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DETECTION AND CLASSIFICATION OF ROI USING OPTIMIZED RADIAL KERNALIZED FCM

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ABSTRACT

The classification system is generally categorized into Neural Network(NN) Classification or Data Mining classification and it comprises the tasks of pre-processing, feature extraction, classification and evaluation. The choice of classification method is related to the classes/groups, patterns/features, feature extraction, feature selection, the selection of training, testing samples and its time complexity. Medical image classification using Neural Networks(NN) is a supervised learning method and it is one of the significant research areas assist to examine the patient's images and is an important task of medical image analysis for computer aided diagnosis. The objective of this work is to segment and classify the Regions Of Interest (ROI) from MRI brain images using semi supervised approach referred as RKFCM-RBF-QPSO. The experimental section of this paper shows that the proposed approach produces accuracy of 98% with Root Mean Square Error(RMSE) of 0.1897 which is found to be better than other learning methods.

KEYWORDS: ***RKFCM, RBF,QPSO,MRI images, Clustering and Classification.***

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INTRODUCTION

Semi supervised learning was initiated in the year 1965 [11]. It is a combination of supervised and unsupervised learning tasks and the majority of the work on this area focuses on pattern recognition and machine learning to exploit both labelled and unlabelled data. The findings on semi supervised learning produce good learning accuracies. During past decades, lots of Semi Supervised Learning methods such as Transductive Support Vector Machine (TSVM)[5], Sparse SSL using conjugate functions[12], Multiview Laplacian Support Vector Machines (SVMs)[13], and graph based methods etc , have been extensively used, referred and adopted when labelled samples are not sufficient while the unlabeled samples are in large numbers. Researchers have shown that the exploitation of labelled and unlabelled data separately do not produce better results[10][2]. The optimization techniques are being used extensively to optimize the results of supervised and unsupervised learning methods where attention is given in designing fitness function. In case of unsupervised learning, the criteria for quality clusters is enhanced using optimization while in supervised learning the classification accuracy is improved with minimum square error. Figure 1 shows the supervised, unsupervised and semi supervised learning structures. In this work, the terms RKFCM-RBF-QPSO, BP-QPSO, MLP-QPSO refers the optimization of Radial Basis Function(RBF), Back Propagation (BP and Multi Layer Perceptron(MLP) using Quantum Particle Swarm Optimization(QPSO). Proposed RBF uses Radial Kernelzed Fuzzy C Means(RKFCM) to detect centres.The number of centres are selected based on the number of inputs of RBF and the centres can be easily selected than Multi-Layer Perceptron.

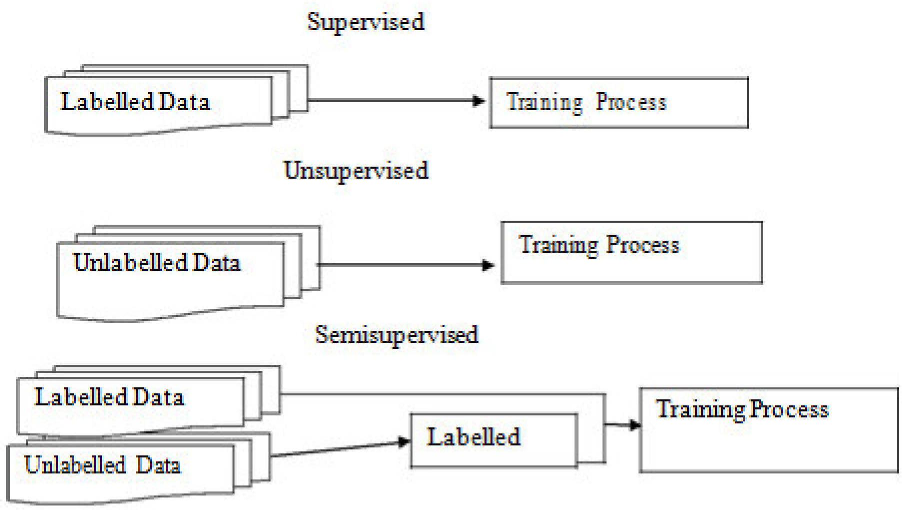


Figure 1
Supervised, Unsupervised and Semi supervised Learning.

