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Automatic Classification and Segmentation of Tumors from Skull Stripped Images using PNN & SFCM

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Automatic Classification and Segmentation of Tumors from Skull Stripped Images using PNN & SFCM

Adapala Praveen Kumar [α] & J Krishna Chaithanya [σ]

Abstract- Automatic classification of brain tumor is area of concern from last few decades for better perceptive analysis in accurate manner. In this paper an automatic brain tumor classification approach namely probabilistic neural network are proposed with image and data processing techniques. The conventional algorithms which are reported in the literature are not automatic in nature and mainly their processing is based on human inspection. Then after some time a new classification approaches came into existence by overcoming the disadvantages of conventional algorithms namely Operator assisted classification methods which proves impractical for huge data amounts and simultaneously it is non-reproducible. The MR brain tumor images contains the noise like content which is mainly caused by the operator performance while processing and this noise results in highly inaccurate classification analysis. For better accuracy in classification of tumor image artificial intelligent techniques like fuzzy logic and neural networks usage are encouraged these days. A new automatic classification and segmentation approach namely probabilistic neural network is presented in this paper and the required decision making is performed in two steps (i) Feature extraction from the tumor images by principle component analysis approach and (ii) probabilistic neural network (PNN). (iii) Segmentation of the abnormal region with spatial fuzzy c- means clustering (SFCM).

The evaluation of PNN classifier performance is evaluated by training performance and classification accuracies. The proposed PNN classifier gives the fast, reliable and accurate classification of the brain tumor for better analysis and the proposed PNN is considered path breaking tool in brain tumor classification.

Keywords: probabilistic neural network (PNN), principle component analysis, SFCM, brain tumor.

I. Introduction

Research on brain and its related tumors are area of concern from last few decades in the medical image processing and data processing techniques. In literature so many different classification algorithms are reported for differentiating the area of tumor region from the respective brain region. Although so many innovative classification techniques are implemented for accurately analyze the situation of patient but due to high complexity and noise related issues this conventional techniques are not considered as promising tool for classification of tumor because this conventional algorithms are not designed meet the practical scenario requirements and produces inaccuracy results.

The drawbacks and disadvantages of conventional classification algorithms gives path to the new way to research on brain tumor and researchers starts to make research on artificial independent techniques like fuzzy logic and neural networks which are considered as promising technologies in many application oriented domains. Automatic image classification of brain tumor is motivated by these artificial independent algorithms in medical image processing domain. As the research relates to human life so the classification results should give less error rate and high accuracy for better analysis and that's why computer assistance is demanded these days for automatic classification.

Advantages of the proposed method stress not only on the classification but also concentrates to extract the abnormal image region using clustering based segmentation algorithm.

Double reading of tumor images can give better accuracy but this could also increase the cost so to tackle the expensiveness of double reading a better software is needed and is in great interest now a days. The main difference between the conventional and artificial intelligent techniques is conventional techniques resolve the issue of handling the large number of patients in accurate manner.

In the proposed work a new automatic approach is presented for classification of brain MR images automatically by make use of some extensive like pixel intensity from the tumor brain image and some anatomical features. The automatic and most reliable methods for detection of tumor is an area of interest and in great need for analyzing the patient scenario by respective physician and these automatic techniques are in great demand mainly because of drawbacks of conventional approaches.

The proposed PNN approach is not yet used to its full extent in the classification of data from the respective brain images which gives the data related to brain tumor and if the Proposed PNN is utilized manually then problems related to handling high amount of data of different patients at intensive care units can be

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handled very efficiently and simultaneously reduces the time consumption significantly. The PNN approach can be efficiently used for both clustering, recognition and classification for better accuracy and it gives scope to introduce the neural networks systems in order to solve the medical problems.

