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A Hybrid Technique for Automatic Classification of MRI Brain Images

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ABSTRACT

Background: Many techniques have been proposed to improve the accurate diagnosis of brain tumors. These techniques are known as Computer-aided detection/diagnosis (CAD) systems. CAD systems help the physician or radiologist to perform the diagnosis in a fast and non-invasive way. Magnetic Resonance (MR) brain images provide detailed information of the brain. Automated and accurate classification of MR brain images using CAD systems is important for the analysis and interpretation of brain tumors. The proposed hybrid technique is to classify the brain MR images into normal or abnormal with respect to the presence or absence of tumors and this technique consists of the following stages: preprocessing, segmentation, feature extraction, dimensionality reduction and classification. The region of interest from the preprocessed image is obtained using segmentation which is then used for classifying it as with or without brain tumor. The techniques used are preprocessing using median filter, segmentation using fast linking pulse coupled neural network, feature extraction using discrete wavelet transform, dimensionality reduction using principal component analysis and classification using radial basis function neural network. **Objective:** The proposed system aims to provide an alternate hybrid technique for brain tumor classification and also considers in reducing the computational cost involved in the diagnosis and providing high accuracy detection rate. **Results:** The performance of this hybrid technique is evaluated on a real human brain MRI dataset and the classification accuracy is found as 91.4%. **Conclusion:** This proposed hybrid technique provides high accuracy with less computational cost compared to other brain MR images classification. The proposed technique is accurate, fast and robust.

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INTRODUCTION

Brain tumor is the abnormal growth of cells in the brain. Brain tumor can be benign or malignant. They can occur in different parts of the brain; its size and shape vary. Malignant tumors are cancerous and benign tumors are non-cancerous. Malignant tumors are life threatening. Medical Imaging plays a central role in the diagnosis of brain tumors. Many imaging techniques can be performed for the early detection of any abnormal changes in tissues and organs such as Computed Tomography (CT), Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI).

MRI is a powerful technique for diagnosis used by physician to detect structural abnormalities responsible for neurological disorder pathology. It is a commonly used imaging technique that uses magnetic fields and radio waves to produce high-quality two or three dimensional images of body. It is a non-aggressive, non-radioactive and pain-free technique for visualizing and detecting the brain tumors without any human involvement. It gives detailed information regarding normal and abnormal tissue. And also diagnosis can be done automatically with more accuracy than other imaging techniques. The identification of tumor is a challenging task and it requires new analysis techniques that improve the diagnostic ability of MR images.

Proposed System:

The accuracy of brain tumor detection technique must be significantly high as the treatment planning is based on this identification. Automated image classification systems with high accuracy are highly essential for real-time applications. An alternate hybrid technique for brain tumor classification is proposed that focuses on reducing the high computational cost involved in the diagnosis and provides a high accuracy detection rate.

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System Architecture:

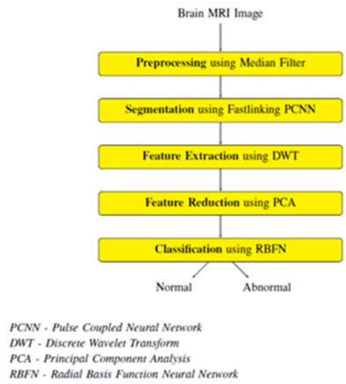

Fig. 1: System Workflow.

Figure 1 represents the overall system architecture.The different stages involved in the proposed system is given in bold letters along with technique used. The detailed procedure for classifying the brain MR images is summarized as follows:

- Read the input MRI brain image.
- Preprocessing is done for enhancing the image and removing the noise.
- Segmentation is performed to detect the region of interest (ROI) in thepreprocessed image. In this process, a binary image is created for the corresponding ROI.
- Feature extraction extracts the useful features from the segmented image. In this process, the wavelet co-efficients of the given image forms the feature space.
- Feature reduction reduces the features which are then sent to the classifier.
- RBFN classifies these reduced features into the desired output which is one of the two categories: normal and abnormal.

