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Dynamic contrast enhanced-magnetic resonance imaging radiomics combined with a hybrid adaptive neuro-fuzzy inference system-particle swarm optimization approach for breast tumour classification

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Abstract

The authors propose a method for breast dynamic contrast enhanced-magnetic resonance imaging classification by combining radiomic texture analysis with a hybrid adaptive neuro-fuzzy inference system (ANFIS)-particle swarm optimization (PSO) classifier. The fast discrete curvelet transform is utilized as a decomposition scheme in multiple scales. The mean and entropy features extracted from the produced scheme are used as texture descriptors. Principal component analysis (PCA) involves reduction of the dimensionality of the initial feature set. The transformed feature vector is subsequently introduced to a hybrid ANFIS-PSO classifier. The average overall classification power of the proposed hybrid ANFIS-PSO classifier is comparatively assessed to that obtained using several classifiers (ANFIS, linear discriminant analysis, Naïve Bayes, artificial neural networks, random forest and support vector machine) by using the 70 training-30 testing data ratio. The comparison performed highlights the superiority of the proposed methodology, thus underlying the potential of ANFIS-PSO for the breast cancer diagnosis with a classification accuracy of 94%.

KEYWORDS

adaptive neuro-fuzzy inference system, breast cancer, dynamic contrast enhanced magnetic resonance imaging, fast discrete curvelet transform, particle swarm optimization, principal component analysis, radiomics, texture

1 | INTRODUCTION

Breast cancer is the most commonly diagnosed cancer in women worldwide, while, following lung cancer; it is also the major cause of cancer-related deaths in women (World Health Organization, 2021). According to the American Cancer Society's estimates, in 2020 about 276,480 new cases of invasive breast cancer will be diagnosed in women in the United States (Cancer Facts & Figures, 2021). Despite the high number of breast cancer cases diagnosed in women, earlier detection and improved treatment over the past few years, resulted to decreased death rates. Consequently, new approaches that will enable the early detection of breast cancer are of major importance for increasing survival rates.

Magnetic resonance imaging (MRI) is a medical imaging technology that was used as an adjunctive screening tool for breast cancer detection (Lee et al., 2010). Dynamic contrast-enhanced MRI (DCE-MRI) constitutes a very promising technique for breast cancer detection. It involves the intravenous injection of a paramagnetic contrast agent followed by a temporal sequence of MR images. This enables the monitoring of the updates in the intensity of the signal in terms of time, thus resulting in higher sensitivity that is key to breast cancer assessment.

Several approaches combining various methods for feature extraction and classification have been presented in the last decade aiming at improving breast DCE-MRI cancer detection. Dynamic and morphological features (Dogan et al., 2018; Fan et al., 2017; Fusco et al., 2017; Razavi et al., 2016) have been used to capture the tumour's temporal enhancement. Furthermore, architectural features (Schnall et al., 2006) have been extracted to characterize tumour's morphology. Kinetic features (Vassiou et al., 2009) have been extracted from breast DCE-MRI lesion in order to capture temporal variations. Textural features (Niu et al., 2018; Nie et al., 2017) have also been examined. It has been proved that spatiotemporal features (Masood et al., 2018; Zheng et al., 2009) constitute key descriptors for tumour characterization.

Multiresolution analysis was recently used for the textural description of medical images. In this context, the wavelet transform has effectively been used in the classification of breast DCE-MRI images (Tzalavra et al., 2016). Curvelet multiresolution texture analysis features (Tzalavra et al., 2014) have yielded high performance in breast DCE-MRI tumour classification since the curvelet transform (Candes et al., 2006) can capture the curve singularities in an efficient way and also derive sufficient directional details from the medical images.

A variety of different classification techniques appear in the bibliography, including artificial neural networks (Twellmann et al., 2005), linear discriminant analysis (LDA) (Zheng et al., 2009), support vector machines (SVM) (Ayatollahi et al., 2020; Onan et al., 2016; Toçoğlu & Onan, 2021) and deep learning methods (Onan, 2020; Onan & Toçoğlu, 2021; Yurttakal et al., 2021) like deep artificial neural networks (Onan, 2020; Onan & Toçoğlu, 2021), recurrent neural networks (Antropova et al., 2018) and convolutional neural networks (Jiao et al., 2020).Additionally, ensemble learning approaches (Onan, 2016; Onan, 2017; Onan et al., 2016b; Onan et al., 2017; Onan & Toçoğlu, 2020) and fusion classifiers (Whitney et al., 2020) have been used. Most methods have been proved to be efficient, though a straightforward comparison cannot be achieved, since these are based on different datasets and feature extraction techniques.

1.1 | ANFIS classification methods used in medicine

Adaptive neuro-fuzzy inference system (ANFIS) comprises a hybrid system of fuzzy logic and neural network techniques (Jang, 1993; Hotelling, 1933). Therefore, it takes advantage of both techniques. As a Fuzzy Inference System (FIS), ANFIS consists of a set of fuzzy if–then rules with appropriate membership functions to map numerical inputs into outputs. Initially these rules are defined by a human expert. Then, ANFIS can apply neural network learning techniques to refine the FIS parameters and eliminate the output error (Walia, Singh & Sharma, 2015). Further to the above, ANFIS is a powerful tool for establishing complex relationships between input and output data. Both numerical and linguistic knowledge (gained of knowledge provided by domain experts) can be combined with the use of fuzzy methods (Hussain et al., 2015). Also, fuzzy membership functions can be set by using optimization algorithms. Additional advantages of ANFIS are the non-linear behaviour (i.e., capability of seizing the non-linear structure of a process), the capacity for fast and accurate learning (i.e., low-computation cost) and the adaptation capability (Navneet, Harsukhpreet & Anurag, 2016) without requiring expert knowledge. ANFIS as being an adaptive neuro fuzzy system has the ability to describe the behaviour of complex systems; therefore, it has been successfully implemented in a wide range of areas (e.g., economics, environment and forecasting).

