A Correlative Analysis of SOM and FCM Classifier for Brain Tumour Detection

Suchita Goswami, Archana Tiwari, Vivek Pali, Ankita Tripathi

Abstract— The task of reading the MRI (Magnetic resonance Imaging) scans is difficult in case of brain abnormality detection because of variance and complexity of tumours. The diagnosis of brain tumour requires a detailed analysis of MRI scan, which includes the detail about area of tumour, blood clotting etc. The process of diagnosis involves painful invasive surgery that can cause discomfort to patients. This paper presents a separate unsupervised learning based NN (neural network) classifier to detect a tumour in the magnetic resonance human being brain images and a separate FL (Fuzzy logic) classifier for the said above. In this paper, the brain tumour diagnostic procedure is divided into the following stages. The first stage comprises of image pre-processing which includes image resizing, noise filtering and thresholding. At stage two, extraction of features from the images got from MR brain was done by the use of GLCM (Grey level co-occurrence matrix). In third stage, brain tumour was diagnosed by using NN (Self organizing map) based classifier and FL (Fuzzy C-means clustering) classifier. The obtained accuracy of NN classifier is 96% and sensitivity is 92% and specificity is 66% and that of FL classifier is 98% and sensitivity as 100% and specificity as 66.6%. The comparative analysis of specificity, accuracy and sensitivity with other techniques based on previous work is used to evaluate the classification technique performance.

Keywords- Magnetic Resonance Imaging (MRI), Fuzzy C-means clustering (FCM), Grey level co-occurrence matrix (GLCM), Accuracy, Sensitivity, Specificity.

I. INTRODUCTION

Now a days in medical applications, most importantly used diagnosis tools are medical imaging techniques like CT, MRI, SPECT, PET etc. These methods assist medical experts in their decisions. Among all the techniques MRI technique is most widely used for soft tissues analysis. MRI provide the detailed analysis of lesions regarding clinical symptoms and signs those were not received from prior CT. Which will also help to define in better way the abnormalities received from CT. MRI is the most helpful modality in the study of human brain and the diseases related to human brain. The most complex and least understood organ in the human body is brain. There are various types of brain diseases. In this paper we are dealing with brain tumours.

Brain Tumours are the abnormal masses in the brain. The main reason for tumour growth is proliferation of the uncontrolled cell, failure to normal pattern of cell death or both. Brain tumours can be of primary brain tumour or secondary brain tumour. Primary tumours are made up of the cells in the brain which supports the nervous system. Secondary tumours are made up of the cells from other parts of the body that spreads in one or more areas.[1]

The criteria are as follows on which the brain tumours can be classified:

i. Location in brain (Cerebral, Cerebellum, Brainstem, Convexity tumours);
ii. Location in the skull (Interaxial, Extra axial);
iii. Location in compartments (Infratentorial, Supratentorial, Posterior fossa, Anterior fossa, Middle fossa, Cerebellopontine angle, Orbital);
iv. Origin of tumour (Glial cells, Neurons, Meninges, Germ cells);
v. Pathology (Benign, Malignant)

II. RELATED WORK

a) Image classification by artificial neural network technique

For brain image classification a number of researchers depend on artificial intelligent techniques. Most predominantly used methodologies in AI techniques are FL and ANN. The advantages of using ANN techniques are that they provide high accuracy and are more adaptive in nature. Alirezaie J et al. [10] demonstrated Linear Vector Quantization (LVQ) application in brain image segmentation. After that they compared the Linear Vector Quantisation (LVQ) technique with Back Propagation Network (BPN) technique in which LVQ technique comes out to be the best technique and the paper also concluded that ANN technique is faster as compared to classical techniques. Carlos A et al. [11] proposed brain image segmentation using LVQ. The convergence rate of the proposed system is good but it has limitation to distinguish the outer layer of the MRI brain image. However, Valdes-Cristerna R [12] used radial basis function (RBF) NN to develop clear contours between different tissues in the MRI. MR image segmentation technique (contour model-based) was also used. Martin-Landrove M et al. [13] used Back propagation (BP) NN technique for brain image classification. In this letter BPNN was comparatively analysed with technique based on inverse Laplace transform. It was concluded that the BPNN technique are more accurate than that of conventional techniques. Yeh J et al. [14] developed an enhanced version of LVQ neural network involving the concept of Genetic Algorithm. The convergence time of the system is fast but the only drawback of the system was the lack of expert's knowledge.

