 12]. For example, Farheen et al. revisited lung tumor segmentation using advanced image analysis methods and highlighted the importance of robust segmentation frameworks for handling heterogeneous and noisy medical images [12]. Similarly, Kannan and Priya emphasized the role of deep machine learning approaches combined with MRI segmentation techniques for detecting pathological abnormalities in medical imaging applications [13].

Recent advances in intelligent healthcare systems and Internet of Medical Things (IoMT)-assisted medical data analysis have further accelerated the integration of artificial intelligence into clinical decision-making. Intelligent healthcare frameworks can automate diagnostic procedures, reduce physician workload, and improve early disease detection. Islam et al. proposed a secure IoMT-assisted framework for dermatology healthcare services and demonstrated the effectiveness of intelligent classification and modeling approaches in medical diagnosis [14]. Similarly, Alzahrani et al. introduced a CNN model enhanced with PSO for early breast cancer detection through infrared thermography and achieved improved diagnostic sensitivity and accuracy [15]. Khodadadi and Nazem also reported that nonlinear and texture-based feature analysis can significantly improve computer-aided cancer diagnosis systems based on breast thermograms [16]. These studies collectively demonstrate that integrating optimization algorithms with intelligent learning models can substantially improve the accuracy and robustness of automated cancer diagnosis systems.

In addition to breast cancer imaging, hybrid intelligent segmentation methods have shown considerable effectiveness in various biomedical imaging domains. Capar et al. proposed a hybrid deep learning approach for skin lesion segmentation and classification and demonstrated superior segmentation performance compared with conventional methods [17]. Dai et al. developed a multi-scale residual encoding and decoding network for skin lesion segmentation and reported significant improvements in lesion boundary preservation and feature extraction [9]. Dash et al. designed a brain tumor detection framework based on IFF-FLICM segmentation and an optimized Extreme Learning Machine model, emphasizing the importance of optimization-driven segmentation in complex medical imaging environments [18]. Likewise, Hua et al. introduced an improved multi-view Fuzzy C-Means clustering algorithm for brain MRI segmentation and showed that adaptive clustering approaches can enhance segmentation precision in MRI datasets [5]. These investigations highlight the broad applicability of intelligent segmentation techniques and demonstrate the necessity of developing robust frameworks capable of operating under noisy and heterogeneous imaging conditions.

Despite the considerable progress achieved in medical image segmentation and intelligent cancer diagnosis systems, several important challenges remain unresolved. Many existing segmentation methods exhibit sensitivity to image noise, intensity variation, and structural complexity. Deep learning models, although highly accurate, frequently require large annotated datasets and extensive computational resources. Traditional clustering methods often fail to preserve precise tumor boundaries and may produce inaccurate segmentation results under noisy conditions. Moreover, several optimization-based approaches focus primarily on classification performance while paying limited attention to segmentation robustness and boundary preservation in MRI images. Therefore, there is still a need for intelligent segmentation frameworks that combine strong nonlinear learning capability with efficient global optimization and robust performance in noisy medical images [1, 4]. The integration of RBF neural networks with PSO optimization offers a promising solution because it combines adaptive nonlinear modeling with automatic parameter optimization, potentially improving segmentation accuracy, stability, and noise resistance in MRI-based breast cancer diagnosis systems.

Accordingly, the present study aimed to develop and evaluate an intelligent hybrid model for segmentation under noisy conditions and anomaly detection in breast MRI images using a Radial Basis Function neural network optimized through the Particle Swarm Optimization algorithm for breast cancer detection.