II. Tumor Image Compression by Principle Component Analysis

Many researchers considered principle component analysis is most promising tool for feature extraction and the main purpose of principle component analysis is reduce the size of large data in terms of dimensionality. The MR brain recognition system is designed to recognize the test image according to the memory. The respective memory which is used to recognize the test

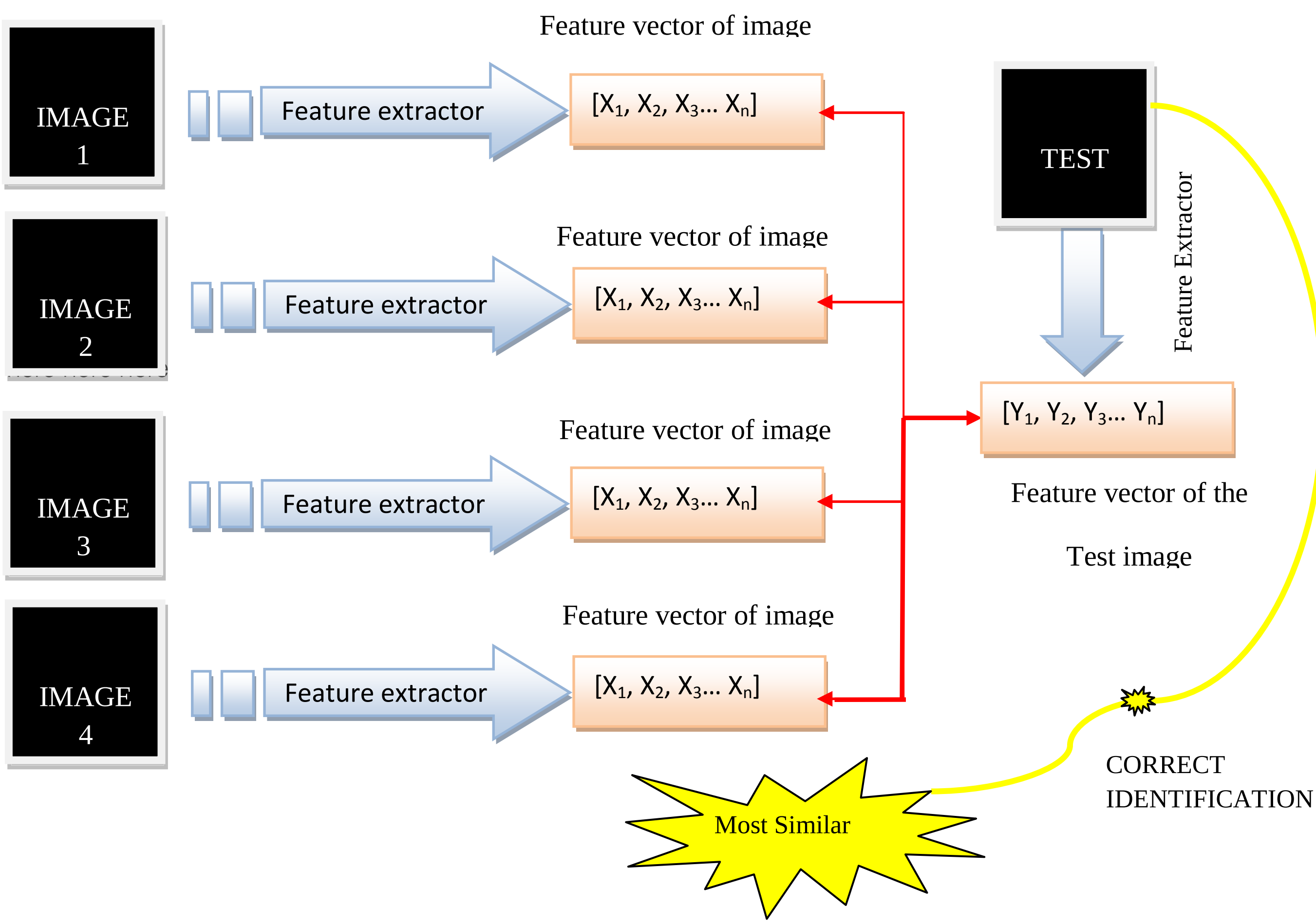

Figure 1 : Schematic diagram MR image recognizer

image according to the memory. The respective memory which is used to recognize the test image is simulated by a training set. The main intention of MR training recognizer is to recognize the most similar vector from the available training set. The most important phase is to extract the feature vectors from the each image from the available training set. Let Ω_1 be a training image of image 1 which has a pixel resolution of $M \times N$ where M represents the number of rows and N represents the number of columns. The conversion of respective image into pixel vector ϕ_1 is essential to extract necessary features of Ω_1 by using the PCA analysis technique and the dimensionality of the vector ϕ_1 will be $M \times N$. In the proposed work the PCA approach is used as reducing the dimensionality reduction technique further it transforms the vector ϕ_1 to a vector ω_1 which has the dimensionality d where $d << M \times N$. For each training image Ω_1 these feature vectors ω_1 are calculated and stored. In the testing phase feature vector of the test image is computed and checks the similarity between the feature vectors using the Euclidian distance approach. The identity of the most similar is treated as recognizer output.

III. Probabilistic Neural Networks

The probabilistic neural networks are also termed as artificial independent algorithm which is developed by Donald Specht and most researchers termed the PNN as ideal solution to the pattern classification related problems and the specific classification is termed as Bayesian classifiers. PNN is simple in structure and its training speed is many times faster than the respective BP network and it is robust to noise too. The most important advantage of PNN is its training is easy and the respective weights are not trained but assigned. The structure of PNN is s follows

a) Input layer

The input vector, denoted as p, is presented as the black vertical bar in Fig. 2. Its dimension is R × 1. In this paper, R = 3.

b) Radial Basis Layer

