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Microcalcification Detection in Mammograms Using Particle Swarm Optimization and Probabilistic Neural Network

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Abstract. Breast cancer is the most typical form of cancer among the female population and the most common form of cancer-related death. However, if the cancer is detected at an early stage, treatment may be more effective. Mammography is one of the most used imaging modalities for the early breast cancer diagnosis. The present paper proposes an intelligent system for the detection and analysis of microcalcifications in mammography using the region growing algorithm, the particle swarm optimization algorithm (PSO), and the Probabilistic neural network (PNN) to detect the presence of breast cancer as early as possible and to avoid resorting to ablation of the breast.

Keywords. Breast cancer, mammography, microcalcification, region growing segmentation, particle swarm optimization, probabilistic neural network.

1 Introduction

Breast cancer is one of the common malignant tumors among women and is the second leading cause of cancer-related death from a tumor that can often be seen on an X-ray or felt as a lump. The tumor is malignant (cancerous) if the cells can grow into surrounding tissues or spread (metastasize) to distant areas of the body.

Cancers that are found early, when they are small and have not spread, are easier to treat and have better outcomes. Microcalcification is the first sign of breast cancer, for now, screening mammography is the only method available for the reliable detection of early and potentially curable breast cancer.

However, radiologists have difficulties to evaluate the enormous number of mammograms generated in widespread screening and breast lesions are missed during routine screening. The aids of computer systems are used by radiologists for breast cancer diagnosis.

It is usually very difficult to distinguish benign from malignant MCCs because of the variability of their appearance. The features are using to classify microcalcifications into benign and malignant. Several methods have been used in the literature for the classification and interpretation of mammographic images: for the analysis and classification of abnormalities in mammograms, a variety of methods have been proposed and are generally categorized as follows: statistical methods [1], method based wavelets [2], method based Markov models [3], and methods using machine learning [4].

In this paper, we propose a new solution to the problem of computer-aided detection and interpretation of breast cancer. In the proposed approach, a region growing algorithm is used for mammogram segmentation. Then, Particle Swarm Optimization is used to train a Probabilistic Neural Network in order to estimate the optimal value of the parameter σ, and classification is done by the PNN network to identify the severity of the abnormality, which can be benign or malignant. The proposed system is tested on images from the Digital Database for Screening Mammography (DDSM).

The experimental results show the efficiency of the proposed approach, resulting in an accuracy

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rate of 96%, sensitivity of 94%, and good specificity of 98%.

The rest of the paper organized as follows: Section 2 describes related works; Section 3 presents in detail the different stages of our proposed approach; Section 4 presents the experimental results; and we offer the conclusion of our work in Section5.

2 Related Works

In recent times, many research and development activities focused on early breast cancer detection since the mortality rate is higher compared to other types of cancer. A variety of approaches have been proposed for analysis and interpretation of mammogram images.

Anuradha C. Phadke et al. [5] developed an approach for the detection and classification of microcalcifications in mammograms by decomposing the mammograms into different frequency sub bands using wavelet transforms, scaling the high frequency sub band, and finally reconstructing the mammogram using a scaled high-frequency sub band. Microcalcifications classification into benign and malignant classes is based on wavelet transformation and two types of classifiers: Support Vector Machine and Artificial Neural Network Classifier.

R. Pavitha and T. Joyce Selva Hephzibah [6] proposed an approach for the detection and classification of breast cancer based on a wavelet transform and co-occurrence matrix for extracting texture characteristics and Probabilistic Neural Networks (PNNs).

Soniya D. Wawhal and Sarang D. Patil [7] developed a method for the detection and classification of breast cancer using a thresholding algorithm for the segmentation step, a wavelet transform for parameter extraction of the segmented image, and classification by PNNs.

Usha and Arumugam [8] proposed an automatic mammogram classification technique using wavelets, a Gabor filter, and a nearest neighbor algorithm to classify benign and malignant tumors.