Module Description:

1. Preprocessing:

Image preprocessing is used to improve the quality of images. It is necessary to remove noise and film artifacts of MRI brain image for image analysis. Median filter is widely used filtering technique (El-Sayed, A., 2014) to remove noise from the MRI images. The advantage of median filter is that it removes the noise without disturbing the edges. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighboring pixels. The pattern of neighbors is called the" window", which slides, pixel by pixel over the entire image. The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value. The output of this stage represents the brain image without noise, film artifacts and labels.

2. Segmentation:

Image segmentation is used to identify regions of interest (ROI) in the MRI images. In this proposed system, Fast linking PCNN technique is used for segmentation.

2.1 PCNN:

PCNN is a biological neural network proposed by modeling a cat's visual cortex (Echkorn model) and developed for high-performance biomimetic image processing (Lindblad, T., J.M. Kinser, 2005). The main goal of this neural network is to detect the region of interest like how the small mammals identify the objects. The PCNN is a two-dimensional neural network. In this work, each network neuron corresponds to an input image pixel, receiving its corresponding pixel's color information (e.g. intensity) as an external stimulus. Each neuron also connects with its neighboring neurons, receiving local stimuli from them. The external and local stimuli are combined in an internal activation system, which accumulates the stimuli until it exceeds a dynamic threshold, resulting in a pulse output. The structure of PCNN is shown in Figure 2. There are three parts that form a neuron: input part, linking part, and pulse generator, which can be described by discrete equations.

The equations are:

$$F_{ij}[n] = S_{ij} + e^{-\alpha F} F_{ij}[n-1] + V_F.(M * Y[n-1])_{ij} \quad (1)$$

$$L_{ij}[n] = e^{-\alpha L} L_{ij}[n-1] + V_L.(W * Y[n-1])_{ij} \quad (2)$$

$$U_{ij}[n] = F_{ij}[n-1]\{1 + \beta L_{ij}[n]\} \quad (3)$$

$$Y_{ij}[n] = \begin{cases} 1, & if\ U_{ij}[n] > \theta_{ij}[n]; \\ 0, & otherwise \end{cases} \quad (4)$$

$$\theta_{ij}[n] = e^{-\alpha\theta} \theta_{ij}[n-1] + V_\theta . Y_{ij}[n-1] \quad (5)$$

In these equations, i and j are indices, n is the iterative step number, S is external stimulation, F is feeding input, L is linking input, U is the internal activities, θ is dynamic threshold. M and W are the constant synaptic weight matrices. β is the linking coefficient constant; αF, αL and αθ are the attenuation time constants; and the V_F, V_L and V_θ are the inherent voltage potential of the feeding signal, linking signal and dynamic threshold respectively. Y is PCNN binary output.

Through iterative computation of Equations (1)-(5), this produces a temporal series of pulse outputs that contains edge, texture and segmentation information at different times.

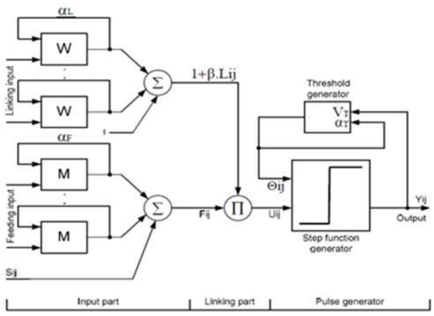

Fig. 2: Pulse Coupled Neural Network Structure.

2.2 Fast Linking Method:

One of PCNN types is fast linking PCNN and the advantage of this method has attractive de-noising and segmenting features. Fast linking PCNN allows the linking wave to progress a lot faster than the feeding wave. The linking is allowed to propagate through the entire image for each iteration. Thus, each neuron receives the neighboring pixels' details in single iteration and it reduces the computation time to produce the desired ROI in an image.

The steps for fast linking PCNN algorithm:

I. Initialization:

Initialize all the parameters of pulse coupled neural network.

(a) Feeding: F, Linking: L, Output: Y, Threshold: θ
(b) Delay constants: αF, αL, αθ
(c) Normalizing constants: V_F, V_L and V_θ
(d) Weights matrix: M, W and linking coefficient β

II. Processing:

(a) n is the iterative variable. Let n = 1; n_{max} = 20
(b) In first iterative step n=1, calculate Equations(1)-(5)
(c) From n=2 iterative, Equation(2) will be replaced by Equation(6)

$$L_{ij}[n] = V_L.(W * Y[n-1])_{ij} \quad (6)$$

(d) Increment the iterative step n = n+1
(e) Test for the stopping condition
if n $< n_{max}$ then
goto step (c)
else
outputY_{ij}
end
(f) The output image Y_{ij} contains the ROI in binary format.