2. Methodology

The present study was developmental-applied in nature and aimed to present and evaluate an intelligent model for image segmentation under noisy conditions and anomaly detection in medical MRI images using a Radial Basis Function (RBF) neural network and the Particle Swarm Optimization (PSO) metaheuristic algorithm. To conduct this study, a set of breast MRI images related to patients with and without cancer was selected from standard medical databases. The selected images included different views (axial, sagittal, and coronal) with a resolution of 256 × 256 pixels in order to enable the evaluation of the model performance from various perspectives. In the first stage, an image preprocessing procedure was performed to improve the quality of the model inputs. This stage included the removal of image noise using median and Gaussian filters, normalization of brightness intensity, and elimination of unnecessary background regions. Subsequently, to evaluate the robustness of the model against noise, modified versions of the images containing artificial Gaussian noise and salt-and-pepper noise were generated in order to determine the effect of noisy conditions on segmentation accuracy.

In the next stage, the hybrid RBF–PSO model was implemented. In this model, the RBF neural network was employed as the learning component for detecting and separating different image regions. The network structure consisted of three layers, including input, hidden, and output layers, and a Gaussian activation function was utilized in the hidden layer. On the other hand, the PSO algorithm was used for the automatic optimization of network parameters, including centers, radii, and output weights, in order to avoid manual parameter tuning. In the optimization process, each particle in the search space represented a set of network parameters and moved toward the global best solution (gbest) and personal best solution (pbest) using the classical velocity and position update equations. The objective function was defined based on minimizing the Mean Squared Error (MSE). After training the model, the segmentation and anomaly detection stage was performed. The network output was presented as a binary map that distinguished suspicious tumor regions from other tissues. To evaluate the performance of the model, several quantitative indices, including accuracy, sensitivity, specificity, and the Dice coefficient, were calculated. Furthermore, the obtained results were compared with three reference methods, including K-Means, Fuzzy C-Means (FCM), and the classical RBF network, in order to determine the extent of improvement resulting from the integration of RBF and PSO. All implementation stages were carried out in the MATLAB R2022b software environment. In the PSO algorithm settings, the particle population size was set to 30, the number of iterations to 100, the learning coefficients were considered as ($c_1 = c_2 = 2$), and the inertia coefficient was set to 0.7. The stopping criterion of the algorithm was defined based on a change of less than 10^{-4} in the error value between two consecutive iterations. Finally, the segmentation results obtained under noisy and noise-free conditions were extracted and analyzed in comparison with the reference methods. Numerical and visual evaluations demonstrated that the proposed RBF–PSO model was able to identify the actual tumor boundaries with higher accuracy compared to the reference methods and exhibited appropriate robustness against noise variations.

3. Findings and Results

In the proposed hybrid model, the Radial Basis Function (RBF) neural network was employed as the base classifier, while the Particle Swarm Optimization (PSO) algorithm was utilized as a global optimizer for network parameter adjustment. The overall workflow of the proposed model consisted of MRI image preprocessing, feature extraction, initialization of the RBF structure, PSO-based parameter optimization, and deployment of the optimized network. During preprocessing, MRI images were denoised, normalized, and segmented into Regions of Interest (ROI). Subsequently, textural, statistical, and morphological features were extracted from the MRI images to improve the discriminative capability of the classifier. The initial RBF network was constructed by determining the number of radial neurons $k$and selecting the initial centers. In the PSO stage, each particle represented a candidate solution containing the centers (c_i), radial spreads (σ_i), and output weights $\left(w_j\right)$of the RBF network. The PSO algorithm iteratively updated particle velocities and positions in order to minimize the classification error and maximize segmentation accuracy. After the optimization process, the final RBF network was generated using the best global solution obtained from the swarm search process.