Deepa Sankar et al. [9] presented a method to classify mammograms into normal ones with benign and malignant microcalcifications and with malignant and benign tumors using fractal features derived from fractal dimensions.

K. K. Rajkumar and G. Raju [13] proposed a method of segmentation of0mammographic images in three phases: automatic choice of the initial germ, identification of the region of interest by a region growing algorithm, and segmentation of this region by a gradient operator.

R. Saranya et al. [11] developed a method to detect and classify microcalcifications in mammography, improved the original image, and eliminated noise using a median filter. Then, they used a region growing algorithm for the segmentation and extraction of the characteristics of segmented regions and for classification using an artificial neural network.

Imad M. Zyout [12] developed a system to aid in the diagnosis of microcalcifications present in mammographic images. First, he segmented the mammographic images using mathematical morphology, and then used PSOs to extract the parameters from the segmented regions. Finally, he used SVMs for the classification step.

Subashini Sundaravinayagam and Bhavani Sankari [13] proposed hybridization between GA genetic algorithms, PSOs, and the nearest-neighbor KNN method for detecting and classifying masses present in mammographic images. For this purpose, they used the gray-level co-occurrence matrix (GLCM) to extract the characteristics of the mammographic images, and then applied a hybrid method called GA-PSO for the selection of the optimal parameters to be used as entered for the classification step using the nearest-neighbor KNN method.

V. Sathya Priya et al. [14] proposed a novel method for the classification of microcalcification clusters in mammograms. They segmented the original image using a k-means algorithm, extracted characteristics by the graph method, and classified suspicious areas by using an artificial neural network.

An ANN and Adaboost application for the automatic detection of microcalcifications in breast cancer was proposed in [15]. In the first stage, all suspicious regions from the mammogram were segmented out. In the next stage, these suspected regions were fed to an ANN classifier, which then detected whether the region was normal, benign, or malignant.