Concerning medical imaging, ANFIS has been used in various applications, such as for the diagnosis of the prenatal truncus arteriosus congenital heart defect (TACHD) from 2D ultrasound images (Sridevia & Nirmalab, 2016), the diagnosis of type II diabetes (Kirisci et al., 2019) and the prediction of kidney disease progression (Yadollahpour et al., 2018). ANFIS was also proposed for brain tumour detection (Chatterjee & Das, 2019; Selvapandian & Manivannam, 2018; Thirumurugan & Shanthakumar, 2016) and for classifying rheumatoid arthritis based on features extracted from artery Doppler signals (Özkan et al., 2010). Furthermore, ANFIS has been used for the analysis of retinal images (Kavitha & Duraiswamy, 2011) as well as for RNA virus image classification (Dogantekin et al., 2013).

Concerning breast tumour diagnosis (Hosseini & Zekri, 2012) ANFIS was used in several studies combined with different feature extraction techniques. In particular, an ANFIS feature selection method was proposed for breast cancer detection (Addeh et al., 2018) based on the row data of Breast Cancer Wisconsin (WBCD) dataset. Additionally, ANFIS was used for breast cancer detection in mammographic images that are non-subsampled shearlet transform (NSST) pre-processed (Padmavathy et al., 2018). Furthermore, it has been used as a classifier in mammograms based on texture features (Fernandes et al., 2010; Sujatha et al., 2020), but also based on the combination of shape and textural features (Bhattacharya & Das, 2009 Bhattacharya & Das, 2010) and also based on features extracted by a genetic algorithm (Das & Bhattacharya, 2011). In breast ultrasound images, ANFIS was proposed breast cancer detection (Huang et al., 2012).

The above reasons motivated the authors to investigate the performance of ANFIS for DCE-MRI-based classification of breast tumours and compare it with other classifiers.

1.2 | Hybrid ANFIS classification methods used in medicine

While ANFIS is used as a classifier in medical image analysis it suffers from considerable architectural complexity and computational cost due to the complexity and the number of the fuzzy rules it evolves. Reducing complexity and increasing accuracy of ANFIS network needs effective training and optimization mechanism.

Hybrid classifiers can combine the advantages of several classification techniques thus resulting in powerful tools. Several hybrid ANFIS classification schemes have been used in medicine including a genetic algorithm (ANFIS-GA) and particle swarm optimization (ANFIS-PSO) algorithm for the diagnosis of type 2 diabetes mellitus (Patil et al., 2021), modified-salp swarm optimization (MSSO–ANFIS) algorithm for the heart disease diagnosis (Khan & Algarni, 2020), a subtractive clustering-based ANFIS (SCANFIS) hybrid system for the Alzheimer diagnosis (Kour et al., 2019). Additionally, an enhanced ANFIS (EANFIS) approach has been used for the classification of cancer genes (Mishra & Bhoi, 2021) whereas ANFIS and also its variants with grasshopper optimization algorithm (ANFIS-GOA), particle swarm optimization (ANFIS-PSO) and breeding swarm optimization (ANFIS-BS) methods are used for classification of epileptic seizures on electroencephalography (EEG) signals, (Shoeibi et al., 2021).

Particle Swarm Optimization (PSO) is an evolutionary optimization approach based on colony aptitude that can be used for ANFIS optimization. PSO is simple to implement, since it has only a few parameters to adjust, it is efficient in solving difficult problems related to finding accurate mathematical models and also, it is very efficient in finding the global optima (Abdmouleh et al., 2017). Additionally, it is usually robust and it has low-computational cost. In the specific study, the authors investigate the combined use of PSO and ANFIS in an attempt to optimize ANFIS and therefore achieve empowered breast tumour classification.

The scope of the current study is to assess the performance of an ANFIS classifier optimized with the use of PSO in characterizing breast DCE-MRI radiomics. To this end, the fast discrete curvelet transform (FDCT) is used to extract breast multiscale texture features, followed by principal component analysis (PCA) to decorrelate them and reduce their dimension by retaining as much information as possible. The transformed features are introduced to a hybrid ANFIS-PSO classifier.

The novelty of the specific study is the combined use of a hybrid ANFIS-PSO classifier with the most important breast DCE-MRI multiscale texture features extracted by FDCT, which is a multiresolution technique. According to the literature, an ANFIS-PSO classifier was never been used for breast DCE-MRI tumour classification. The classification results of the proposed hybrid ANFIS-PSO approach are comparatively assessed against the classification results of ANFIS, LDA, multilayer perceptron (MLP), Naïve Bayes and SVM classifiers.

The rest of this article is organized as follows: Section 2 introduces the image data and presents the classification process used in this work. In Section 3 the classification performance of the proposed methodology is evaluated and discussed whereas Section 4 summarizes the conclusions of the presented work.

2 | MATERIAL AND METHODS

The article analyses the efficiency of an ANFIS-PSO classifier in discriminating between benign and malignant breast DCE-MRI tumours when fed by breast radiomics extracted from a multiresolution analysis scheme. The flowchart of the presented framework is presented in Figure 1.

2.1 | Image data

We performed meta-analysis of breast DCE-MR images collected in a previous study (Zheng et al., 2009) in the Department of Radiology, University of Pennsylvania. The collected data are acquired from 44 patients with breast tumours (23 malignant and 21 benign) in a 1.5 T scanner (Siemens Sonata) or a 3 T scanner (Siemens Trio). A rapid bolus injection of 0.1 mmol/kg Gadopentetate dimeglumine followed by a 10 ml saline flush was administered in all cases. Sequential postcontrast acquisitions were acquired for approximately 6 min following the contrast injection. The spoiled gradient echo sequence had a minimum spatial resolution of 20 cm over a 512,256 matrix and a minimum time of 90 s in the sagittal plane and slice thickness of 2–3.5 mm. One slice can contain either 384,384 pixels of 0.470.47 mm^2, 512,512 pixels of 0.350.35 mm^2 or 896,896 pixels of 0.220.22 mm^2, depending on the scanners or the protocols. All samples were histologically verified. Details on the imaging protocol can be found in (Zheng et al., 2009).