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SuchitaGoswami,MTech,Nagpur,India**.**
(suchita1.goswami@gmail.com)
Archana Tiwari, Electronics Engineering Department, Shri. Ramdeobaba College of Engineering & Management, Nagpur, Maharashtra. (tiwariar@rknec.edu)
Vivek Pali, Department of Computer Science Engineering. Chhattisgarh Institute Of Technology, Rajnandgaon, Chhattisgarh. (Vivekpali1986@gmail.com)
Ankita Tripathi, MTech Nagpur, India (Ankita9tripathi@gmail.com)

For brain image classification El-sayed a. El-dahshan et al. [21] proposed a hybrid method of ANN which includes feed forward back propagation artificial neural network (FP-ANN) and k-nearest neighbour method (K-NN). The only limitation of the work was the requirement of fresh training for increased database. Dipali M. Joshi et al. [22] proposed a GLCM based feature selection of MRI brain image and neural network classification. Using said system gives precise results of Astrocytoma type cancer detection and classification.

b) Image Classification by Fuzzy Logic Technique

Cheng T et al. [15] has proposed a modified FCM (Fuzzy C-means) algorithm for brain image classification. The proposed system has high convergence time but gives lack of quantitative analysis on segmentation efficiency. In image pre-processing applications the significance of weights in fuzzy rules based on real time datasets through simulations was shown by Ishibuchi H et al. [16]. The method also framed the Fuzzy IF-THEN rules for Image classification. Auephanwiriyakul S et al. [17] proposed a comparison between extension principle based linguistic algorithm with conventional FCM. Zheng Y et al. [18] has proposed a fuzzy connectedness technique for image classification but the disadvantage of the technique is the requirement of several initial parameters including the seed pixel. Dou W et al. [19] proposed that the incorporation of the fuzzy information in MR brain image classification gives advantage. The use of fused fuzzy features increases the accuracy of the system. Xiao K et al. [20] proposed a gaussian smoothing based FCM algorithm.

III. METHODOLOGY

The work involves following three steps: -

I. Image pre-processing which removes noise from MR brain images.
II. Transformation of input data into a reduced feature sets (feature vectors) called Feature extraction.
III. Development of a NN and FL classifier which classifies the brain images.

The schematic block of architecture proposed for MR brain images classification is shown below.

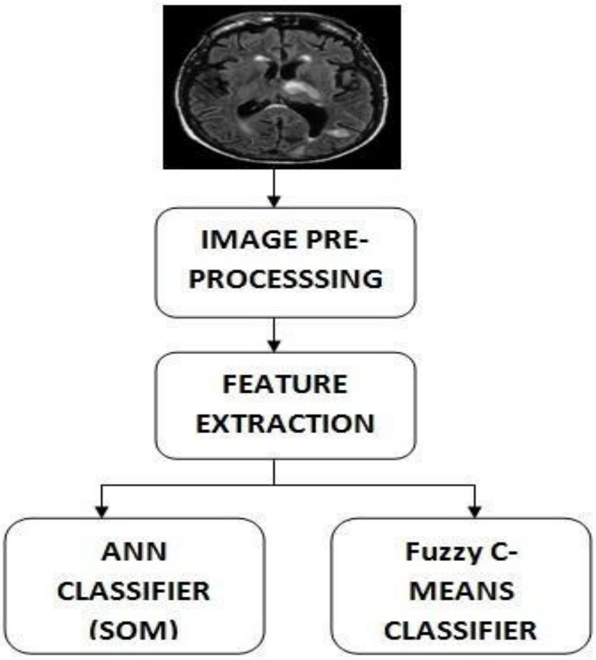

Figure 1: The proposed block schematic of MR brain image classification.

IV. IMAGE PRE-PROCESSING

Improvement in the image data quality and suppression of the distortions in image can be done by using Image pre-processing. Through this process the enhancement of image features for further processing is done. The basic image pre-processing includes simple noise removal While, the advanced image pre-processing includes some operations like image registration and segmentation.[2]

V. FEATURE EXTRACTION

Feature extraction is a technique through which one can reduce the dimension of an image making it feasible for further processing. Feature Extraction is mainly used for the large input and redundant data. To differentiate one input pattern from other, certain measure properties or features are needed that was provided by the technique feature extraction [17][3]. Hence for feature extraction GLCM (Grey-level Co-occurrence Matrix) Method is used.

Texture Feature Extraction through GLCM

In remote sensing, automatic visual inspection, image classification and medical image analysis process, the most important feature of an image which is used widely is Textual. [23] [24] [25].