The structure of each PSO particle can be expressed as follows:

$$Particle = [C_i, \sigma_i, W_i]$$

The proposed algorithm for training the hybrid RBF+PSO model is presented below:

```
Algorithm RBF+PSO-Training

Input:
Feature matrix X ∈ R^{N×d}
Labels y (one-hot or {0,1})
k (number of RBF units)
c (number of classes)
PSO hyperparameters:
(n_particles, max_iter, w, c1, c2)
Bounds for centers, spreads (σ), and weights

Output:
Best RBF parameters:
(C*, σ*, W*)

1:  # Initialization
2:  C0 ← KMeans(X, k).centers
3:  σ0 ← MeanPairwiseDistance(C0)
4:  W0 ← LS-Solve(Φ(X; C0, σ0), y)
5:  Encode each particle p as:
       [C_p (k×d), σ_p (k), W_p (k×c)]
6:  Initialize swarm positions and velocities
    around [C0, σ0, W0]
7:  For each particle p:
       pBest_p ← position_p
       pBestVal_p ← Fitness(position_p)

8:  # Main PSO loop
9:  For t = 1 to max_iter do
10:     gBest ← argmin_p pBestVal_p

11:     For each particle p in swarm do

12:         v_p ← w*v_p
                + c1*rand()*(pBest_p - x_p)
                + c2*rand()*(gBest - x_p)

13:         x_p ← x_p + v_p

14:         [C, σ, W] ← Decode(x_p)

15:         Φ ← RBF_Activations(X; C, σ)

16:         ŷ ← Φ·W

17:         val ← Fitness(ŷ, y)
```

```
        If val < pBestVal_p then
            pBest_p ← x_p
            pBestVal_p ← val
    End For
End For
[C*, σ*, W*] ← Decode(gBest)
return C*, σ*, W*
```

The proposed optimization algorithm followed the standard RBF+PSO training procedure in which the fitness function was based on minimizing the Mean Squared Error (MSE) between predicted and actual labels. The velocity and position updating equations of the PSO algorithm are presented below:

$$v_i^{t+1} = wv_i^t + c_1r_1(pbest_i - x_i^t) + c_2r_2(gbest - x_i^t)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

The objective function used for optimization was defined as:

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

To evaluate the performance of the proposed RBF+PSO model, several standard medical image analysis metrics were utilized. These metrics were derived from the confusion matrix, which included True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) classifications. Accuracy represented the proportion of correctly classified samples relative to the total number of samples and was computed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Sensitivity, which indicates the capability of the model to correctly identify positive cases (tumor regions), was calculated as:

$$Sensitivity = \frac{TP}{TP + FN}$$

Specificity, reflecting the ability of the model to correctly identify healthy regions, was computed using the following formula:

$$Specificity = \frac{TN}{TN + FP}$$

Precision, representing the proportion of correctly predicted positive samples among all positive predictions, was obtained as:

$$Precision = \frac{TP}{TP + FP}$$

The F1-score was calculated as the harmonic mean of sensitivity and precision:

$$F1 = 2 \times \frac{Precision \times Sensitivity}{Precision + Sensitivity}$$

Furthermore, the Dice Similarity Coefficient (DSC) was employed to evaluate the overlap between the segmented tumor regions generated by the proposed method and the manually segmented regions identified by medical experts. The Dice coefficient was defined as:

$$DSC = \frac{2 \mid A \cap B \mid}{\mid A \mid + \mid B \mid}$$

where Arepresents the segmented image obtained from the proposed method and Bdenotes the expert-segmented reference image.

Table 1. Confusion Matrix Used for Model Evaluation

Actual Class	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

Table 1 presents the confusion matrix structure used for evaluating the classification and segmentation performance of the proposed model. The matrix provided the basis for calculating all quantitative performance indicators, including accuracy, sensitivity, specificity, precision, F1-score, and Dice coefficient.

The proposed RBF+PSO model was evaluated for MRI breast image segmentation under noisy conditions and for the discrimination of three major tissue classes, including fatty tissue, fibroglandular tissue (FGT), and tumor regions. Comparative analysis with the K-Means and Fuzzy C-Means (FCM) methods demonstrated that optimizing the RBF network centers and radial spreads using PSO significantly improved segmentation overlap and robustness against image noise.