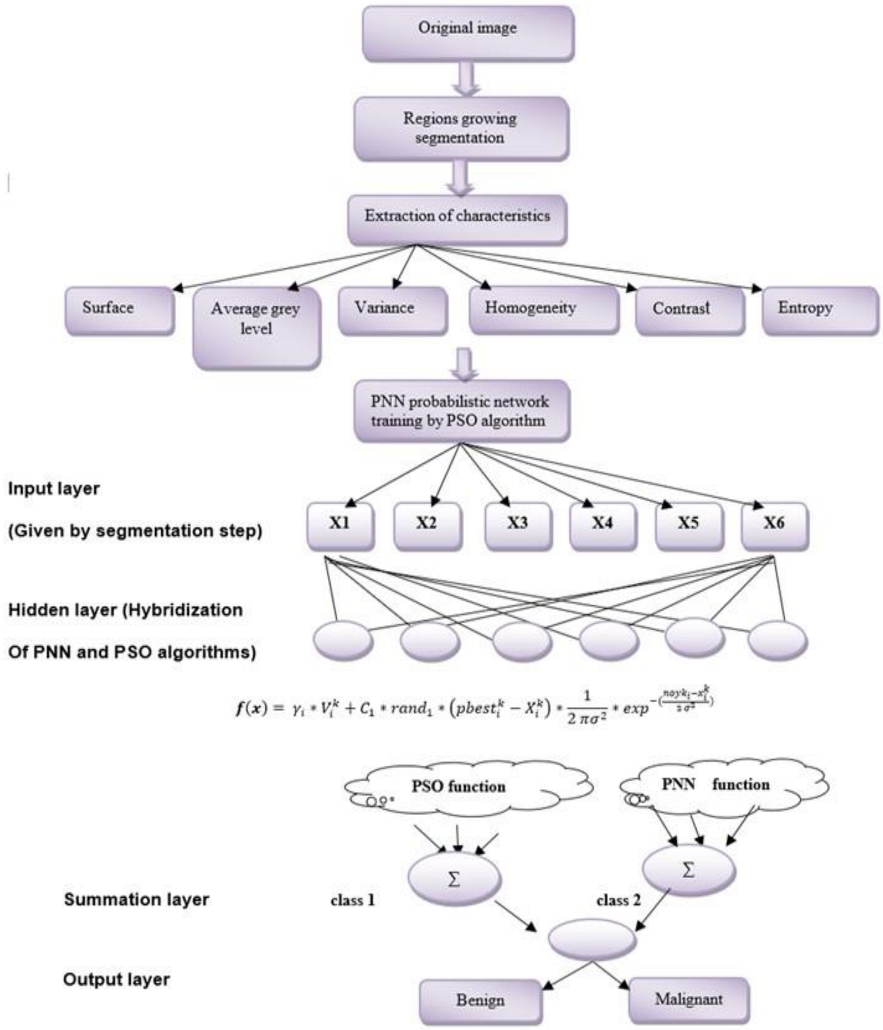

Fig. 1. Steps of proposed approach

M. Mohsin Jadoon et al. [16] proposed a novel classification technique for mammograms. The proposed model targets a three-class classification study (normal, malignant, and benign cases). In this model, they presented two methods: convolutional neural network-discrete wavelet (CNN-DW) and convolutional neural network-curvelet transform (CNN-CT). To enhance the contrast of the mammogram images, the data set is filtered by contrast-limited adaptive histogram equalization (CLAHE). In the CNN-DW method, enhanced mammogram images are decomposed into four sub bands by means of a two-dimensional discrete wavelet transform (2D-DWT), while in the second method, a discrete curvelet transform (DCT) is used. In both methods, the dense scale-invariant feature (DSIFT) for all sub bands is extracted. An input data matrix containing these sub band features of all mammogram patches is created and is processed as the input to a CNN. A Softmax layer and SVM layer are used to train the CNN for classification.

Brundhak et al. [17] proposed a computer-aided detection and diagnosis system for breast cancer. In the proposed method, breasts are first partitioned adaptively into regions.

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The GLCM features are extracted from wavelet sub bands. Then, features derived from the detection of lesions (masses and microcalcifications) and textural features are extracted from each region and combined in order to classify mammography examinations as “normal” or “abnormal”. Whenever an abnormal examination record is detected, the regions that induced that automated diagnosis can be highlighted. Manual segmentations of lesions are used to train a BPN that assigns an anomaly index to each region. Local anomaly indices are then combined into a global anomaly index.

Y. Patil and S. A. Patil [18] proposed an automatic system for the mass segmentation on mammograms. This method used the Otsu segmentation method for foreground detection and the gray-level co-occurrence matrix method for feature extraction and the PNN classifier.

T. Gopalakrishnan, J. Rajeesh, and S. Palanikumar [19] proposed a technique for the automated diagnosis of breast cancer histopathology images. They used a k-means algorithm for the segmentation step and a wavelet algorithm for feature vector extraction and classification.

Deepa Parasar and Vijay R. Rathod [20] proposed a segmentation algorithm for fetus ultrasound images using PSO and a k-means clustering algorithm with a fuzzy filter. They eliminated the noise present in the images using a fuzzy filter, and then they hybridized the algorithm of the PSO and the k-means algorithm in order to segment the image.

Fouzia Boutaouche and Nacéra Benamrane [21] proposed a method for detection and interpretation for breast cancer. A Local Chan-Vese (LCV) model is used for the mass lesion segmentation step to detect a suspected abnormality in a mammogram. The classification approach is based on the hierarchical fuzzy partitioning (HFP) for fuzzy partitions construction. Fuzzy decision trees are used to detect the class of the abnormality and its severity.

Nashid Alam et al. [22] proposed an approach for classification of malignant and benign microcalcification cluster in digital mammograms based on morphological operations and a stack generalization classifier.

Birmohan and Manpreet [23] proposed a method for classification of malignant and benign microcalcification clusters using morphological operations and Support Vector Machine method.

3 Proposed Approach

Our proposed approach uses region growing, PSO, and PNN (see Figure 1).