Texture represents the structure arrangement present in the image or pattern of information. As texture information plays an important role, texture feature extraction is very important parameter in medical image processing. It is also important in retrieval of content-based image. The commonly used method is statistical texture analysis method used for extraction of texture features amongst all other methods used for the same like statistical texture-based method, structural based method, model-based method and

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transform information-based method etc.

In a statistical texture analysis method, the texture features are calculated based on a statistical distribution of pixel intensity at a given position related to others in a matrix. Feature extraction using GLCM or grey tone spatial dependency matrix is a second-order statistics which could be used for the analysis of the MR brain images as a texture. A number of useful textural properties can be computed from GLCM to extract the details about the content of the image.

The spatial distribution of grey values is an important quality of texture. Therefore, in the image processing literature, the study of statistical features is one of the early studies presented. Haralick [26] presented GLCM which uses the spatial relationship between two neighbouring pixels, the first pixel is a reference pixel and the second is a neighbour pixel. In addition, there are eight directions which include 0, 45, 90, 135, 180, 225, 270, and 315. Figure below shows all the directions of adjancy i.e from left- right and from top-bottom.

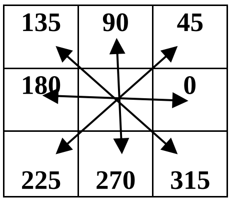

Figure 2: Eight direction of adjancy

Below figure shows the distance of d = 1 and an angle of 0° of the GLCM of the 4-grey-level image formation [27].

0	0	1	1	1
0	0	1	1	1
0	2	2	2	2
2	2	3	3	3
2	2	3	3	3

	0	1	2	3
0	2	2	1	0
1	0	4	0	0
2	0	0	5	2
3	0	0	0	4

Figure 3: (a) Four grey level image (b) GLCM for distance d=1 and angle θ=0°.

VI. CLASSIFICATION

To determine and classify different features of an image, image classification technique is used. The identification of features in an image is performed in terms of objects. Supervised image classification and unsupervised image classification are the two categories of image classification techniques. The classification of MRI brain images is done through unsupervised Neural & Fuzzy classifier separately. The algorithm used for NN classifier is SOM (Self-Organizing Map) and for FL classifier FCM (Fuzzy C-means) Algorithm is used.

a) Self Organizing Map (SOM)

SOM is a special type of ANN technique which uses competitive unsupervised learning. In SOM the output neurons compete among themselves to get fired. So, at a time only one output neuron is active. The output neuron which is active wins the competition and considered as winner-takes-all neurons.

The architecture of SOM is shown in figure 4. In a SOM, at the nodes of a lattice the placement of neurons was done. The lattice can be 1-dimensional or 2-dimensional. The non-common maps are Higher-dimensional maps. Then the tuning of neurons on the basis of some selective input patterns or classes were performed. Different input features form a meaningful coordinate system over the lattice by the ordered adjustment of the locations of the winning neurons. The Self-Organizing Map algorithm mainly consists of following steps:

1) The random initialization of every node is performed.

2) A random selection of vector from the data set was done and is presented to the network [32].

3) The weight of each node is examined to find out the similarity in weights of node and the input vector. The similar weight node to the input vector is considered as the winning node or the BMU (Best Matching Unit) [33].

4) The radius of the neighbourhood of the BMU is calculated and considered as the radius of the network, fading each time-step [32].

5) Each node within the calculated radius of BMU is adjusted to make it similar to input vector. The node which is closer to BMU is more likely to weight change.

6) Repeat step 2 for N iterations.[9]

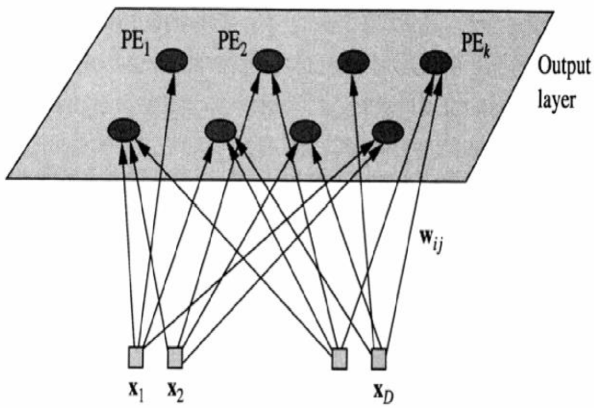

Figure 4: Architecture of a SOM

b) Fuzzy C-means Algorithm (FCM)

FCM is an advanced clustering algorithm uses membership function in which every cluster is associated with its own pattern [4][5]. While in traditional clustering algorithm the generated pattern belongs to only one cluster. It is a widely used method to obtain fuzzy models from data. The objective function is minimized as below:

$$k_m = \sum_{i-1}^{N} \sum_{j-1}^{C} vij\|pi - qj\|^2, \; 1 \le n < \infty$$

where

vij- degree of membership of pi in the cluster j,

n (real number) > 1,

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pi- the it h of d-dimensional measured data,

qj- d-dimension centre of the cluster, and

||*||- similarity between any measured data.