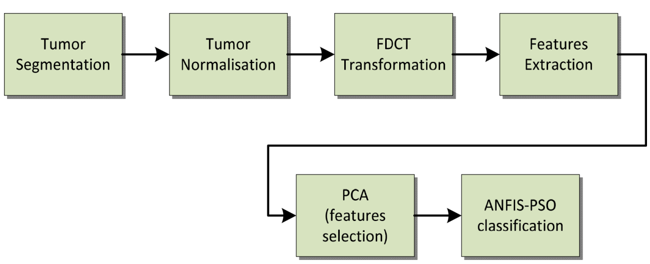

FIGURE 1 Flowchart of the proposed framework

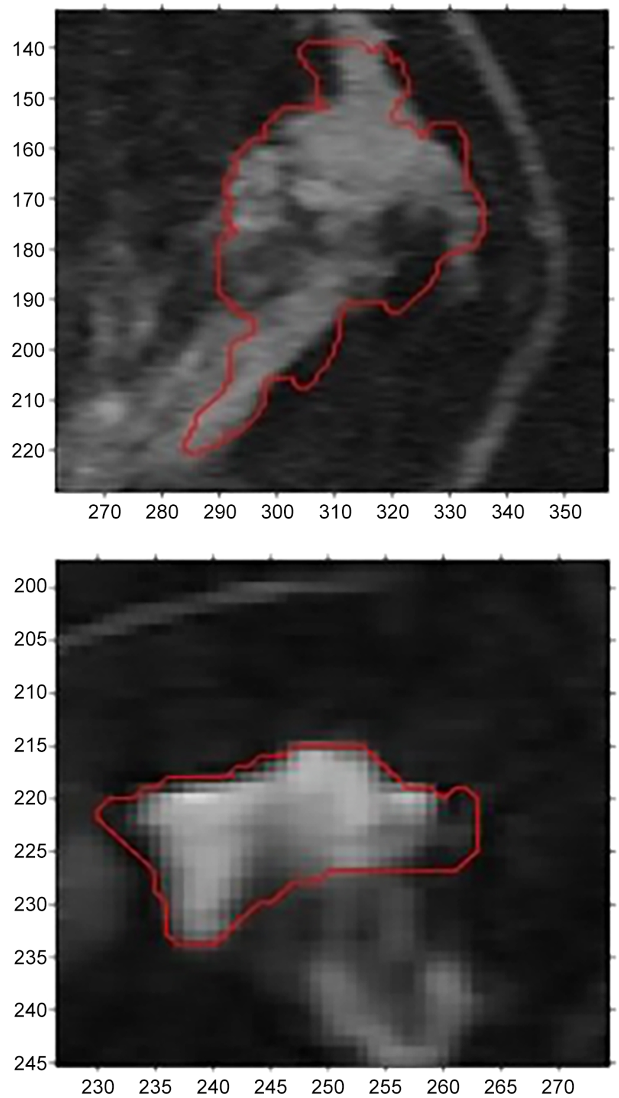

FIGURE 2 Examples of a manually segmented malignant (top) and a benign (down) tumour

The borders of the suspicious tumours on the DCE-MRI images were roughly designed by a radiologist (FC) having expertise in breast images. Examples of benign and malignant tumours are shown in Figure 2. It should be noted that due to differences in the current lesion segmentation masks (as compared to [Zheng et al.]), the classification results are not directly comparable across studies.

The temporal enhancement for a pixel p is defined as follows:

$$C(p,t) = \frac{I(p,t) - I(p,0)}{I(p,0)}, t = 1 \ldots T-1, \tag{1}$$

where $I(p,t)$ is the intensity of pixel p at time t and T is the total number of time instances. The current dataset involves $T = 4$ instances, that is, three temporal enhancement maps are produced per outlined tumour.

2.2 | Tumour normalization

Prior to the features' elicitation from the manually segmented tumour regions, tumour normalization was performed to eliminate both scale difference and variations in tumour size. In order to normalize tumours, the authors use eigen decomposition of the covariance matrix related to the pixel distribution of the segmented images. Additionally, tumours dimensions are adjusted so that their principal directions are in line with reference coordinates whereas their eigen modes are aligned with a predefined size.

2.3 | Multiresolution analysis

In image classification analysis, the extraction of the most important features from an image is a task of major importance. The extracted features may be of any format including lines, edges, curves, textures and so forth. These can be analysed in terms of scale, location and direction, a fact that leads to use of multiresolution transforms for feature extraction (Karthik & Menaka, 2017; Tsiaparas et al., 2012). Wavelet transform has widely been used in image processing due to its capacity in encapsulating localized time-frequency information. Although the conventional wavelet transforms (discrete wavelet transform [DWT], stationary wavelet transform [SWT]) can successfully represent 1D shapes (i.e., points), they cannot treat 2D shapes (i.e., lines, curves, etc.) because of they lack directional and scaling representations.