MATERIALS AND METHODS

The classification of labelled training data is costlier than unlabelled data in many pattern classification problems. The recent researches are focused on semi supervised classification due to its efficiency. Semi-supervised approaches are demonstrated in outlier detection in order to overcome the time-consuming process of labelling training data. The semi supervised pattern recognition involving clustering and classification takes the advantageous of clustering if it gets applied first. The output function of supervised learning method is written as O= (XWY) where X is the input vector, Y is the output vector and W is the weight. The figures 2 and 3 represent the two way processes of semi supervised clustering and classification of medical images. ROI detection followed its classification using optimized approach is depicted in Figure 2 while Figure 3 shows an optimized approach of classifying the images followed by detection of ROI . The former one classifies the images based on statistical features of ROI. Grouping of pixels refers segmenting the ROI from retinal images has been proposed[[6]. Principal component analysis is performed to detect Alzheimer's Disease using Multitracer Positron Emission Tomography Imaging[3]. An unsupervised learning method based on Kohenen Neural Network has been proposed to perform analysis on robot soccer competitions. The objective c function for extracting ROI from medical images is designed and it is segmented using clustering algorithms[15]. The segmented ROI's are given as input to the classifiers. The classifiers in turn classify ROI based on their statistical properties. The later one takes input as collection of images and classifies them as abnormal and normal images. The abnormal images are given as input to clustering algorithm to segment ROI which represents the abnormalities.

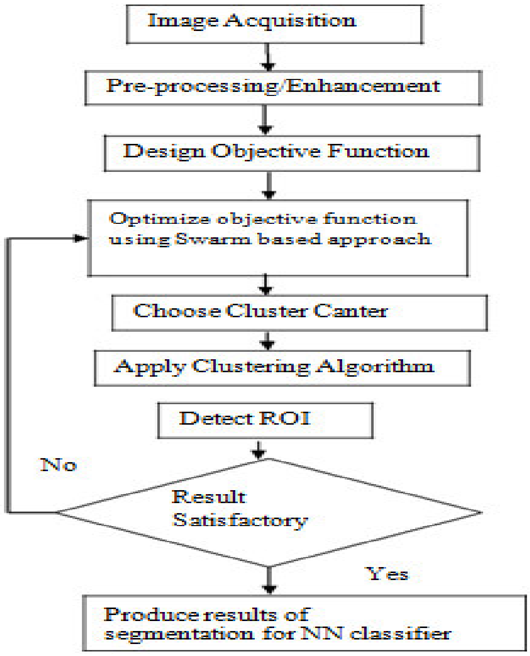


Figure 2
Classification of Region Of Interest(ROI) after segmentation of medical images.

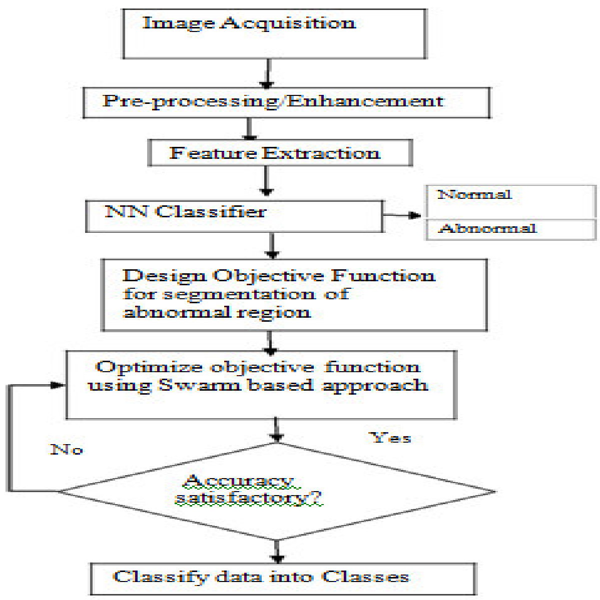


Figure 3
Segmentation of Region Of Interest(ROI) after the classification.