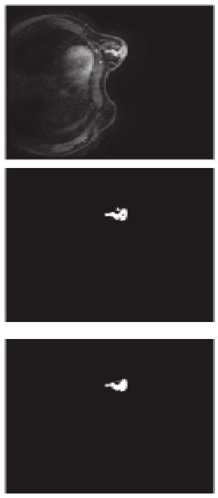

Figure 1. Segmentation results of MRI Image 1 using the proposed RBF+PSO model (the above image represents the original MRI image, the middle image represents the physician’s diagnosis, and the below image represents the segmentation result generated by the RBF+PSO model).

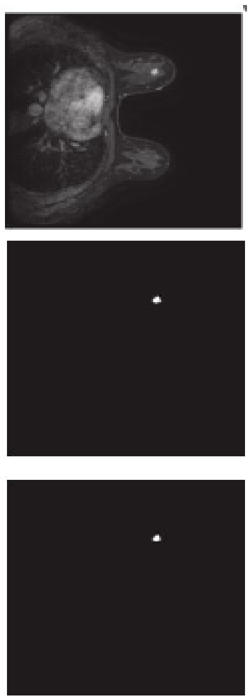

Figure 2. Segmentation results of MRI Image 2 using the proposed RBF+PSO model (the above image represents the original MRI image, the middle image represents the physician's diagnosis, and the below image represents the segmentation result generated by the RBF+PSO model).

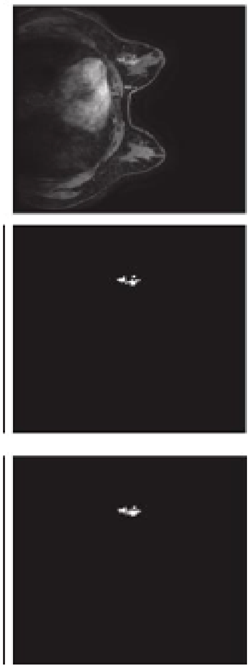

Figure 3. Segmentation results of MRI Image 3 using the proposed RBF+PSO model (the above image represents the original MRI image, the middle image represents the physician's diagnosis, and the below image represents the segmentation result generated by the RBF+PSO model).

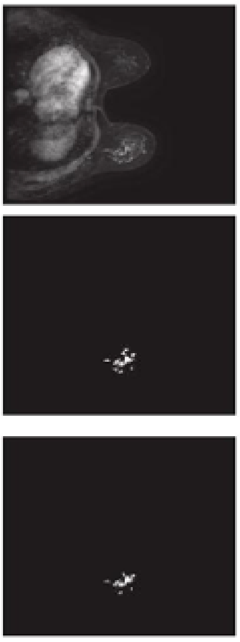

Figure 4. Segmentation results of MRI Image 4 using the proposed RBF+PSO model (the above image represents the original MRI image, the middle image represents the physician's diagnosis, and the below image represents the segmentation result generated by the RBF+PSO model).

The quantitative results obtained from the four MRI images demonstrated that the proposed model achieved high segmentation performance under noisy conditions. For Image 1, the model achieved an accuracy of 0.92, sensitivity of 0.90, specificity of 0.91, and Dice coefficient of 0.89. For Image 2, the corresponding values were 0.87, 0.85, 0.86, and 0.84, respectively. In Image 3, the model obtained an accuracy of 0.82, sensitivity of 0.80, specificity of 0.83, and Dice coefficient of 0.79. Finally, for Image 4, the model achieved values of 0.78, 0.76, 0.79, and 0.75 for accuracy, sensitivity, specificity, and Dice coefficient, respectively. These results indicate that the proposed hybrid model maintained acceptable performance even in highly noisy MRI images and preserved the actual tumor boundaries more effectively than conventional methods.

