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Hamzeh Ghorbani, Sahar Lajmorak, Simin Ghorbani,
Parvin Ghorbani, Nina Khlghatyan, Harutyun Stepanyan,
Samaneh Bahrami, Seyed Mohammad Rasaei,
Mehdi Ahmadi Alvar and Rituraj Rituraj

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Hamzeh Ghorbani
Faculty of General Medicine, University of Traditional Medicine of Armenia (UTMA), 38a Marshal Babajanyan St., Yerevan 0040, Armenia

Sahar Lajmorak
Department of Earth Sciences, Institute for Advanced Studies in Basic Sciences, Zanjan, Iran

Simin Ghorbani
Department of Nursing and Midwifery, Faculty of Nursing, Ahvaz Jundishapur University of Medical Sciences Ahvaz, Iran

Parvin Ghorbani
Department of Cardiology Faculty of Medicine, Ahvaz Jundishapur University of Medical Sciences Ahvaz, Iran

Nina Khlghatyan
Faculty of General Medicine, University of Traditional Medicine of Armenia (UTMA), 38a Marshal Babajanyan St., Yerevan 0040, Armenia

Harutyun Stepanyan
Faculty of General Medicine, University of Traditional Medicine of Armenia (UTMA), 38a Marshal Babajanyan St., Yerevan 0040, Armenia

Samaneh Bahrami
Faculty of English Litreture, Hafez Institute of Higher Education, Shiraz, Iran

Seyed Mohammad Rasaei
Faculty of General Medicine, University of Traditional Medicine of Armenia (UTMA), 38a Marshal Babajanyan St., Yerevan 0040, Armenia

Mehdi Ahmadi Alvar
Faculty of Engineering, Department of Computer Engineering, Shahid Chamran University, Ahwaz, Iran

Rituraj Rituraj*
Doctoral School of Applied Informatics and Applied Mathematics, Obuda University Budapest, Hungary Rituraj88@stud.uni-obuda.hu

***Abstract*— Breast cancer is the second leading cause of death after lung cancer. The only possible way to save patients' lives is early diagnosis of the disease; Because if this disease is diagnosed in the early stages and with a high level of accuracy, the chance of survival increases. Different fuzzy-based soft computing techniques have been proposed. In this research, the proposed fuzzy hybrid algorithm - particle swarm has been used to detect the type of breast tumors based on the analysis of features in mammography images. The proposed method in this study, the fuzzy hybrid algorithm - the proposed particle swarm algorithm, has a remarkable performance of 94.58% in breast cancer diagnosis. The results obtained from this study can be used for timely diagnosis and providing effective treatments for breast cancer.**

Keywords*— *Breast cancer, Fuzzy-PSO, hybrid machine learning, mammography image.

I. INTRODUCTION

Breast cancer is caused by the abnormal proliferation of cells in the breast tissue [1]. After lung cancer as the first deadly cancer among women ,breast cancer ranks second [2]. Therefore, early detection of breast tumors can be mentioned as one of the reasons for reducing mortality from breast cancer [3]. The most common type of cancer in Iranian women is breast cancer, and research shows that about 7,000 women are diagnosed yearly in Iran [4]. The average age of onset of breast cancer among Iranian women is between 45-55, which is 10-15 years lower than the global statistic. However, in western regions of Iran the age of onset is 50-60. The lower age of onset average age of contracting this disease and the young population of Iran cause the growing trend of this disease in the next 10 years [5]. The inputs and outputs in breast cancer diagnosis are uncertain, and the data are inaccurate and qualitative rather than quantitative [6]. The quest for resolving the uncertainties in breast cancer has led to diagnosis has caused a fuzzy inference model to be designed in this study to detect and manage the uncertainty of input data in cancer diagnosis. In this research, new methods have been modeled to solve the limitations and problems in cancer diagnosis. For the early detection of breast cancer and the reduction of mortality caused by it, different effective and innovative optimization algorithms are used according to the data sample size, processing time, and classification rate with high accuracy to adjust the parameters of the system based on the fuzzy rule and compare the advantages and disadvantages of the methods used on the Mammography Image Analysis Association database. Computer-aided systems for medical diagnosis are a set of automatic and semi-automatic tools that improve the accuracy and reliability of radiological diagnostic methods in terms of interpreting images in breast cancer diagnosis. These tools are designed to help radiologists detect breast cancer tumors [7]. The Mammography Image Analysis Society (MIAS) database was used in the reviewed article to diagnose breast cancer. In the method presented by Sulami et al. (2017), first, the target area of the breast is extracted from the obtained data with the particle swarm optimization algorithm. The features of the breast shape and texture of the tumors are extracted in order using the Fourier transform and the gray level co-occurrence matrix [8]. The classification of identified tumors has been done with a support vector machine (SVM) that classifies the segmented area into normal and abnormal based on the features extracted using the mentioned methods. The classification accuracy rate is 87.83% [8].