Fuzzy partitioning is performed through an iterative optimization of the above given objective function, by regularly updating membership uij and the cluster centers Ci by:

$$S_{ij}=\frac{1}{\sum_{k=1}^{c}\left[\frac{\|xi-cj\|}{\|xi-ck\|}\right]^{\frac{2}{m-1}}},$$

$$C_j=\frac{\sum_{i=1}^{N} s.xi}{\sum_{i=1}^{N} s_{ij}^{m}}$$

Steps of algorithm are:

1: Initialization of S=[Sij] matrix, S(0)

2: Now you need to calculate the centre vectors at the kth step: C(k)=[cj] with S(k)

3: updation of S(k), S(k+1)

4: If || S(k+1) - S(k)||< ζ then STOP; otherwise return to step 2.

Where k is the no of iterations and ζ is a termination criterion between 0 and 1.

In this algorithm, every pattern in input data is bound to each n every cluster by using a Membership Function. Membership function is mainly used to represent the fuzzy behaviour of the algorithm. The membership function determines the fuzzy behaviour by building an appropriate matrix named U. The matrix U contains the number between 0 and 1 which are used to represent the degree of membership between data and centres of clusters [6][7][8].

VII. RESULT AND CONCLUSION

In this project I have used an unsupervised NN classifier and FCM classifier approach for MRI brain image classification. This section shows how an applied MRI brain image is pre-processed and how the features of the applied image are extracted using GLCM and finally it is classified as a normal or abnormal image with the help of Neural and Fuzzy classifier separately. A comparative analysis of both the methods has been done. The obtained accuracy of fuzzy c-means brain image classifier is 98% and sensitivity is 100% and specificity is 66.6% which is better as compared to SOM-NN classifier whose accuracy is 96% and sensitivity is 92% and specificity is 66%. A Graphical user interface has been developed which shows the pre-processed image and respective clustered output is generated. It also classifies whether the image is normal or abnormal and calculates the area of abnormality in the image. I have used this classification algorithm for a number of images from various repository sites.

When the brain image classification is performed by employing ANN the accuracy attained is not high and the process becomes computationally heavy. Moreover, in order to achieve high accuracy a large training set is required. whereas fuzzy logic technique is more accurate subject to expert knowledge. Less convergence time is required in Fuzzy logic technique and trial and error method is used to determine the fuzzy rules or fuzzy membership functions.

Simulation Result

The outputs for some of the applied images are shown in figures below:-

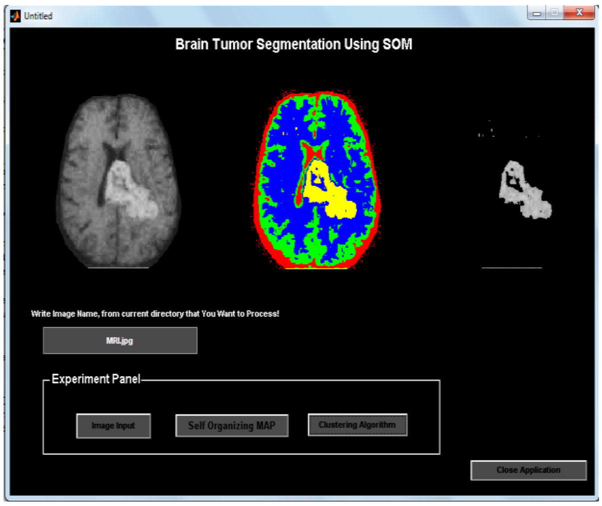

Figure 5: GUI of a SOM based neural network classifier

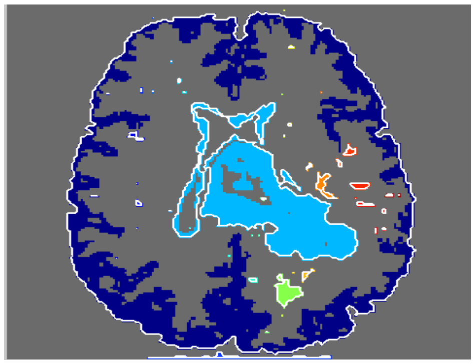

Figure 6: Output of SOM based neural network classifier.