3.1 Region Growing Segmentation

A region is a set of connected pixels with similar properties. Region growing starts from seeds, and the region is grown based on specified criteria. Region-based approaches group pixels with the same properties, combining nearness and correlation. Region-based paths are based on the properties of pixels such as the identity and spatial nearness [24].

Image segmentation by region growth consists of growing a region from an initial pixel named seed. Neighboring pixels will be added to this region if they check a predicate of homogeneity; otherwise, a new region is created. During the region growing phase, pixels near the seed are added to the region based on homogeneity criteria, thereby resulting in a connected region [25].

In the region growing algorithm, an agglomeration condition implies the definition of a similarity term between a candidate point and the segmented region. This criterion is used by the predicate to decide whether to add a pixel. In practice, the criterion almost always implies a homogeneity measure on the point intensities of the segmented region [26].

The aggregation process of new regions stops according to two conditions:

- If all regions have been formed and there are no more pixel candidates.
- If the criterion is no longer satisfied for all pixels neighboring the region being formed.

For each region of the segmented image, the following parameters are extracted:

Surface (*S*): Sum of the pixels constituting a region *R*.

Average Gray Level (*NGM*): The average gray level of a region *R* is the average of the gray levels of all pixels in the region:

$$NGM = \frac{\sum I[i][j]}{S(R)} \qquad i = 0, \dots \dots, n . \tag{1}$$

Variance (*var*): This attribute characterizes the variation of gray levels in a region *R*:

$$var = \frac{\sum (I[i][j] - NGM)^2}{S(R)} . \tag{2}$$

Perimeter (*Per*): *Per* is the sum of the length of each side of the boundary (*B*) of ROI:

$$Per = \sum_{x \in B} x . \tag{3}$$

Compactness (*com*): This is also called a circularity factor and is defined:

$$com = \frac{4\pi * S(R)}{per^2} . \tag{4}$$

Homogeneity: This characterizes the texture of a region. The more the same pair of pixels is found, the higher the index, calculated as follows:

$$Ho = \sum_x \sum_y \frac{p(x,y)}{1 + (x-y)^2} . \tag{5}$$

Contrast: The contrast of the image represents a measure of the magnitude of the local variation of the image. Contrast features extracted are used in classification to locate microcalcifications:

$$c = \sum_x \sum_y (x - y) I(x,y) . \tag{6}$$

Entropy: This is a measure of the randomization of the gray-level values. A low entropy value means that the elements of the matrix are very dependent on each other:

$$e = \sum_x \sum_y p(x,y) log[p(x,y)] , \tag{7}$$

where ***p*** is the probability of occurrence of a pixel value and I ***(x, y)*** the intensity of the pixel.

3.2 Particle Swarm Optimization (PSO)

PSO, introduced by Eberhart and Kennedy in 1995, is a population-based heuristic search approach inspired by the social behavior of flocks of birds and schools of fish. In this case, a group of individuals (particles) located in a given environment searches for the optimal solution.

The set of particles is initialized with random data; that a particle moves to the optimal position of the individual or swarm it will depend on the value of the weight parameter. In addition, the particles move with certain randomness, allowing a particle to come out of its current situation, hence the local optimum. PSO algorithm has the fastest search speed, and its particles have memories [27].

A swarm of particles is defined by:

- The number of particles constituting the swarm.
- The maximum velocity of a particle.
- The inertia of a particle.
- Weighting coefficients.

The velocity and position vectors of particle *i* are modified as follows [28]:

$$V_i^{k+1} = \gamma_i * V_i^k + C_1 * rand_1 * \left(pbest_i^k - X_i^k\right) + C_2 * rand_2 * \left(gbest^k - X_i^k\right) , \tag{8}$$

$$X_i^{k+1} = X_i^k + V_i^k , \tag{9}$$

where X_i^k and V_i^k are, respectively, the position and velocity (inertia) of the *i*th particle at the *k*th iteration; $pbest_i^k$ is the best position found by the particle, and $gbest^k$ is the best position found by all particles.