Magenda et al. (2015) have investigated the classification performance of a classifier called "Adaptive Artificial Immune System (A^2 INET)" to classify images into "normal" and "asymmetric" cases. To test the algorithm's efficiency, the mammography image analysis and analysis association database was considered. The results showed that the A^2 INET system achieves better results compared to more conventional classifications. The classification accuracy rate in this system is 85% [9]. In the research presented by Pawar and Talbar (2016), the method of co-occurrence wavelet feature selection using the fuzzy system of co-occurrence wavelet feature selection using the fuzzy genetic system is proposed in the problem of classifying mammography images [10]. The features extracted from the feature extraction stage include energy, cluster projection, cluster shadow, the sum of variance, and the sum of mean and entropy calculated from the gray level co-occurrence matrix (GLCM) co-occurrence wavelet features. The co-occurrence wavelet features are obtained from the details of the wavelet coefficients at each level of image decomposition. In four levels of analysis, features are selected, and the best average classification rate in the fourth level of analysis by selecting 16 features out of 72 features is 89.47% [10]. The system presented by Srikrishna et al. (2016) uses an accurate identification using differential evolution based on a fuzzy clustering algorithm to detect lesions in mammography images. The location of the lesion that the radiologist marked manually was compared with the lesion obtained automatically by the system. Segmentation with a fuzzy clustering-based differential evolution algorithm is close to the radiologist's actual marking and can be proposed for medical diagnosis [11]. The research by Zhang et al. (2016) has developed a new method based on wavelet entropy energy and linear regression classification. First, the area in question is separated from the mammography images. In the second step, the wavelet energy entropy was calculated for segmented images, and in the last step, linear regression classification was used to classify normal and abnormal cases. The accuracy rate in this method is 91.85% [12].

II. Materials and Methods

Recently, the use of artificial intelligence algorithms to develop and determine and predict the key parameters of industries and the diagnosis of human problems and diseases is very evident.

A. *Proposed fuzzy-based soft computing techniques*

In this section, the proposed fuzzy-based soft computing techniques, including fuzzy-evolutionary hybrid algorithms, are proposed for parameter optimization and their application for breast cancer diagnosis. In the present study, first, the data are pre-processed. The membership functions and rules of the fuzzy inference system are designed with expert knowledge. Then, the parameters of the membership functions of the fuzzy inference system are set with evolutionary hybrid algorithms [13]. The graphical representation of the process of fuzzy-based soft computing techniques used in research using fuzzy-based evolutionary hybrid algorithms is introduced in Figure 1.

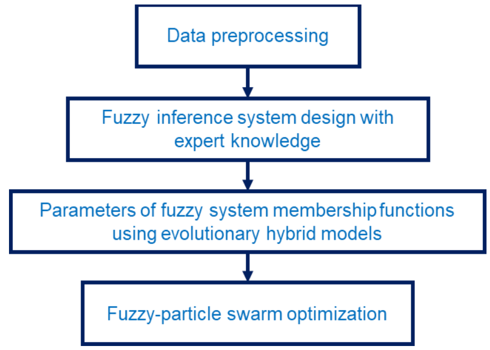

Fig. 1. Methods used in this article.

B. *Database*

To evaluate the proposed models, the information of 322 actual mammography image samples of patients was used, which was taken from the database of the mammography image analysis and delivery association. Each image contains information on background tissue characteristics, the class of abnormality of the tumor, the radius from the center of the tumor, the X and Y coordinates of the center of the tumor, and the intensity of the abnormality of the tumor as determined by the radiologist. From these 322 cases, 62 were known to have benign tumors, 51 - malignant, and 209 were normal cases. According to the data frequency of each class, its weighted average is considered and applied in the fitness function.