The proposed approach RKFCM-RBF-QPSO follows the architecture shown in figure 2 which invokes both clustering and classification in the process of identifying and classifying ROI to improve the overall performance in terms of quality and computation time. In this work, medical images are selected, enhanced and segmented using clustering algorithms then each cluster is labelled by classification step by evaluating its statistical parameters. The proposed semi supervised approach involves Kernelized Fuzzy C Means (KFCM) to cluster or segment the ROI and RBF to classify it. Fuzzy C-Means is a Fuzzy Partitioning clustering algorithm allows data to belong to multiple clusters based on their membership grade. Fuzzy C Means has been widely used to segment the images. FCM gathers much information from the images but the main drawback is more sensitiveness to noise. The spatial information in the image is not considered by FCM. The variant of FCM called KFCM segments even the noisy images with good accuracy. The objective function of KFCM designed to consider the spatial constraints. RBF Neural Network construction and learning involves two stages: RBFNN structure initialization and parameter optimization. In the stage of Neural Network initialization, the number of hidden neurons are to be identified. The better initialization improves the accuracy of the networks. Generally, clustering algorithms such as K-means and FCM determine the initial structure of RBF. Optimization algorithms were employed for system initialization and parameter optimization of RBF. Genetic algorithm, Particle Swarm Optimization (PSO), Differential evolution are popular optimization methods hybridized with RBF for better performance. PSO is used to train RBF and to find optimal parameters for fuzzy clustering[4]. A hybrid approach combining PSO and RBF is proposed to solve classification problems[7]. A new Optimum Steepest Decent (OSD); a combination of PSO and gradient decent proposed to initialize RBF more accurately and interesting outcomes are found[14]. To train RBFNN, a novel Fuzzy C-Means clustering is described for effective outcome [1] and the learning ability of the system is improved by employing maximum entropy based RBF system[8]. In this work, the radial basis function is used as the kernel function of KFCM and is referred as RKFCM. The kernel function of RKFCM is given in Eq. 1

$$J_{RKFCM} = 2\sum_{i=1}^{c}\sum_{k=1}^{n}\mu_{ik}^{m}\left\|\varphi(x_k)-\varphi(v_i)\right\|^2 + \sum_{i=1}^{c}\eta_i \; {}^{1-\eta_i} \qquad (1)$$

Where

$$\left\|\varphi(x_k)-\varphi(v_i)\right\|^2 = \varphi(x_k)-\varphi(v_i).\varphi(x_k)-\varphi(v_i)$$

$$= \varphi(x_k).\varphi(x_k) - 2\varphi(v_i).\varphi(x_k) + \varphi(v_i).\varphi(x_k)$$

$$= K(x_k, x_k) - 2K(x_k, v_i) + K(v_i, v_i)$$

$$J_{RKFCM} = 2\sum_{i=1}^{c}\sum_{k=1}^{n}\mu_{ik}^{m}(1-K(x_k, v_i)) + \sum_{i=1}^{c}\eta_i e \; {}^{1-\eta_i} \qquad (2)$$

The fitness function to be optimized is defined as

$$F_{RKFCM} = \frac{1}{J_{RKFCM} + 1} \qquad (3)$$

The block diagram of proposed method is shown in the figure 4

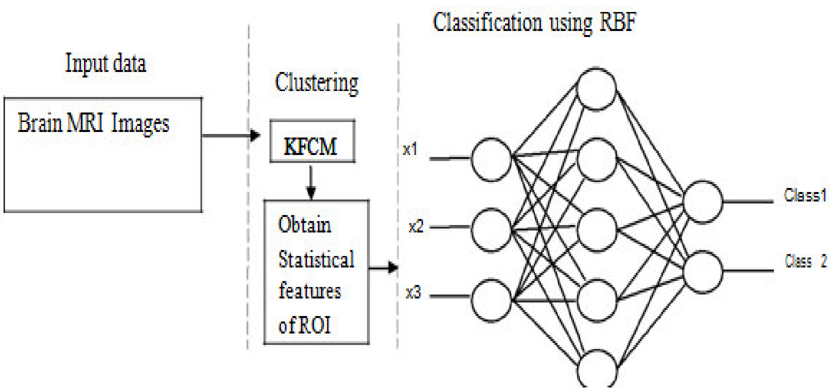


Figure 4
Proposed Classification of ROI using RKFCM-RBF-QPSO.