γ_i is a weighting function, C_1 and C_2 are positive weighting factors (positive weight factors), and $rand_1$ and $rand_2$ are random numbers between 0 and 1.

Particle Swarm Optimization Algorithm

Step 1: Initialize each particle vector of the swarm by assigning a random velocity and position in the search space.

Step 2: Calculate the fitness function of each particle and compare it with that of its best personal value ($\boldsymbol{fitpbest_i^{k-1}}$). If the current value is better than the value ($\boldsymbol{fitpbest_i^{k-1}}$), update the value of ($\boldsymbol{fitpbest_i^{k}}$) and its best position ($\boldsymbol{pbest_i^{k}}$).

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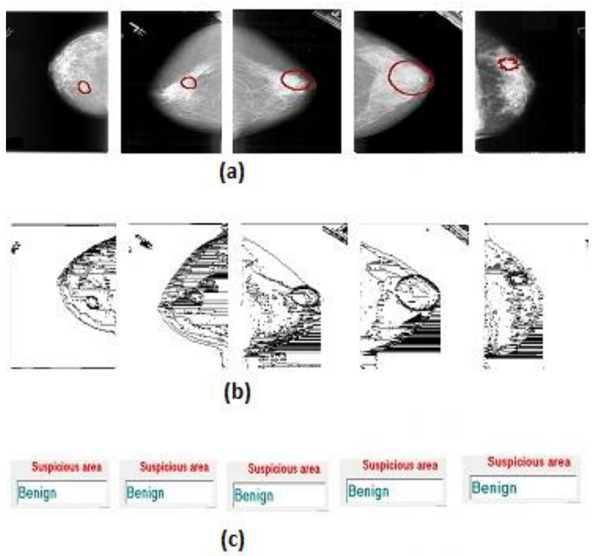

Fig. 2. (a) Original benign image, (b) segmented image, and (c) result of analysis

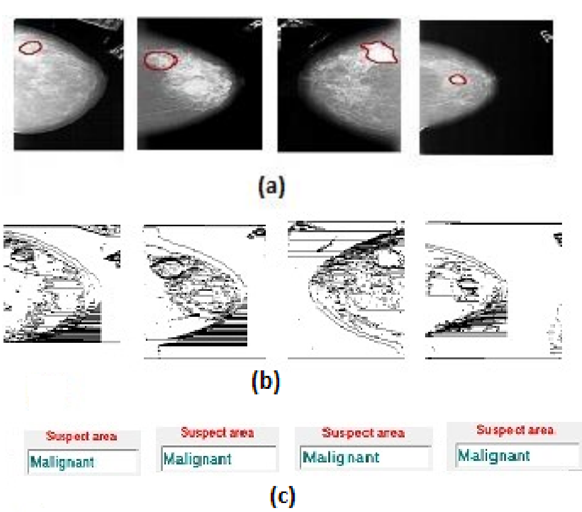

Fig. 3. (a) Original malignant image, (b) segmented image, and (c) result of analysis

Step 3: Identify the particle that has the best fitness function. The value of its fitness function is identified as ($\boldsymbol{fitgbest^k}$) and its position as ($\boldsymbol{gbest^k}$).

Step 4: Actualize the velocities (V_i^{k+1}) using equation 2.1 and the positions (X_i^{k+1}) using equation 2.2 for all particles.

Step 5: Replace the initial particle vectors in Step 2 with the updated particle vectors.

Step 6: Repeat steps 2-5 until the stop criterion is met (maximum number of iterations or convergence to the correct fitness value).

3.3 Probabilistic Neural Network

A probabilistic neural network is based on a Bayesian classification and a probabilistic estimation of the density function (PDF) [29].

It is a class of radial basic function (RBF) network, which is useful for automatic pattern recognition nonlinear mapping and the estimation of probabilities of class membership and likelihood ratios.