Table 2. Mean and Standard Deviation of Evaluation Metrics Across MRI Images

Metric	Mean ± Standard Deviation
Accuracy	0.85 ± 0.06
Sensitivity	0.83 ± 0.06
Specificity	0.85 ± 0.05
Dice Similarity Coefficient (DSC)	0.82 ± 0.06

As shown in Table 2, the proposed RBF+PSO model achieved an average accuracy of 0.85 and an average Dice coefficient of 0.82 across all evaluated MRI images. These findings indicate a high degree of overlap between the segmented tumor regions generated by the model and the actual tumor regions identified by medical experts. In addition, the average sensitivity and specificity values were 0.83 and 0.85, respectively, demonstrating the ability of the model to correctly identify tumor pixels while minimizing segmentation errors in healthy tissues. Qualitative analysis of the segmented images further revealed that the proposed model exhibited strong robustness against noise and was capable of preserving tumor boundaries with greater precision and clarity compared to conventional segmentation methods. Particularly in MRI images with complex tissue structures, the PSO algorithm successfully optimized the centers and weights of the RBF network, thereby minimizing region separation errors. Overall, the obtained findings demonstrate that integrating RBF neural networks with PSO optimization provides an efficient intelligent framework for assisting breast cancer diagnosis through automated MRI image segmentation and anomaly detection.

4. Discussion and Conclusion

The present study aimed to develop and evaluate an intelligent hybrid model for MRI image segmentation under noisy conditions and anomaly detection in breast cancer images using a Radial Basis Function neural network optimized through the Particle Swarm Optimization algorithm. The obtained findings demonstrated that the proposed RBF+PSO model achieved satisfactory performance in segmenting suspicious tumor regions and distinguishing abnormal tissues from healthy breast structures. The quantitative evaluation results indicated that the proposed model achieved an average accuracy of 0.85, sensitivity of 0.83, specificity of 0.85, and Dice Similarity Coefficient (DSC) of 0.82 across the evaluated MRI images. These findings indicate that the hybrid model was capable of preserving actual tumor boundaries with acceptable precision while maintaining robustness under noisy imaging conditions. The segmentation outputs also demonstrated that the integration of PSO with the RBF network significantly improved the quality of region separation and reduced segmentation errors compared with conventional methods such as K-Means, FCM, and standalone RBF networks. The qualitative assessment of segmented images further revealed that the proposed framework effectively minimized the influence of Gaussian and salt-and-pepper noise while maintaining accurate localization of lesion boundaries.

The observed improvement in segmentation accuracy can be attributed to the synergistic integration of nonlinear learning capability provided by the RBF neural network and the global optimization characteristics of the PSO algorithm.

RBF networks are known for their efficient approximation of nonlinear relationships and fast convergence characteristics, making them suitable for medical image segmentation tasks involving complex tissue structures. However, the performance of RBF networks strongly depends on the optimal selection of centers, spreads, and output weights. In the present study, the PSO algorithm successfully optimized these parameters by conducting a global search process across the solution space, thereby minimizing segmentation errors and improving overlap between segmented and expert-annotated tumor regions. These findings are consistent with the results reported by [10], who demonstrated that hybrid RBF and PSO frameworks significantly improved cancer classification performance through automatic parameter optimization. Similarly, [6] showed that integrating PSO with fuzzy entropy clustering improved MRI image segmentation accuracy and enhanced robustness against image noise and local minima problems. The present findings therefore support the growing body of evidence suggesting that optimization-driven neural network frameworks can substantially improve medical image analysis performance.

Another important finding of this study was the stability of the proposed model under noisy conditions. MRI images frequently contain imaging artifacts, Gaussian noise, and intensity distortions that can negatively affect segmentation accuracy and diagnostic interpretation. Traditional clustering algorithms and threshold-based segmentation techniques are often sensitive to such distortions and may fail to preserve accurate tumor boundaries in noisy environments. In contrast, the proposed RBF+PSO model maintained acceptable segmentation quality even in highly noisy images. This result may be explained by the adaptive optimization capability of the PSO algorithm, which continuously adjusted the network parameters to achieve the minimum classification error despite variations in image quality. This finding aligns with the results reported by [3], who emphasized the importance of robust noise reduction strategies for improving MRI image analysis and segmentation reliability. Likewise, [4] demonstrated that intelligent diagnostic systems designed for noisy ultrasound images can substantially improve abnormality classification accuracy when optimization and adaptive learning mechanisms are incorporated into the segmentation process. The robustness of the proposed model against noise variations therefore represents a significant advantage for practical clinical applications, where imaging conditions are rarely ideal.