The stepwise procedure of the proposed RKFCM-RBF-QPSO is given below

Procedure of RKFCM-RBF-QPSO
Begin
Initialize population size M and Dimension of search D
Find the random positions for all particles and assign as Initial positions
For each particle i
Assign initial positions as personal best positions of particles (pbest[i])
End For

Calculate mean best positions(mbest) of particles as

$$mbest = \left(1/M\sum_{i=1}^{M}Pbest_{i,1},\ /M\sum_{i=1}^{M}Pbest_{i,2}, \ldots\ldots, 1/M\sum_{i=1}^{M}Pbest_{i,D}\right)$$

While(population size & maximum number of iterations)
Calculate fitness as given in Eq. 3
Update the pbest, mbest and find gbest
Set gbest as cluster centers
For each dimension
Update the positions

End For
End While
Classify the segmented regions using RBF.
End
The positions of particles M in D dimensional search space is given in Eq. 4

$$X_i(t+1) = p \pm \beta \left| mbest - X_i(t) \right| * \ln(1/u) \qquad (4)$$

Where p is obtained by the Eq. 5

$$p = rand(0,1) * Pbest + (1 - rand(0,1)) * Gbest \qquad (5)$$

and Beta is calculated as

$$\beta = (\beta_1 - \beta_2) x \frac{(MAXITER - t)}{MAXITER} + \beta_2, \beta_1 \text{ is}$$

normally assigned with 1.0 and □2 with 0.5.
The mean, standard deviation, Skewness, Kurtosis and homogeneity features of ROI are considered for classification are given in Eqs 6, 7, 8, 9 and 10 respectively.

$$Mean(\mu) = \frac{1}{MxN} \sum_{i=1}^{M} \sum_{j=1}^{N} I(i,j) \qquad (6)$$

Where MxN is the size of an image, M refers the number of rows and N refers the number of columns of I ,I(i,j) is the Intensity of pixel at the localtioni,j

Standard Deviation(SD)
The amount of variationon I is calculated as

$$SD = \sqrt{M * N \sum_{i=1}^{M} \sum_{j=1}^{N} (I(i,j) - \mu)^2} \qquad (7)$$

Skewness(S)
Skewness is measure of symmetry.A dataset is a symmetric if the left and right pixels of centre measured as same. The shape of the distribution is characterized with skewness S

$$S = \frac{1}{MxN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[\frac{I(i,j) - \mu}{\sigma} \right]^3 \qquad (8)$$

Kurtosis(K)
The peak and flat points of dataset is measured by Kurtosis

$$K = \frac{1}{MxN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[\frac{I(i,j) - \mu}{\sigma} \right]^4 \qquad (9)$$

Homogeneity is an another statistical feature torepresent ROI and it is written as

$$Homo_{x,y} = \sqrt{\sigma^2} \times \sigma^2 / \mu \qquad (10)$$

RESULTS

The statistical features of ROI are given as input to RBF Neural Network classifier. The sample MRI slices mentioned in Table 1 are considered as input to proposed RKFCM-RBF-QPSO. The ROI segmented output of MRI slices of two patients are given in Tables 1 and 2 respectively.

Table 1
Segmented ROI from different slices of Patient-1.