A PNN is formed of nodes with four layers as input and output layers. RBF was introduced by D. F. Specht. Owing of their effectiveness in solving classification problems, they have quickly become a reference tool in the field of neural classification. PNNs offer many advantages: they do not suffer from the local minima problem as MLPs do, learning is very fast since the network is created after a single pass on the learning set, they can be used interactively, and the principle itself has a very solid mathematical basis.

In contrast to MLP networks, probabilistic networks use radial functions rather than sigmoid activation functions to construct a local decision function centered on a subset of the input space. To solve the problem of local minima, the global decision function is defined as the sum of all the local functions [30]. APNN employs radial and spherical Gaussian functions centered on each learning vector. The probability of a vector belonging to a certain class can be expressed as follows:

$$F_{i(X)} = \frac{1}{2\pi p^{p/2}\sigma^p M_i}\sum_{j=1}^{M} \exp\left(-\frac{(X-X_{ij})^T(X-X_{ij})}{2\sigma^2}\right), \qquad (10)$$

where *i* is the number of classes, *j* is the number of forms to be recognized, $\boldsymbol{X_{ij}}$ is the *j*th training vector of class *i*, *x* is a test vector, M_i is the number of learning vectors of class *i*, *P* is the dimension of the vector *X*, *σ* is the smoothing factor (standard deviation), and $\boldsymbol{F_{i(X)}}$ is the sum of the multivariable spherical Gaussian centered on thelearning

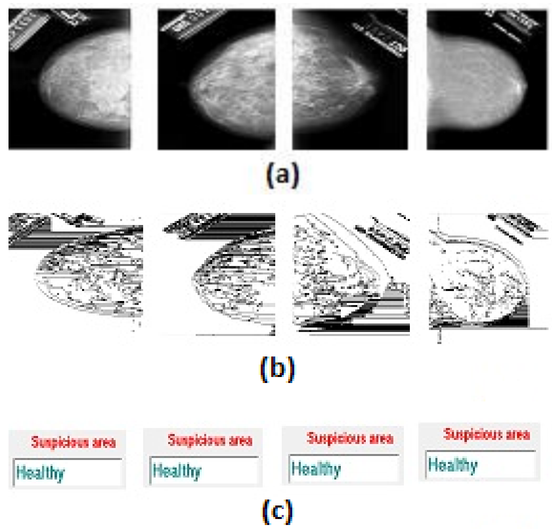

Fig. 4. (a) Original healthy image, (b) segmented image, and (c) result of analysis

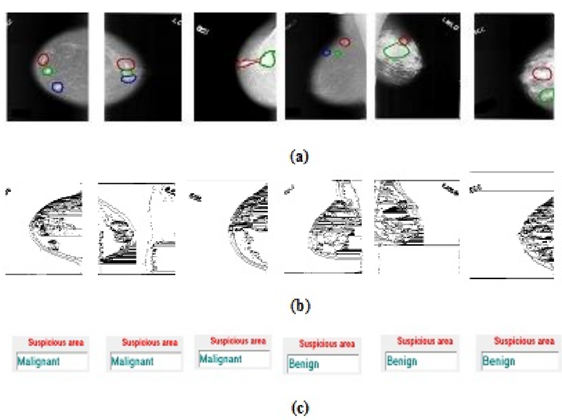

Fig. 5. (a) Original images with several suspicious areas, (b) segmented images, and (c) result of analysis.

vectors used to estimate the probability density function of class i. Classification decisions are made according to a Bayes decision rule:

$$d(x) = Ci \; if \; F_i(x) > F_k(x) \; for \; k \neq i \, , \qquad (11)$$

where $\boldsymbol{Ci}$ is the class of *i* [31].

This type of network consists essentially of four layers:

1. The input layer: contains the variables presented as input to the system.
2. The processing layer: (or the hidden layer) uses radial-based Gaussian functions.
3. The classification layer: also known as the summation or competition layer.
4. The output layer.