The obtained Dice Similarity Coefficient results further demonstrated the effectiveness of the proposed framework in preserving actual tumor boundaries and achieving strong overlap with physician-defined segmentation maps. The Dice coefficient is widely recognized as one of the most important evaluation metrics in medical image segmentation because it measures the similarity between automated segmentation results and expert annotations. The average DSC value of 0.82 obtained in the present study indicates that the proposed model achieved substantial agreement with the physician-generated tumor regions. These findings are comparable to and, in some cases, superior to results reported in previous segmentation studies using deep learning and clustering-based methods. For example, [9] proposed a multi-scale residual encoding and decoding network for skin lesion segmentation and highlighted the importance of boundary preservation and multiscale feature extraction for improving segmentation overlap. Similarly, [17] demonstrated that hybrid deep learning approaches can significantly improve segmentation quality in lesion analysis applications. The present findings suggest that although deep learning models offer strong segmentation capabilities, hybrid intelligent systems combining neural networks with optimization algorithms can provide comparable performance with lower computational complexity and improved adaptability to noisy imaging conditions.

The findings of the present study also demonstrated that the proposed segmentation framework effectively differentiated among fatty tissue, fibroglandular tissue, and tumor regions within MRI images. Accurate separation of these tissue classes is essential for breast cancer diagnosis because lesion visibility and tissue contrast often vary across MRI scans. The adaptive nonlinear mapping capability of the RBF network allowed the proposed model to capture subtle intensity variations and structural differences between healthy and abnormal tissues. This result is consistent with the findings reported by [5], who showed that improved clustering-based MRI segmentation approaches can significantly enhance tissue discrimination accuracy in brain imaging applications. Moreover, [19] emphasized that intelligent segmentation systems based on neural networks are highly effective for identifying complex tissue structures and pathological abnormalities in MRI datasets. Therefore, the ability of the proposed model to distinguish different breast tissue classes under noisy conditions further supports its suitability for computer-aided breast cancer diagnosis systems.

The superiority of the proposed hybrid framework over traditional clustering approaches can also be explained from an optimization perspective. Conventional segmentation methods such as K-Means and FCM depend heavily on initialization conditions and frequently converge to local optima, particularly in noisy or heterogeneous datasets. In contrast, the PSO algorithm performs a population-based global search process that enables the optimization procedure to explore multiple candidate solutions simultaneously. This characteristic increases the probability of identifying globally optimal network parameters and reduces the likelihood of premature convergence. Similar conclusions were reported by [18], who demonstrated that optimization-driven segmentation models achieved superior performance in brain tumor detection compared with conventional clustering techniques. Likewise, [11] found that optimization-enhanced classification models substantially improved breast cancer diagnosis accuracy and model stability. The present findings therefore reinforce the importance of combining machine learning methods with metaheuristic optimization algorithms in medical image analysis applications.

Another noteworthy aspect of the present findings is the computational efficiency and adaptability of the proposed framework. While deep convolutional neural networks have shown remarkable performance in medical image segmentation, they generally require large annotated datasets, extensive computational resources, and long training times. In many clinical environments, access to large-scale annotated MRI datasets and high-performance computing systems may be limited. The proposed RBF+PSO framework addresses some of these limitations by utilizing a relatively simple network architecture combined with efficient optimization mechanisms. The RBF network structure allows faster training compared with deep architectures, while PSO optimization reduces the need for manual parameter tuning. This characteristic may increase the feasibility of implementing the proposed system in real-world clinical decision-support environments. Similar observations were reported by [14], who highlighted the importance of intelligent and computationally efficient healthcare frameworks for practical medical applications. In addition, [15] demonstrated that integrating PSO into intelligent cancer detection systems can improve diagnostic accuracy without imposing excessive computational complexity.