In order to overcome the drawbacks of the conventional wavelet transforms, the curvelet transform (CT) was presented (Cands & Donoho, 2000), as being a robust multiresolution geometric analysis system. CT is described as being the inner product of a bivariate function $C(p,t)$ and a curvelet $\psi_{\alpha,\beta,\theta}(x)$:

$$CT(a,b,\theta) = \int_{R^2} \psi_{a,b,\theta}(x) f(x) dx, \tag{2}$$

where:

$$\psi_{\alpha,b,\theta}(x) = a^{-\frac{3}{4}} \psi(D_\alpha R_\theta (x-b)). \tag{3}$$

$$D_a = \begin{pmatrix} \frac{1}{a} & 0 \\ 0 & \frac{1}{\sqrt{a}} \end{pmatrix}. \tag{4}$$

In the equations above R_θ is a rotation through θ radians and D_α is a parabolic scalic matrix. Additionally, the parameter $a = 2^{-j}$ where $j = 0,1, \ldots$ is the scale.

The CT is localized in scale and orientation. It can effectively represent the texture, edges, curves and structural elements of an image in wedges, thus offering directional representations, by using a small number of coefficients.

The first generation of discrete curvelet transforms (DCT) involves a discrete ridgelet transform of a specific image. The second generation of DCT, known as the FDCT is considered to be simpler, faster, more accurate and less redundant (Candes et al., 2006) compared to the first generation. It involves the application of a 2D fast Fourier transform (FFT) on the image, the resampling of the FFT transformed images to obtain sampled values for each scale and angle and then parabolic windowing of these (in parabolic wedges). Finally, inverse FFT (IFFT) is used per scale and angle of the transformed images.

The parabolic wedges in the Fourier frequency plane are shown in Figure 3 (Candes et al., 2006). The highlighted area illustrates a parallelogram wedge that is the frequency response at a specific scale and orientation.

2.4 | Feature extraction

The maximum level of decomposition for the proposed scheme equals to ($log2\,(min\,(N,M))$ – 3) where N is the number of rows and M is the number of columns of the image. In the current study, $N = M = 150$. Therefore, 7 is the maximum decomposition level. The mean and entropy of the

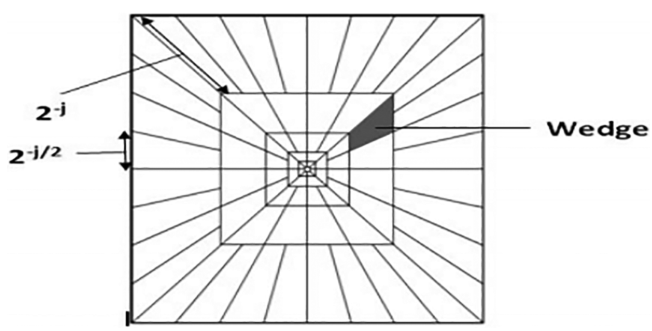

FIGURE 3 Cartesian tiling structure of FDCT. FDCT, fast discrete curvelet transform

absolute value of each of the generated sub-images were used as textural features. The specific features were calculated from the following equations:

$$\mu_j = \frac{1}{N*M}\sum_{1}^{N}\sum_{1}^{M}|C_{a,b,\theta}(x,y)|, \tag{5}$$

$$e_j = -\frac{1}{N*M}\sum_{x=1}^{N}\sum_{y=1}^{M}\mu_j^2 log(\mu_j)^2, \tag{6}$$

where, $C_{a,b,\theta}$ is the curvelet coefficient (Equation (2)) of an image with dimensions $N \times M$ in every orientation θ, translation b and decomposition scale a. In the current study, the bivariant function applied in Equation (1) is the temporal enhancement function. Four decomposition levels were used. Sixteen (multiple of 4) angles were used in the second decomposition level and complex valued curvelets were applied at the first level coefficients. Taking into consideration that curvelets produce symmetric coefficients for angles θ and $\theta + \pi$, just half of the coefficients were used in every decomposition level. There were totally produced 150 curvelet coefficients that resulted to 300 texture features.

2.5 | Dimensionality reduction by PCA

The high number of the generated features increases the classification computational cost. This led us consider dimensionality reduction techniques in order to gain the most relevant features among the long generated feature list. to be used for breast tumour classification. The scope of dimensionality reduction techniques is to obtain an optimum subgroup of the initial feature list, which maintains the data attributes by preventing over-fitting (Onan & Korukoglou, 2015; Onan & Korukoglou, 2016). In the current study, principal components analysis (PCA) is applied to obtain dimensionality reduction of the initial dataset to a considerably smaller group of variables named principal components (Hotelling, 1933; Pearson, 2010). The new variables are produced by a linear combination of the initial coordinates. More specifically, PCA decomposes a matrix $X_{n\times p}$, of which n depicts the quantity of samples and p depicts the quantity of variables obtained according to the following equation:

$$X_{n\times p} = T_{nxp}P^T_{p\times p}, \tag{7}$$

where P is a new set of orthogonal axes. The scores T, represent the variables of the samples in space P. The first principal component explains the largest variation of the dataset. Then, the second and subsequent principal components are computed under the constraint of being orthogonal to the already computed principal components and having the largest possible inertia, respectively. In the current study, the total number of 300 features per subject was reduced to only three PCA scores, which explained 95% of variation of the data.

2.6 | Adaptive neuro-fuzzy inference system

ANFIS is a hybrid methodology combining fuzzy logic and neural network techniques. It is a FIS implemented to facilitate learning and adaptation. For first-order Takagi–Sugeno fuzzy model, the ANFIS architecture is based on the following two fuzzy if–then rules (Jang & Sun, 1995):

First rule: If (x is A1) and (y is B1).

then

$$(f_1 = p1_x + q1_y + r_1). \tag{8}$$

Second rule: If (x is A2) and (y is B2).

then

$$(f_2 = p_{2x} + q_{2x} + r_2), \tag{9}$$

where x and y depict the input variables, A_i and B_i depict the fuzzy groups, f_i depicts the outputs, p_i, q_i and r_i depict the design parameters produced during training.