The vector distances between input vector p and the weight vector made of each row of weight matrix W are calculated. Here, the vector distance is de fined as the dot product between two vectors [8]. Assume the dimension of W is Q×R. The dot product between p and the i-th row of W produces the i-th element of the distance vector ||W–p||, whose dimension is Q×1, as shown in Fig. 2. The minus symbol, "–", indicates that it is the distance between vectors.

Then, the bias vector b is combined with ||W–p|| by an element-by-element multiplication, represented as ".∗" in Fig. 2. The result is denoted as n = ||W– p|| .∗p. The transfer function in PNN has built into a distance criterion with respect to a center. In this paper, it is de fined as

radbas(n) = e −n 2 1

Each element of n is substituted into Eq. 1 and produces corresponding element of a, the output vector of Radial Basis Layer. The i-th element of a can be represented as

ai = radbas(||Wi − p|| .∗bi) 2

where Wi is the vector made of the i-th row of W and bi is the i-th element of bias vector b.

c) Some characteristics of Radial Basis Layer

The i-th element of a equals to 1 if the input p is identical to the ith row of input weight matrix W. A radial basis neuron with a weight vector close to the input vector p produces a value near 1 and then its output weights in the competitive layer will pass their values to the competitive function. It is also possible that several elements of a are close to 1 since the input pattern is close to several training patterns

d) Competitive Layer

There is no bias in Competitive Layer. In Competitive Layer, the vector a is firstly multiplied with layer weight matrix M, producing an output vector d. The competitive function, denoted as C in Fig. 2, produces a 1 corresponding to the largest element of d, and 0's elsewhere. The output vector of competitive function is denoted as c. The index of 1 in c is the number of tumor that the system can classify. The dimension of output vector, K, is 5 in this paper.

IV. Spatial Fuzzy C-Means Clustering

A conventional FCM algorithm does not fully utilize the spatial information in the image. In this paper, we present a fuzzy c-means (FCM) algorithm that incorporates spatial information into the membership function for clustering. The spatial function is the summation of the membership function in the neighborhood of each pixel under consideration. The advantages of the new method are the following: (1) it yields regions more homogeneous than those of other methods, (2) it reduces the spurious blobs, (3) it removes noisy spots, and (4) it is less sensitive to noise than other techniques. This technique is a powerful method for noisy image segmentation and works for both single and multiple-feature data with spatial information.