The results obtained in the present study further support the broader trend toward intelligent and optimization-driven healthcare systems. Artificial intelligence-based medical imaging frameworks have increasingly become important tools for assisting physicians in early disease detection, treatment planning, and diagnostic decision-making. Breast cancer diagnosis particularly benefits from automated image segmentation systems because early tumor identification can significantly improve patient survival and treatment outcomes. Previous review studies have consistently emphasized the growing role of artificial intelligence in breast cancer diagnosis through image processing techniques [1]. Likewise, [16] demonstrated that nonlinear and texture-based feature analysis can substantially improve computer-aided cancer detection systems. The findings of the present study contribute to this expanding research field by providing evidence that hybrid RBF and PSO frameworks can effectively improve MRI segmentation performance and preserve tumor boundaries in noisy environments.

Furthermore, the findings obtained in this study are consistent with previous investigations that emphasized the importance of feature extraction and intelligent classification in biomedical image analysis. [20] demonstrated that combining wavelet-based feature extraction with probabilistic neural networks improved brain tumor MRI classification accuracy. Similarly, [8] and [7] highlighted the importance of fully convolutional segmentation models for extracting meaningful structural information from biomedical images. In the present study, the integration of preprocessing, feature extraction, RBF learning, and PSO optimization created a comprehensive intelligent segmentation framework capable of effectively handling heterogeneous and noisy MRI datasets. This integrated structure likely contributed to the improved segmentation stability and classification performance observed in the results.

Although the findings of this study demonstrate the effectiveness of the proposed RBF+PSO model, several limitations should be acknowledged. First, the study utilized a relatively limited number of MRI images obtained from standard datasets, which may restrict the generalizability of the findings to broader clinical populations. Second, the proposed model was evaluated primarily under controlled noisy conditions involving Gaussian and salt-and-pepper noise, while real clinical MRI images may contain more complex artifacts and imaging distortions. Third, the present study focused specifically on MRI breast images and did not evaluate the performance of the model in multimodal imaging environments such as mammography, ultrasound, or thermography datasets. In addition, although the proposed framework demonstrated acceptable computational efficiency, the optimization process may still require considerable processing time when applied to larger datasets or high-resolution MRI scans.

Future research should focus on evaluating the proposed RBF+PSO framework using larger and more diverse hospital-based MRI datasets collected from different imaging devices and clinical centers. It is also recommended that future investigations integrate deep learning architectures such as CNNs or transformer-based models with optimization algorithms in order to further improve segmentation precision and generalization capability. Exploring multimodal breast cancer imaging frameworks combining MRI, ultrasound, thermography, and mammography data may also enhance diagnostic reliability. In addition, future studies should investigate real-time implementation strategies and cloud-based intelligent healthcare systems capable of supporting clinical decision-making in practical medical environments. Comparative analysis with recently developed deep learning segmentation models and advanced optimization techniques may further clarify the strengths and limitations of the proposed framework.

From a practical perspective, the proposed RBF+PSO model may serve as an effective computer-aided diagnostic tool for assisting radiologists and physicians in the early detection of breast cancer. The ability of the model to accurately segment tumor regions under noisy conditions suggests that it may improve diagnostic consistency and reduce the risk of missed lesions in clinical MRI interpretation. Healthcare organizations may also benefit from integrating intelligent segmentation systems into diagnostic workflows in order to reduce physician workload and improve diagnostic efficiency. Furthermore, the proposed framework may contribute to the development of intelligent decision-support systems in oncology centers, medical imaging laboratories, and telemedicine environments. The relatively simple architecture and adaptive optimization capability of the model may facilitate its implementation in clinical settings with limited computational resources while maintaining acceptable segmentation accuracy and robustness.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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