C. *Proposed fuzzy inference system*

The steps required to design a fuzzy inference system are:

1. Gathering information. Knowledge about the problem statement, data and input and output variables is obtained from an expert.
2. The input and output variables and the number of linguistic expressions related to each variable are identified.
3. The fuzzy inference model is defined as Sogno or Mamdani type.
4. Rules are extracted using the knowledge of a relevant expert.
5. Membership functions and their parameters are designed.
6. The designed system is evaluated with real data.

The proposed fuzzy inference system includes 4 input variables including background texture characteristics, tumor type, tumor abnormality class, tumor size, tumor location and 1 output variable, i.e., intensity of abnormality. Input and output variables and language expressions related to each variable are given in Table 1. The membership functions of the fuzzy inference system corresponding to all fuzzy sets are defined as Gaussian due to the dispersion of medical data around a point.

A number of if-then fuzzy rules extracted by expert are shown in Table 2.

TABLE I. INPUT AND OUTPUT VARIABLES OF THE FUZZY INFERENCE SYSTEM.

Input and output changes	Language expressions related to each variable
Tissue characteristics	1- fatty form 2 - fat glands, form 3 - dense glands
Type tumor	1-calcium accumulation 2-obvious 3- needle-shaped 4-unknown 5-crooked and lopsided 6-asymmetry 7-normal
Size tumor	1-small 2-medium 3-large
Tumor's position	1- internal superior 2- internal inferior 3- external superior 4- external curvature
Abnormal intensity	1- malignant 2- benign 3- normal

TABLE II. A NUMBER OF RULES IF - THEN FUZZY INFERENCE SYSTEM.

1	If the position of the upper tumor is external, the severity of the abnormality is malignant.
2	If the type of tumor (benign vs malignant) is clear and the size of the tumor is small, the abnormality is classified as benign.
3	If the type of lump is named (a unique name is assigned to a certain lump) and the size of the lump is medium, the abnormality is classified as malignant.
4	If the type of tumor is needle-shaped and the size of the tumor is small, the abnormality is classified as malignant.

D. *Proposed fuzzy-evolutionary hybrid algorithms for parameter optimization*

The proposed fuzzy-based hybrid algorithms include fuzzy algorithm - based on training and learning, fuzzy - particle swarm optimization and fuzzy - based on training and learning - particle swarm, which are used for the process of optimizing the parameters of the fuzzy inference system with the rules and knowledge of an expert [14]. The implementation steps of hybrid systems used based on fuzzy are introduced as follows:

1. The fuzzy inference system is designed with expert knowledge [15].
2. The necessary parameters for displaying the membership functions of input and output fuzzy sets have been determined.
3. The initial solution is generated by arranging the parameters of the membership functions of each input and output variable, taking into account the necessary restrictions to produce valid answers.
4. The initial vector is evaluated.
5. The initial vector is considered the best path obtained.
6. The parameters of the proposed evolutionary hybrid algorithm are set for optimization.
7. The proposed fuzzy-evolutionary hybrid algorithm has been implemented.

E. *Hybrid algorithm Fuzzy -particle swarm optimization*

Particle Swarm Optimization (PSO) is another optimization method inspired by nature. Kennedy and Eberhart invented this method in 1995. In this algorithm, inspired by the group life of animals, especially birds and fish, to solve an optimization problem, a population of candidate solutions is randomly moved in the problem domain using a global formula. In the particle swarm optimization algorithm, each unit is called a particle, and each particle is a candidate solution. A particle can correspond, for example, to an individual bird or in a flock of flying birds. The implementation steps of the proposed fuzzy-particle swarm algorithm are given below;

1. The proposed fuzzy inference system is designed, and its parameters are determined.
2. A collection of particles with initial position and velocity is evaluated using the parameters of the membership functions of the fuzzy system. At the algorithm execution's beginning, all particles' speed is considered equal to zero.
3. The value of each particle is evaluated, and P_b (position vector of the most optimal point found from each particle) and G_b (position vector of the most optimal point found from all particles) are selected [16].
4. The parameters of the particle swarm algorithm are set.
5. The velocity of the j^{th} particle is updated in the i^{th} iteration using Equations 1 and 2.

$$v_j(i) = K * (V_i(i-1) + c_1 r_1 [P_{best,j} - X_j(i-1)] + c_2 r_2 [G_{best} - X_j(i-1)]) \quad (1)$$

$$K = 2/\left|2 - \emptyset - \sqrt{\emptyset^2 - 4\emptyset}\right| \quad (2)$$

Where; j=1,2,...N, c_1 and c_2 are cognitive (individual) and social (or group) learning coefficients, respectively, and r_1 and r_2 are two random numbers with a uniform distribution in the range of 0 to 1. K is a function of c_1 and c_2 where $\emptyset>4$ and $\emptyset = \emptyset_1 + \emptyset_2$. C1 and c_2 are also obtained from Equation 3 [17-20].