The ANFIS architecture consists of layers as illustrated in Figure 4. Layer 1 presents the input layer, layer 2 the fuzzification layer, layer 3 the base of the fuzzy rules layer, layer 4 the normalization layer and layer 5 the classification layer. It is noted that layer 1 and layer 2 are adaptive.

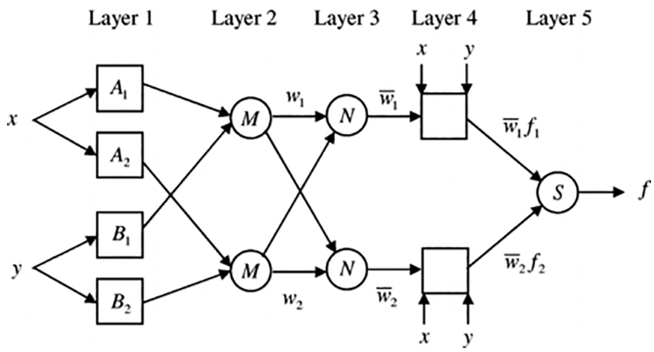

FIGURE 4 ANFIS architecture. ANFIS, adaptive neuro-fuzzy inference system

More specifically, in layer 1, there are the premise parameters {ai, bi, ci} that are associated with the input membership functions. In layer 4, there are the consequent parameters $(p_{i,}q_i,r_i)$, related to the first order polynomial (Jang, 1992). In order to obtain a satisfactory performance of the system, the fuzzy membership function metadata (i.e., number, type) and rules should carefully be selected. Proper selection of the specific parameters involves the trial-and-error method, thus illustrating the importance of a tuned fuzzy system.

2.7 | Particle swarm optimization

PSO consists of a swarm intelligence methodology being used for refinement issues (Kennedy & Eberhart, 1995). It simulates the attitude of group of animals that do not have a chief, like bees, birds and fishes (Eberhart & Kennedy, 1995). Typically, these societies find their food in a non-organized way. More specifically, they usually follow one of their members, that is nearest to the nourishment (potential solution) compared to the other members. The birds, through communication among members who already are closer to the food source, move simultaneously towards the food source place. This happens repeatedly until the food source is reached (Chen et al., 2009; Rini et al., 2011). This way, by simulating animal societies, PSO can provide a potential solution to a fine-tuned task (Engelbrecht, 2005).

As a first step of the methodology, the particles are allocated in the space in a random manner. Then PSO searches for an optimal solution and the particles are updated through a best solution search procedure. Each particle moves at a specific rate based on a velocity vector that is governed and updated by two behavioural variables that is memory and awareness. After sufficient time (i.e., iterations), particles can be expected to swarm towards the locations where their needs are met at an optimum level (optimum solutions). If $x_i(t)$ denotes the location of particle i at time t, the position of the particle is updated overtime by adding a velocity, $v_i(t)$ to the current location as follows:

$$x_i(t+1) = x_i(t) + v_i(t), \tag{10}$$

where:

$$v_i(t) = c_1 r_1 (pbest(t) - x_i(t)) + c_2 r_2 (gbest(t) - x_i(t)), \tag{11}$$

with c_1 and c_2 depicting the acceleration coefficients, r_1 and r_2 random vectors in the space (0 1) and *pbest* and *gbest* local best solution and global best value obtained, respectively. One of the major benefits of using PSO is that it can be easy to implement, it is robust and it has a low-computational cost while being efficient in solving difficult problems that require to find accurate mathematical models (Navneet, Harsukhpreet & Anurag, 2015).

2.8 | Hybrid ANFIS-PSO classifier

ANFIS, when used as a classifier, may have some limitations:

- It needs training and this may be time consuming.
- Rules must be linguistically defined.
- According to the back-propagation error rate, weights should be changed until no errors are found.

In order to bypass the limitations described above, a new method is proposed for breast tumour classification. This method introduces the PSO technique within the ANFIS. PSO, as a meta-heuristic optimization algorithm, can be used to train ANFIS and optimize its' membership function parameters.

In the proposed hybrid ANFIS-PSO classifier approach, ANFIS can be considered a one particle that represents a possible solution to the classification problem, whereas the dimensions are ANFIS parameters. Figure 5 represents the hybrid ANFIS-PSO classification scheme that was used in the current approach.

The best-known FIS are Mamdani and Sugeno. The main difference between them is that the Sugeno output membership functions continuous (either linear or constant) whereas Mamdani's are not. However, the output membership functions of the Mamdani system can be discontinuous (e.g., triangular, Gaussian). Sugeno FIS provides more flexibility in the system design and is more computational efficient compared to Mamdani (Blej & Azizi, 2016). In the specific study, a Sugeno-type FIS structure was created. The Gaussian membership function was applied, since it was proved to have a better accuracy results with less computational cost than other ANFIS membership functions (Talpur et al., 2017).

The ANFIS structure consists of three layers with three inputs (the PCA scores) and a single binary output. The ANFIS model structure is developed with the use of the fuzzy logic toolbox of MATLAB software package and is shown in Figure 6.

With a view to increase the prediction efficiency of the ANFIS model, a hybrid model was formed by using the PSO algorithm to fine-tune the ANFIS parameters. These consist of the number of particles, the inertia weight, the damping ratio and the personal and global learning coefficients. The initial values of these parameters were defined by using the trial-and-error method for a random training dataset and they are summarized in Table 1. More specifically, first these parameters were randomly initialized. Then by trying different combinations of values, the set of values leading to the best results in the specific DCE-MRI tumour classification problem was selected.