The following are the steps involved in SFCM based clustering algorithm

a) Calculate the cost function

$$J = \sum_{j=1}^{N} \sum_{i=1}^{c} U_{ij}^{m} \left\| x_j - v_i \right|$$

Where it represents the membership of the pixels with 'c' number of clusters

b) The membership function is given as

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\left\| x_j - v_i \right\|}{\left\| x_j - v_k \right\|} \right)^{2/(m-}}$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\left\| x_j - v_i \right\|}{\left\| x_j - v_k \right\|} \right)^{2/(m-1)}}$$

c) To exploit the spatial information a spatial function is defined as

$$h_{ij} = \sum_{k \in NB(x_j)} u$$

d) The new membership function can be rewritten as

$$u'_{ij} = \frac{u_{ij}^{p} h_{ij}^{q}}{\sum_{k=1}^{c} u_{kj}^{p} h}$$

Where p & q are parameters to control relative importance of both functions.

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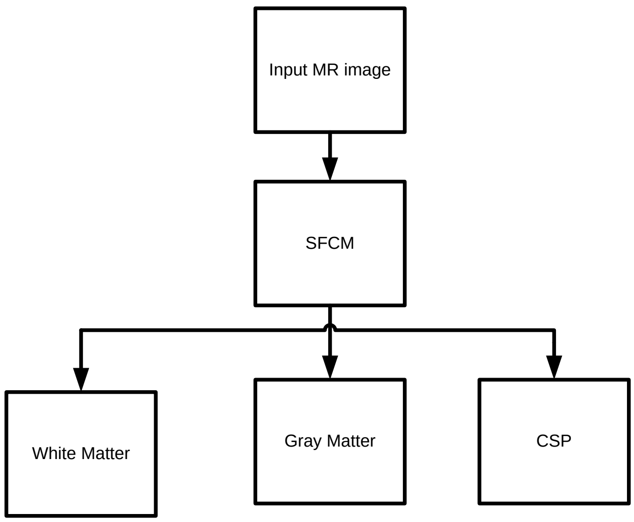

Figure 2 : Segmentation Flow

e) Methodology

PNN classification is used to better accuracy and to get better analysis. It requires less time for classification, high speed and better robustness. The following figure shows the flow of proposed method from the input image to exit. The initial step is should be the image processing step. Basically in image processing system, image acquisition and image enhancement are the steps that have to do. In this paper, these two steps are skipped and all the images are collected from available resource. The proposed model requires converting the image into a format capable of being manipulated by the computer. The MR images are converted into matrices form by using MATLAB.