$$C_1 = K * \emptyset_1, C_2 = K * \emptyset_2 \quad (3)$$

6. The position of the j^{th} particle is updated in iteration i^{th} using Equation 4.

$$X_j(i) = X_i(i-1) + V_j(i); j = 1,2,\ldots.N \quad (4)$$

7. The merit of each particle is evaluated and updated.
8. The stop condition is checked. The algorithm is repeated from step 5 until it reaches the stopping condition
9. The optimal value of the parameters is determined.

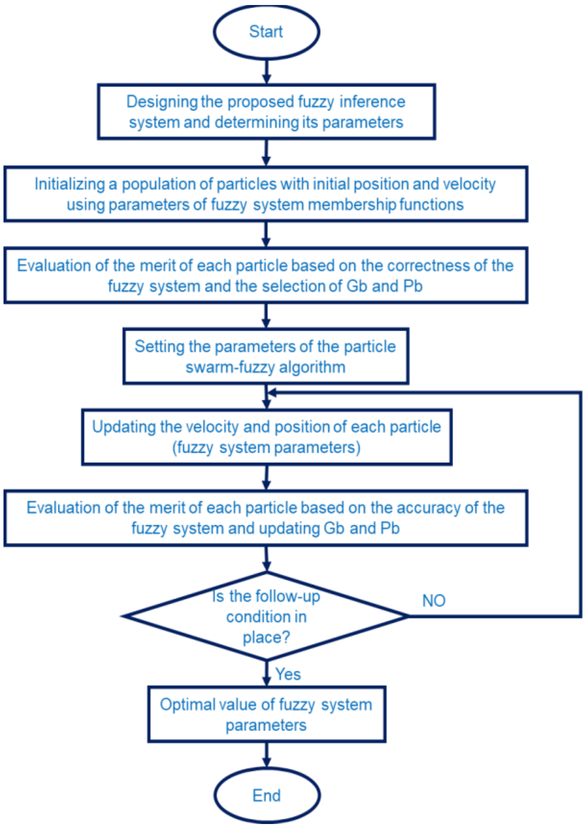

Fig. 2. Flowchart of implementation of fuzzy algorithm - proposed particle swarm.

III. RESULTS

A. Data preprocessing

Data pre-processing includes noise removal and data normalization [21-24]. First, the data is normalized, then the beginner clustering method is used to identify the outlier data, and removal of the out-of-range data is performed [25-30]. The steps of the clustering method based on outlier data identification to remove several noisy data are as follows [18].

1. The number of clusters equals the number of output classes. Each cluster includes all input variables related to each output class; Therefore, there are three clusters: malignant, benign, and normal.

2. The average is calculated for each cluster's input variables.

3. For each of the input variables in each cluster, covariance is obtained using Equation 5.

$$S_i = \frac{1}{n_i - 1} \sum_{X \in m_i} (X_i - m_i)(X_i - m_i)^T \tag{5}$$

Where X_i is the i^{th} cluster, m_i is the mean for the input variables of each cluster, and n_i is the size of the i^{th} cluster.

4. The statistically normalized radius of T squared data is obtained using Equation 6.

$$T_i^2 = (X_i - m_i) S_i^{-1} (X_i - m_i)^T \tag{6}$$

Where X_i is the i^{th} cluster, m_i is the average for the input variables of each cluster, and $S_i^{-1}$is the inverse of the variance obtained for the input variables in each cluster with the formula of the previous step.

5. The value of α is determined according to the dimensions of the problem and in such a way that the essence of the problem is not lost. The higher α is, the more data will be excluded. α is assumed to equal 5 by trial and error.

6. The values obtained for the radius are compared with the value of α with the T-square formula for each data, and the data whose value is greater than α are identified as outliers and will be removed. According to the value determined for α, 27 data items have been excluded.

First, 322 real patient data from the Mammography Image Analysis Association database were normalized. Subsequently, 27 data items were removed using the method based on outlier data identification described above. After the data preprocessing step, the remaining 295 data were used to evaluate the methods' effectiveness. Figure 4 shows an example of input images from the database and its information.