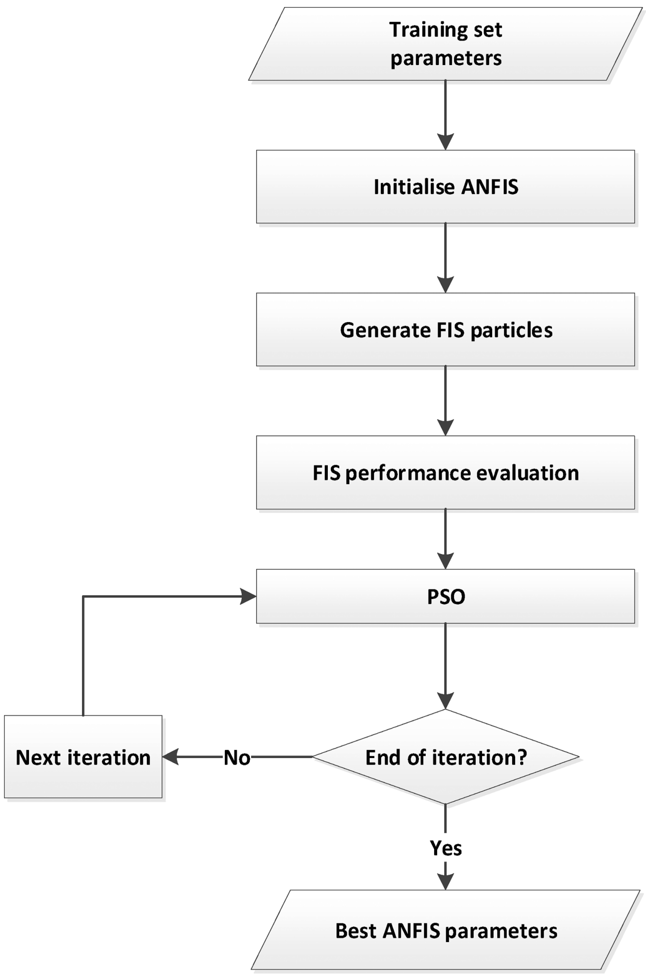

FIGURE 5 Flow chart of the proposed ANFIS-PSO approach. ANFIS, adaptive neuro-fuzzy inference system; PSO, particle swarm optimization

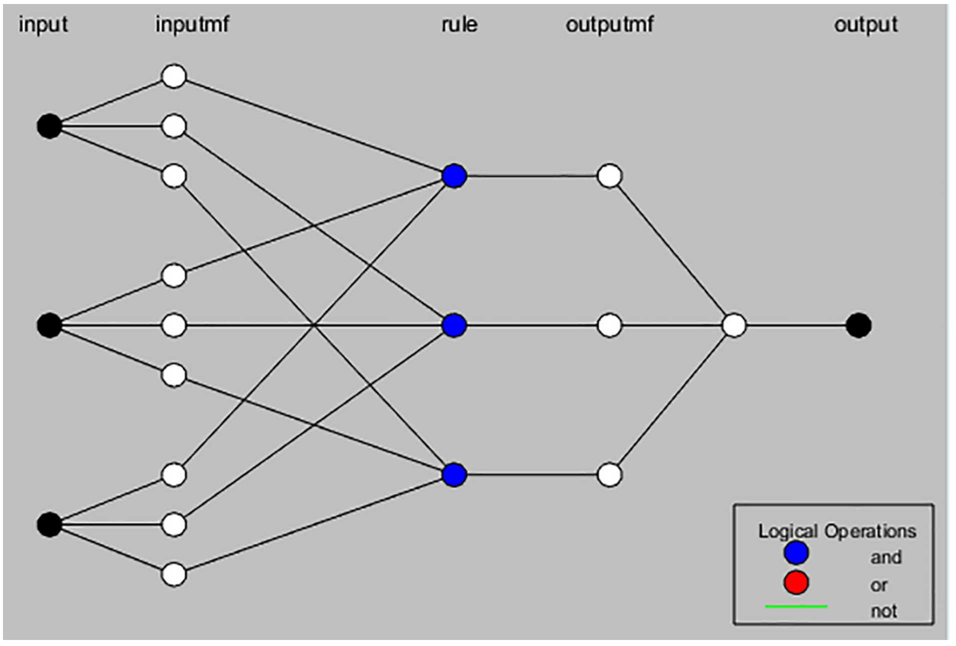

FIGURE 6 ANFIS model structure. ANFIS, adaptive neuro-fuzzy inference system

TABLE 1 Specification of PSO initial parameter setting

PSO parameter	Value
Number of particles	25
Number of iterations	1000
Inertia weight	$w = 1$
Damping ratio	$wdamp = 0.99$
Personal learning coefficient	$c_1 = 1$
Global learning coefficient	$c_2 = 2$

Abbreviation: PSO, particle swarm optimization.

3 | RESULTS AND DISCUSSION

3.1 | Results

Several investigations were conducted to assess the classification efficiency of the described approach. The data were randomly split into two separate data sets that is training and testing, by using the 70%–30% stratified ratio. The training dataset (30 subjects) was utilized to train the hybrid ANFIS-PSO classifier. The testing dataset (14 subjects) was used to validate the accuracy and the efficiency of the proposed model in the diagnosis of breast tumours. Ten different random splits of the initial dataset were performed and the overall accuracy was calculated by averaging the accuracy of all the 10 testing datasets.

Considering the evaluation and the comparatively assessment of the results of the ANFIS-PSO classifier, the features extracted from the multiresolution analysis were fed into the following classifiers:

- a LDA classifier (Fisher, 1936; Lachenbruch, 1975)
- an ANFIS (without use of PSO)
- Naive Bayes (John & Langley, 1995), which was implemented with the Scikit-learn library in python.
- Artificial neural network (Haykin, 1999) or MLP, which was implemented with the Tensorfow library in python. The artificial neural network consisted of three hidden layers with 5 units each and the 'ReLu' as the transfer function. The output layer used the 'sigmoid' transfer function.