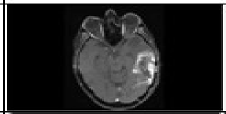
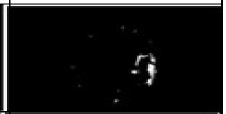
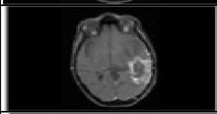
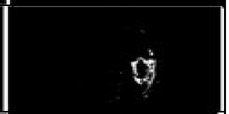
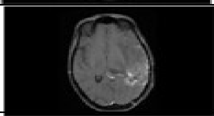
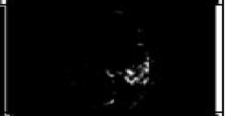
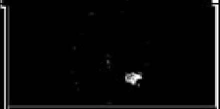
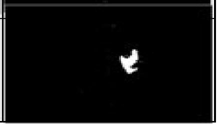
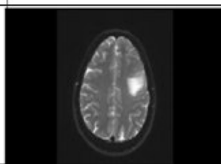
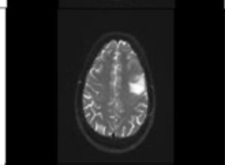
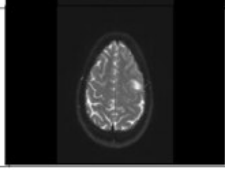
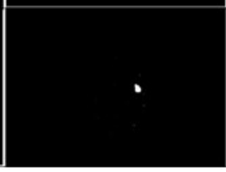
MRI SAMPLE(SLICE NO)	ORIGINAL IMAGE	SEGMENTED IMAGE
MRI S1(Slice 2)		
MRI S1(Slice 4)		
MRI S1(Slice 5)		
MRI S1(Slice 14)		
MRI S2(Slice15)		

Table 2.
Segmented ROI from different slices of Patient-2.

MRI Sample(Slice no)	Original Image	Segmented Image
MRI S2(Slice 16)		
MRI S2(Slice 17)		
MRI S2(Slice18)		

The statistical measures for the segmented regions (ROI) shown in Table 1 and Table 2 are given in Table 3. The accuracy and root mean square error are mentioned in Table 4. The proposed approach produces 98% accuracy with 0.1897 mean square error which is comparatively better than BP-QPSO and MLP-QPSO. In this experiment, the training set considered to have 70 % of total images and testing test consists of remaining 30% of the total images . The original images shown in Table 1 and Table 2 are the sample images collected from Scan World Diagnostic Centre, Chennai

Table 3
The statistical results of ROI on various MRI samples.

Statistical Parameters	MRI-S1 (Slice2)	MRI-S1 (Slice 4)	MRI-S1 (Slice 5)	MRI-S1 (Slice 14)	MRI-S2 (Slice15)	MRI-S2 (Slice16)	MRI-S3 (Slice 17)	MRI-S3 (Slice 18)
Mean	2.9002	1.853	1.5884	0.988	1.8543	1.4715	1.4975	1.8817
Standard Deviation	27.0398	21.6721	20.0629	15.8422	21.660	18.9861	19.4839	21.8239
Skewness	9.2160	11.5950	12.5517	15.97	11.5985	13.2811	12.9340	11.5120
Kurtosis	85.9354	135.4451	158.5449	256.0887	135.5241	177.3887	1168.2880	133.543
Homogeneity	6.8167e+003	5.4862e+003	5.0842e+003	4.1479e+003	5.4847e+003	4.8145e+003	4.9392e+003	5.5240e+003
Entropy	0.0898	0.0621	0.0546	0.0363	0.0645	0.0498	0.0520	0.0629

Table 4
RMSE and Accuracy of MLP-QPSO, BP-QPSO and proposed approach.

Classifiers	RMSE	Accuracy
Multi Layer Perceptron (MLP)-QPSO	0.25145	91%
Back Propagation-QPSO	0.2714	
Proposed Approach	0.1897	98%

DISCUSSIONS

The proposed semi supervised approach uses clustering followed by classification as the convergence rate of clustering is lesser than the classification and the segmentation of desired ROI is always ensured. In this work, supervised learning involving RBF as classifier is adopted for ROI classification. The accuracy of 98% is obtained using this proposed approach which is found to be better than other approaches such as MLP-QPSO(accuracy 91%) and BP-QPSO(accuracy 89%.The work mentioned in this paper is exercised only on brain images but it can also be extended to Liver images. Future work focuses on the automatic segmentation and classification of tumour and cysts present in the MRI and CT images.

CONFLICT OF INTEREST

Conflict of interest declared none.

Contribution of Authors
The work mentioned in this paper is the original work of the author Anusuya S.Venkatesan.

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