B. Data preprocessing

The computational intelligence techniques proposed in the research have been designed and implemented in MATLAB software [31-34]. The same evaluation parameters have been used in the research to compare the proposed method for classification. According to the data frequency of each class, the weighted average of the data is considered and applied in fitness functions. The characteristic curve of system performance has been drawn for all methods [35-40]. The data has been divided into two parts to validate the systems, training, and testing, using the 10-part cross-validation method. The field value of the area under the characteristic curve of the system performance on the training and test data with 10 repetitions of the cross-validation method of 10 parts with random selection for each part is obtained. A confusion matrix is also given for all methods to compare correct and incorrect system detections per output.

C. Fuzzy classification function

A fuzzy inference system is designed in Sogno mode. The parameters set to design the fuzzy system are given Fis (Sugeno), And (min), Or (max), Imp (prod), Agg (max), and Defuzz (wtaver). The membership functions corresponding to each input linguistic phrase can be seen in Figure 2 before setting the parameters of the Sogno fuzzy system membership functions. Figure 3 shows the membership functions of inputs of Sogno's fuzzy inference system for breast cancer diagnosis. The output type in Sogno's fuzzy inference system is a fixed number. The radiologist has determined the parameters and language terms associated with each variable from the information extracted from the images.

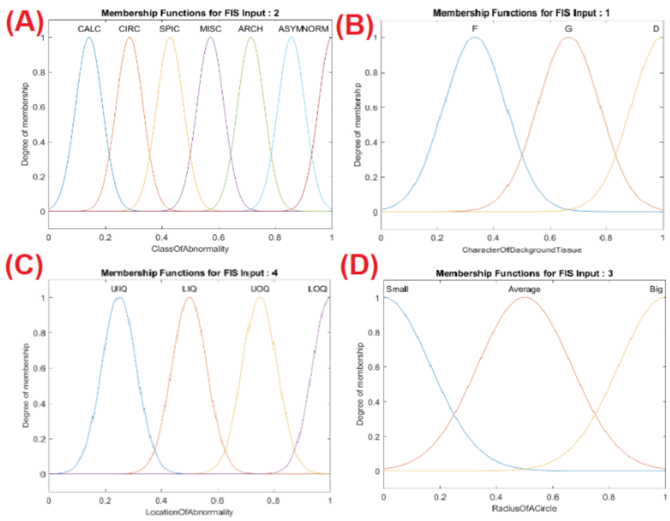

Fig. 3. The membership functions of the Sogno fuzzy inference system before the parameter setting process, a) the membership function of the background texture feature including 3 linguistic expressions of fatty, sebaceous glands and dense glands, b) the membership function of tumor type including 7 linguistic expressions of calcareous accumulation, clear, needle-shaped, unknown, crooked and lopsided, asymmetric and normal, c) the membership function of tumor size including 3 language terms small, medium and large, d) the membership function of tumor position including 4 language terms upper internal, lower internal, upper external, lower external.

D. Data preprocessing

The parameters of the membership functions of the Sogno fuzzy inference system with the particle swarm optimization algorithm are set and listed in Table 3. In the resulting research, the particle structure is defined as a vector of the parameters of the membership functions of the fuzzy system (Gosdin and variance) corresponding to each linguistic variable (corresponding to the fuzzy system). Figure 4 shows the shape of the membership functions of the fuzzy Sogno-particle swarm system after the parameter setting process. Similar cases, yet in other applications are provided in e.g., [45-50] Figure 5 shows the best and average implementation of the particle swarm algorithm to optimize the parameters of the Sogno fuzzy system.

TABLE III. PARAMETERS OF THE PARTICLE SWARM OPTIMIZATION ALGORITHM TO SET THE PARAMETERS OF THE MEMBERSHIP FUNCTIONS.