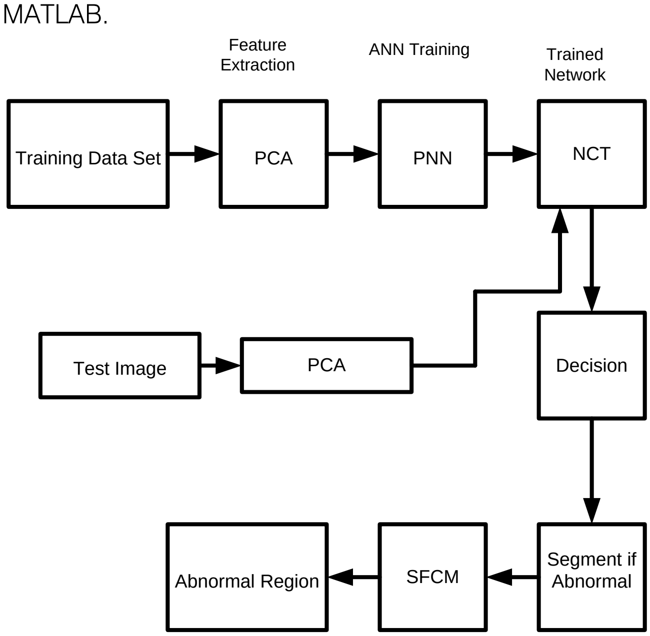

Figure 3 : Block diagram of the proposed method

Then, the PNN is used to classify the MR images. Lastly, performance based on the result will be analyzed at the end of the development phase. The proposed brain MR images classification method is shown in Fig. 3.

In addition to the brain classification a new spatial fuzzy C- means clustering approach is implemented to extract the abnormal regions of the given image is abnormal. The man advantage of using SFCM in this approach is extract the very keen regions from the abnormal region fast & accurately than the conventional FCM (Fuzzy C-means) algorithm. The proposed approach proves to be more effective for the given set of images.

V. Experimental Results

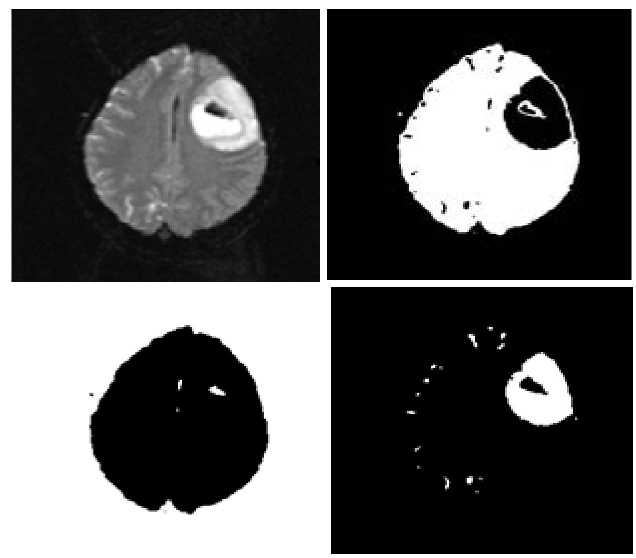

Figure 4 : (a) original Image (b) Cluster region 1 (c) Cluster region 2 (d) Cluster region 3

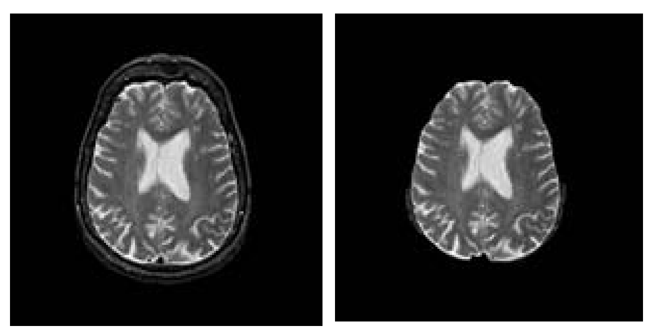

Figure 2 : (a) original Image (b) Skull Stripped Image

Table 1 : performance Analysis

Spread Value	Accuracy
1	72
2	78
3	100

VI. Conclusion

In the area of medical image processing, classification and analysis of MR brain image is the challenging task. The proposed PROBABILISTIC NEURAL NETWORKS is unique in terms of simple structure and performs fast on training with high speed when compare to conventional classification approaches. In this paper 23 different types of MR brain images are taken into consideration for training and testing to yield the better accuracy in terms of analysis and the respective the testing were conducted on different set of images. The reported PROBABILISTIC NEURAL NETWORKS classifier is examined under different spread values and these spread values also considered as the smoothing factor. In the experimental simulation results the accuracy of proposed classifier varies from 100% to 70% which depends on the taken spread values. In addition to the brain classification a new spatial fuzzy C- means clustering approach is implemented to extract the abnormal regions of the given image is abnormal.

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