TABLE 2 Classification results obtained for several classifiers when fed with radiomic features extracted by the FDCT multiresolution scheme

	Classification performance			
Classifier	**ACC**	**SN**	**SP**	**AUC**
LDA	0.84	0.91	0.76	0.79
Naïve Bayes	0.79	0.84	0.72	0.8
MLP	0.74	0.75	0.74	0.75
Random forest	0.69	0.68	0.73	0.71
SVM-RBF	0.74	0.78	0.69	0.74
ANFIS	0.84	0.79	0.92	0.85
ANFIS-PSO (proposed)	**0.94**	**0.94**	**0.94**	**0.94**

Note: The results are the average value obtained from the 10 used datasets. The results of the classifier with the highest obtained ACC are highlighted in bold.
Abbreviations: ACC, accuracy; ANFIS, adaptive neuro-fuzzy inference; AUC, area under the curve; LDA, linear discriminant analysis; MLP, multilayer perceptron; PSO, particle swarm optimization; SN, sensitivity; SP, specificity; SVM-RBF, support vector machine-radial basis function.

TABLE 3 Average ANFIS-PSO classification performance for SWT and FDCT extracted features

	ANFIS-PSO classification performance		
Mulitiresolution scheme	**ACC**	**SN**	**SP**
SWT (sym9, L = 3)	0.71	0.5	0.98
FDCT (4 scales)	**0.94**	**0.94**	**0.94**

Note: The results of the multiresolution scheme with the highest obtained ACC are highlighted in bold.
Abbreviations: ACC, accuracy; ANFIS, adaptive neuro-fuzzy inference; FDCT, fast discrete curvelet transform; PSO, particle swarm optimization; SN, sensitivity; SP, specificity; SWT, stationary wavelet transform.

- Random forest (Breiman, 2001), which was implemented with the Scikit-learn library in python with 100 base classifiers (decision trees) and maximum depth equal to 5.
- SVM with the radial basis function (RBF) kernel (Cortes & Vapnik, 1995), which was implemented with the Scikit-learn library in python.

Table 2 illustrates the classification performance of the investigated methods while exploiting the most powerful FDCT texture features. The classification accuracy (ACC), sensitivity (SN), specificity (SP) and area under the curve (AUC) were estimated.

The ANFIS-PSO classifier yielded superior performance compared to the various investigated classifiers, since it achieved an accuracy of 0.94. ANFIS (without use of PSO) and LDA both achieved an accuracy of 0.84. Both SVM and MLP scored an accuracy 0.74. Naïve Bayes and SVM-RBF classifier yielded an accuracy of 0.79 and 0.74 accordingly, as also indicated in Table 2.

The classification performance of ANFIS-PSO classifier was also evaluated using breast texture features extracted by the SWT (Kumar & Nagaraj, 2013). SWT is a wavelet-based method outlined to overwhelm the shift invariance absence of the DWT (Fowler, 2005). In the specific study, three decomposition scales were used. This led to nine reconstructed sub-images per time point; hence 27 detail sub-images and 54 texture features (including mean and entropy) were produced for each data sample. Sym9 was used as the basic (mother) function. The same 10 different sets of train and testing data (as those used in Table 2) were also incorporated for the assessment of the SWT-based textural features. The overall accuracy was provided by computing the average accuracy of the 10 data splits.

As shown in Table 3, the use of texture features extracted by the FDCT multiresolution scheme outperforms the use of those extracted by the SWT multiresolution scheme when classified by an ANFIS-PSO classifier. More specifically, FDCT extracted texture features yielded an accuracy of 0.94 while SWT texture features yielded an accuracy of 0.71 when fed into an ANFIS-PSO classifier. FDCT multiresolution scheme has the ability to extract the curve-like characteristics from the DCE–MRI images hence it extracts the best texture and edges features when compared with SWT (Shanker & Bhattacharya, 2020).

The fitted region of convergence (ROC) curves (John, 2017) are given in Figure 7 and illustrate that the ANFIS-PSO classifier significantly improves tumour classification when compared to LDA and ANFIS classifiers. The high AUC value allows to conclude that the hybrid ANFIS-PSO classifier may effectively be used for distinguishing between benign and malignant tumours. It is highlighted that ROC curves were indicatively represented for 1 of the 10 different used sets of data (same dataset, different distribution in benign and malignant cases).

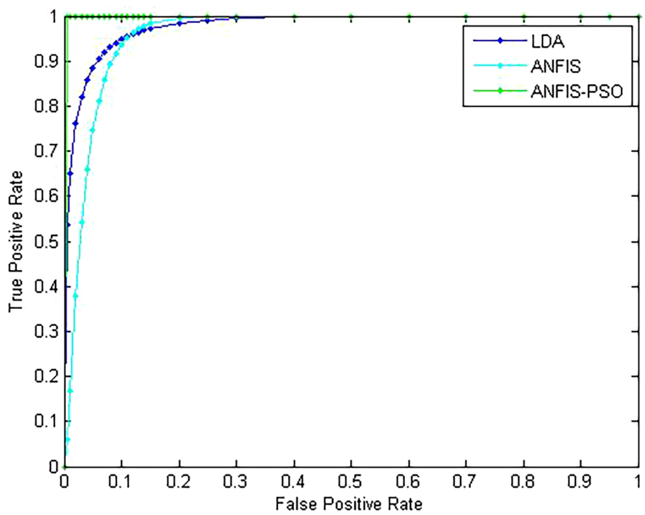

FIGURE 7 Fitted ROC curves for LDA, ANFIS and ANFIS-PSO classifiers (3 features). ANFIS, adaptive neuro-fuzzy inference system; LDA, linear discriminant analysis; PSO, particle swarm optimization

3.2 | Discussion

It is concluded that as soon as FDCT radiomics are fed in a hybrid ANFIS-PSO classifier, they can effectively characterize breast tumours, as depicted in Table 2. More specifically, they provide an accuracy of 0.94 with both sensitivity and specificity reaching 0.94. Therefore, the proposed methodology outperforms the other investigated classifiers by achieving a high-classification rate with low-computational cost.