Number of population	100
Number of generations	500
Inertia of weight	0.72
Personal learning coefficient of particles	1.49
Collective learning coefficient of particles	1.49

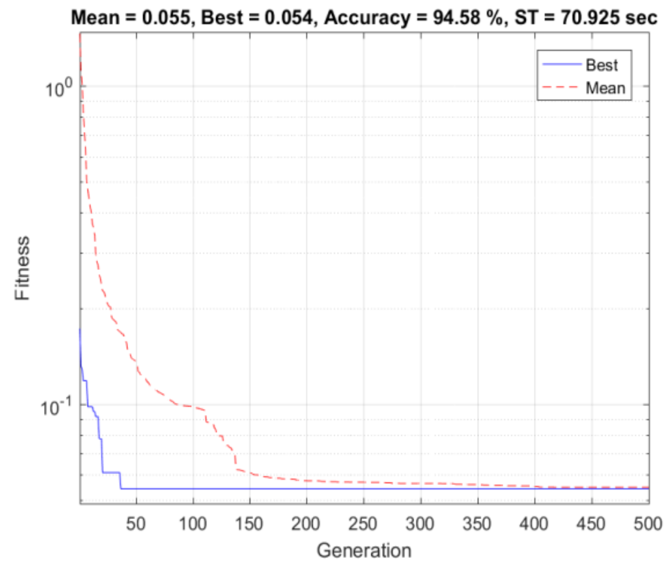

Fig. 4. The best and average implementation of the particle swarm algorithm to optimize the Sogno fuzzy system parameters.

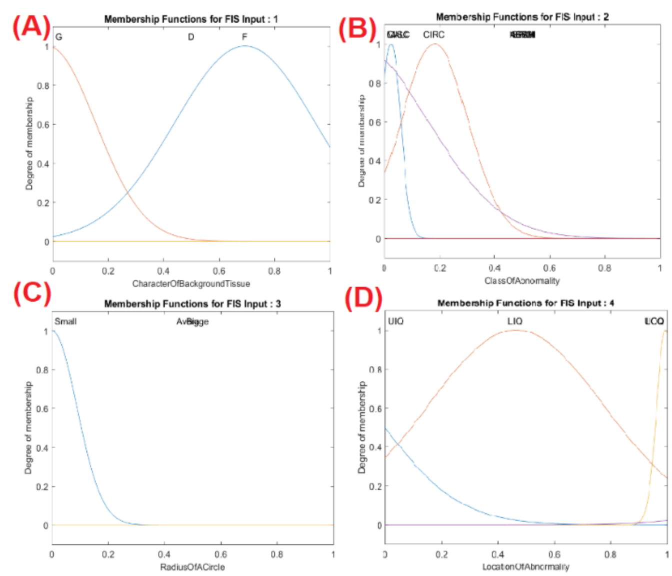

Fig. 5. The membership functions of the Sogno fuzzy system - particle swarm optimization after the parameter setting process, a) the membership function of the context characteristic, b) the membership function of the tumor type, c) the membership function of the tumor size, d) the membership function of the tumor position.

In general, in order to predict this important, other artificial intelligence methods can also be used such as those proposed in e.g., [51-55]. Among them the hybrid machine learning and deep learning which are proven efficient in other applications, e.g., [56-58] will be used for breast cancer prediction to explore their suitability and performance.

IV. CONCLUSIONS

Despite the development and advancement of technology in diagnosis and treatment, breast cancer is still the second leading cause of death among cancers after lung cancer. The only possible way to save patients' lives is early diagnosis of the disease, because, if this disease is diagnosed in the early stages and with a high degree of accuracy, the prognosis is generally more favorable, and the chance of survival increases. In the current research, a computer-aided system is proposed to identify and classify tumors into "normal", "benign", and "malignant" cases with different fuzzy-based soft computing techniques. One of the main advantages of this research compared to other methods performed on the database of the Mammography Image Analysis Association is the minimum number of input features in the proposed system that the radiologist extracts manually, and the position and size of the tumors are hereby determined according to the extracted information and this reduces the complexity of the system. In most other methods, image processing techniques have been used to extract features from images with a high level of noise. In the proposed approach, new methods and different efficient and innovative optimization algorithms are used according to the data sample size, processing time and classification rate with high accuracy to adjust the parameters of fuzzy-based systems to manage the sources of uncertainty to overcome the limitations. Reassuring criteria have been used to measure the efficiency of the systems and the results have been validated. The obtained results show that the proposed method in this research has achieved a classification accuracy rate that is competitive with other previously presented methods, and the particle learning has improved the accuracy of the classification performance in breast cancer diagnosis compared to other previously presented methods, have been given. Considering that radiologists and medical image information have extracted the input features in the proposed efficient systems, it is suggested to use image processing methods to extract features from medical images to automate the system classification process and the results with the systems Introduced to be evaluated. Also, the proposed systems can be implemented on the databases collected from other reputable clinical centers with more data. In order to improve system performance, rules can also be taught using optimization algorithms. Different and combined membership functions can also be used to improve system performance.

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