The input neurons number is equal to six variables. The number of hidden neurons is equal to the number of input variables.

For each sample of the learning base, a neuron is created in the hidden layer with the corresponding connections to the input neurons so that $w_k = x_k$ for $k = 1, 2, ..., n$. A single connection is then created on the neuron of the classification layer corresponding to the class of the sample. The global decision function is the sum of all local functions**.**

The summation layer sums the Gaussian functions of each class that were generated in the previous steps. In this way, there will be two probabilities corresponding to the two malignant and benign classes, and the class that has the highest probability is declared a winner and presented at the exit layer.

PNN Algorithm

Step 1: Extract the characteristics of the segmented regions using the region growing algorithm.

Step 2: Use the extracted features as input to the PNN neural network.

Step 3: Calculate the objective function *f(x)*, which represents the hybridization between the Gaussian function of the PNN network and the function of the PSO algorithm for these characteristics at the level of the hidden nodes.

Step 4: The resulting values are given as input to the single output node.

Step 5: Calculate the sum of all the inputs of the output node and multiply the result by an optimal constant.

Step 6: look for as many classes as possible. Assign 1 to the maximum of these classes and 0 to the other classes.

4. Experimental Results

We tested our approach on the digital mammograms of the Digital Database for

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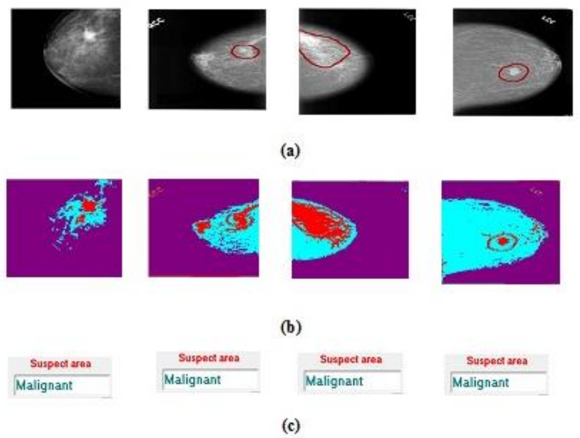

Fig. 6. (a) Original malignant image, (b) segmented image, and(c) result of hybridized PSO/PNN

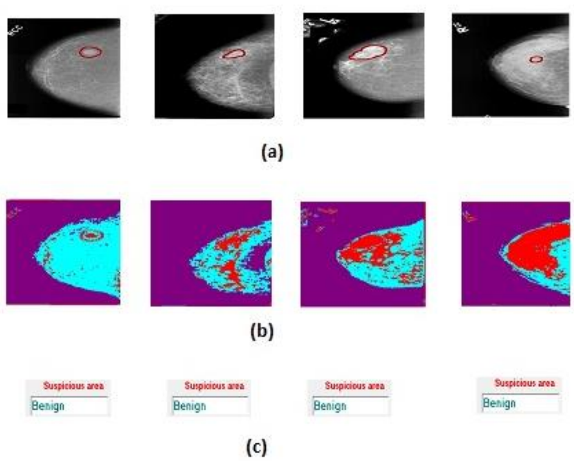

Fig. 7. (a) Original benign image, (b) segmented image, and (c) result of analysis

Screening Mammography (DDSM)[1]. The database consists of 110 images in two categories: benign and malign. Figures 2 and 3 show the results of detecting and analyzing microcalcification using the proposed method.

We tested the proposed approach on a set of 28 healthy images and another set of 16 images with several suspicious areas. We obtained a recognition rate of 89.28% for healthy images and 87.5% for images with multiple suspicious areas.

To evaluate our approach, we used the following evaluation parameters:

γ_i = 0.03,
V_i^k = 0.02,
C_1 = 2,
$rand_1$ = 0.6,
$pbest_i^k$ = Current position of pixel x_i,
$noyk_i$= Value of the Gaussian kernel,
σ = 0.5.