After thorough evaluation of the advantages and disadvantages of the textural features used in the literature for breast tumour classification (Dogan et al., 2018; Fan et al., 2017; Fusco et al., 2017; Masood et al., 2018; Niu et al., 2018; Razavi et al., 2016; Tzalavra et al., 2016; Zheng et al., 2009) in the current work we adopted the multiresolution approach. FDCT, as a complete directional multiresolution transform provides high spatiotemporal information. The superiority of this technique insists to its' capacity to hold both frequency and spatial information while including directional information. This characteristic is of major importance for the analysis of breast DCE-MRI data. In previous study (Tzalavra et al., 2016) FDCT was used to classify breast DCE-MRI features and it was shown that FDCT outperforms other wavelet transforms (DWT, SWT) in terms of overall accuracy. In the current study, PCA was used to more compactly represent the information encoded in the FDCT breast radiomic features.

Concerning the classification approach, in this article we employed fuzzy logic and specifically an ANFIS-based approach. Such an adaptive fuzzy system has the potential to learn from the data it handles. The variables associated with its' membership functions can be updated throughout the training procedure.

According to the literature, although ANFIS has provided promising results in brain cancer detection (Chatterjee & Das, 2019; Selvapandian & Manivannam, 2018; Thirumurugan & Shanthakumar, 2016) and in mammography-based breast cancer detection (Addeh et al., 2018; Padmavathy et al., 2018; Sujatha et al., 2020) it has never been applied to breast DCE-MRI data.

In order to train the FIS and enhance ANFIS performance, we used PSO. PSO is an optimization approach based on colony aptitude that helps us determine the antecedent ANFIS parameters with low-computational cost. Therefore, we considered a hybrid ANFIS-PSO approach as a powerful classifier (Goldar et al., 2020; Kour et al., 2020).

The LDA classification method assumes normal distribution of the data. It derives linear discriminant functions and classifies the sample into the group with the highest score. Such behaviour is enabled by considering that it is simpler to discriminate data (linear features; combination) which have a greater divergence between two classes and smaller divergence within each class. However, the multivariate normality is particularly restrictive and reduces LDA's classification effectiveness when the features within each class are not normally distributed.

Statistical approaches, such as the Bayesian networks are characterized by the ability to take into account prior knowledge about the domain of interest, in terms of structural relationships among its features. However, Bayesian models are often less accurate that other more sophisticated methods.

MLP is affected by the manner biological neural networks work and is typically organized in weighted interconnected layers. It may perform well even in cases of no linearity between the input and the output data. However, neural networks' performance depends upon several parameters, such as the input features, the activation functions of the neurons, the weights of the connections, and the overall network architecture.

An ensemble of decision trees may achieve a good combination of accuracy and speed and is comprehensible by humans, but, since most decision tree algorithms divide the output space in hyperrectangles, its performance is aggravated for problems that require diagonal partitioning.

ANFIS is effective at solving no linear and complex problems since it combines fuzzy logic and neural network techniques. In the current study, we trained ANFIS using PSO. The incorporation of PSO optimizes ANFIS by seeking the best solution based on tuning of the membership functions.

According to our experimental results, the ANFIS-PSO classifier outperforms the other classification schemes when fed with FDCT radiomic features. It shall be noted that lower classification results are obtained by ANFIS-PSO when SWT radiomic features are used instead of FDCT. This is justified by the fact that, although both SWT and FDCT are both multiscale transforms that provide rich frequency representation, FDCT provides also directional information. Additionally, in comparison with SWT, FDCT is also effective in representing edges and curve-like characteristics which is a desirable feature for breast DCE-MRI images.

Several studies have been performed on breast DCE-MRI images radiomics. These indicated different performance indicators, since they are associated with different datasets, feature extraction algorithms and classifiers. Therefore, it is not possible to carry a direct comparative assessment between all these studies.

More specifically, Zheng et al. (Zheng et al., 2009) reported an AUC of 0.97 with the use of spatiotemporal features and LDA classifier in a group of 36 (22 malignant and 14 benign) cases. Yao et al. (Yao et al., 2009) extracted texture characteristics and also frequency features with the use of DWT in 18 breast tumour cases (10 malignant and 10 benign tumours identified in these). In this case, classification based on SVM illustrated an AUC of 0.966 and 0.949 in the training and testing datasets accordingly. Agner et al. (Agner et al., 2010) illustrated 89% classification accuracy on 41 cases (24 malignant and 17 benign) with the use of kinetic and morphologic attributes when fed in a probabilistic boosting tree.

4 | CONCLUSIONS

In this study, it is demonstrated that a hybrid ANFIS-PSO classification method may be promising for characterizing multiresolution breast DCE-MRI texture. The use of FDCT seems to be particularly effective for breast DCE-MRI data. It obtains radiomic features with position, scale and orientation, which can serve as texture descriptors. The use of PCA has contributed to the reduction of the dimensionality of the investigated dataset, thus increasing interpretability but at the same time minimizing information loss.

ANFIS as being a hybrid system of fuzzy logic and neural network techniques is proved to efficiently classify the extracted FDCT radiomic features, whereas its' use as a classifier is further optimized with the use of PSO which is simple to implement, it has low-computational cost and it requires small number of parameters and correspondingly lower number of iterations to adjust. Therefore, the hybrid ANFIS-PSO classifier has demonstrated high-classification results when fed with FDCT texture features. Challenges to be addressed in the future are mostly related to assessing the proposed methodology in larger populations and also in different medical data sets.

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CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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