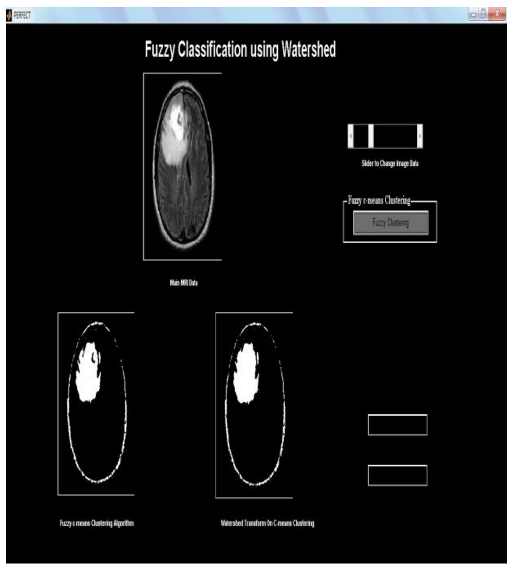

Figure 7 : GUI of a FCM based Fuzzy logic classifier

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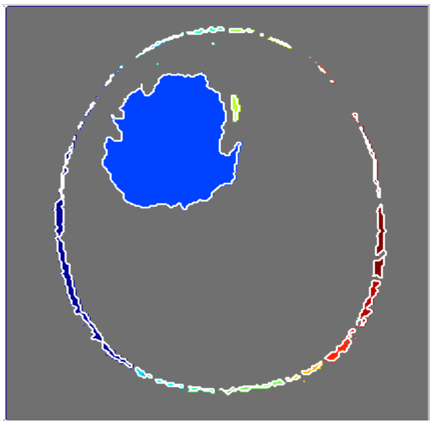
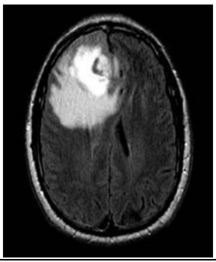
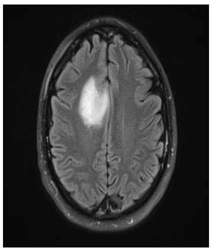
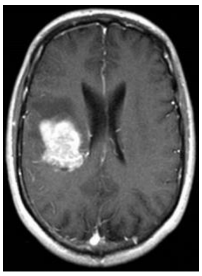
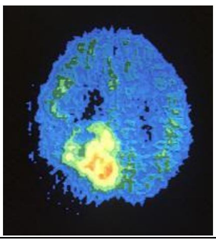
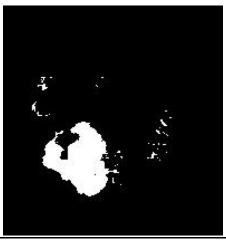


Figure 8: Output of FCM based Fuzzy logic classifier.

Figure 5 and 6 shows the GUI of Neural network classifier and clustered output of tumour, while figure 7 and 8 shows the GUI of FCM based fuzzy logic classifier and the clustered output respectively. The table shows some of the applied input images , FCM outputs and calculated area of tumour.

Images	**FCM o/p**	**Area of tumor**
		13050
		196608
		55689
		131400

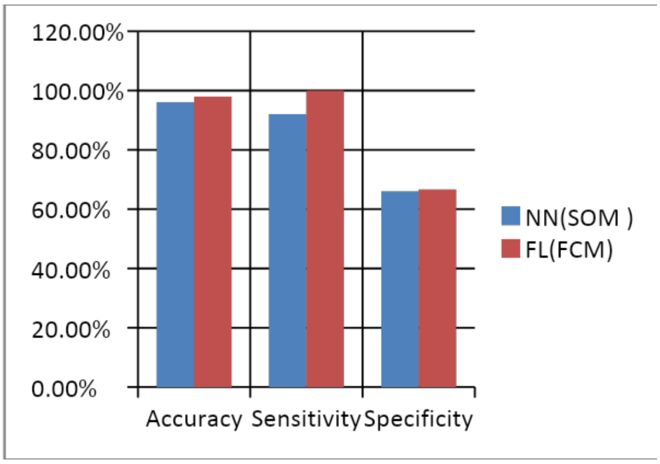


Figure 4: Comparison of NN & FL approaches

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