Sensitivity: The capacity of a classifier to identify the positive results quantitatively. This is given as:

$$\text{SE} = \frac{TP}{TP+FN} * 100.$$

Specificity: Capacity of a classifier to identify the negative results. This is given as:

$$\text{SP} = \frac{TN}{TN+FP} * 100.$$

Accuracy: Determines the efficiency of the classifier in terms of true positive and true negatives, indicating the proportion of true results:

$$\text{AC} = \frac{TP+TN}{TN+TP+FP+FN} * 100.$$

We used the same set of images to test our proposed approach with our previous segmentation method [32]. In the first step, we applied a wavelet transform at level 2, and extracted the characteristics; which are used as input for the k-means classifier and refined by a Parzen window algorithm.

In the second step, we applied the hybridization of the PSO algorithm with the PNN probabilistic neuron network with parameter σ = 0.3 for interpretation phase and we obtained the following showed in figure 6 and 7.

Table 1 is a comparison of the results between our proposed approach and our previous method of segmentation with particle swarm optimization and a probabilistic network.

We obtained a sensitivity of 82.27%, a specificity of 52.72% and an accuracy of 70% for mammographic images from the DDSM database.

From the obtained results, we observe that the approach proposed in this article tested on the same sets of images from the DDSM database

[1] http://marathon.com/.csee.usf.edu/Mammography /Database.html

Table 1. Comparison of results between proposed approach and previous method of segmentation with particle swarm optimization and probabilistic network

Nbr of examples	Technique	Sensitivity	Specificity	Accuracy
55 benign images 55 malignant images	Our proposed approach	94%	98%	96%
55 benign images 55 malignant images	Our previod segmetation aprproach [32], particle swarm optimization and Probabilistic network	82.27%	52.72%	70%

Table 2. Comparison between proposed method and other methods.

		Nbr of exemples	Technique	Sensitivity	Specificity	Accuracy
Our proposed approach	DDSM Database	55 malignant images 55 benign images	Region growing algorithm, particle swarm optimization and probabilistic network	94%	98%	96%
Nashid Alam et. al. [22]	DDSM Database	132 malignant images 148 benign images	Morphological features and stack generalization based classifier			76.28%
Birmohan et Manpreet	DDSM Database	276 malignant images 155 benign images	Morphological operations and support vector machine	96.57%	89.57%	94.25%

gives better results in terms of sensitivity, specificity and accuracy.

To test the effectiveness of our approach, we compared the proposed approach with two other methods from the literature using the same DDSM database, basing our comparison on sensitivity, specificity and accuracy (see Table 2).

Nashid Alam et al [22] achieved an accuracy of 76.28% and Birmohan et al [23] achieved a sensetivity of 96.57%, a speseficity of 89.57% and an accuracy of 94.25%.

Compared with these two methods, the obtained results of the proposed approach show an improvement in classification performance in terms of specificity and accuracy.

5. Conclusion

In this paper, we proposed a novel approach for the detection, analysis, and classification of microcalcifications on mammograms. The proposed approach is based on segmentation steps by region growing, extraction of the characteristic step by a PSO algorithm, and a classification step by using PNNs.

The proposed combinatorial algorithm proved to be efficient in the feature extraction, segmentation, and classification of mammogram images. We achieved an average accuracy of 96%, sensitivity of 94%, and specificity of 98% by using 110 mammogram images taken from the DDSM database. The proposed approach gives promising results.

As future work, we propose to use more parameters as input to the PNN. We can change the parameters for the PSO algorithm; and we can use another database to validate the sensitivity, specificity, and accuracy rate.

Appendix. Abbreviation list

We use the following abbreviations:

- Mccs: Microcalcifications.
- PSO: Particle Swarm Optimization.
- SVM: Support Vector Machine.
- GA: Genetic Algorithms.
- KNN: K nearest neighbors.
- ANN: Artificial Neural Network.
- BPN: Back Propagation Network.
- ROI: Region of interest.
- MLP: Multi-Layer Perceptron.

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