Fast linking method helps to reduce the cycles required to extract ROI from the image compared to PCNN. In this module, Fast Linking PCNN technique segments the regions of interest from the filtered (preprocessed) image and the resultant ROI acts as a binary mask. Then, the final ROI is segmented from the filtered image based on the binary mask. The output of image segmentation is a set of contours extracted from the brain MR images from which desired features are to be extracted.

3. Feature Extraction:

Feature extraction is the transformation of an image into a set of features. The purpose of feature extraction is to extract useful features from MRI images that describe the overall image accurately. The extracted features are used as inputs to the classifier. In this proposed system, Discrete Wavelet Transform (DWT) technique is used to extract the features i.e., wavelet co-efficients that represent the overall image.

3.1 DWT of an image:

DWT is a mathematical function used to decompose an image into the corresponding sub-bands with their co-efficients. Cascaded filter bank (low pass and high pass filters) is used in this technique and it produces four sub-band (LL, LH, HH, HL) images at each scale. The sub-bands LH, HH and HL contain directional information of the image. The sub-band LL contains more information of the image and only sub-band LL is used for next level decomposition and other sub-bands will be neglected. The sub-band LL at level 3 is the desired output of this module.

Consider, Level 3 decomposition of an image and it is shown in Figure 3, where the functions h(n) and g(n) represent the coefficients of the high pass and low-pass filters respectively. The image is filtered by low pass filter g and high pass filter h in horizontal direction and then down sampled by a factor of two to create low-frequency and high-frequency coefficient matrices. Then, the coefficient matrices are both low pass and high pass filtered in

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vertical direction and down sampled by a factor of two to create sub bands LL, LH, HL and HH.

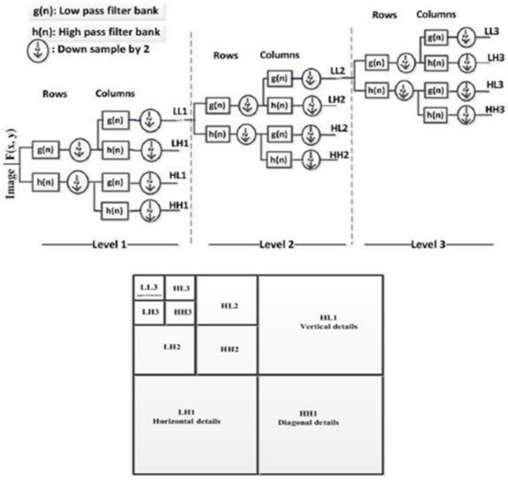

Fig. 3: Level 3 Discrete Wavelet Transform Decomposition.

In this module, wavelet coefficients are extracted from each MRI image using DWT technique. A reduction technique is then applied on these to reduce the number of wavelet coefficients which are the actual inputs to the classifier. The integration between feature extraction and feature reduction helps to gain high classification accuracy with less number of features that can be extracted with less computational cost.

4. Feature Reduction:

Feature reduction, in general, is used to reduce the dimensionality of data thus reducing the computation time, complexity and memory storage. The reduced features are used as inputs to the classifier. In this proposed system, Principal Component Analysis (PCA) is used to reduce the number of features.

4.1 PCA:

PCA is an efficient tool to reduce the dimension of a data set, consisting of a large number of interrelated variables. It is achieved by transforming the data set to a new set of ordered variables according to their variances or their importance. This technique has three effects: orthogonalizes the components of the input vectors, orders the resulting orthogonal components and eliminates those components which contribute the least variation in the data set. PCA is to reduce the dimensionality of the wavelet coefficients which helps the classifier to produce accurate results in a more efficient manner. Figure 4 shows the steps involved in PCA. In this module, the number of wavelet coefficients is reduced for each MRI image using PCA. The reduced wavelet coefficients are the input to RBFN classifier. This step is done for all the images in the training dataset and the reduced feature values obtained for each image are called as a feature vector. The feature vector for the training images is stored in a database and used for classification purpose.

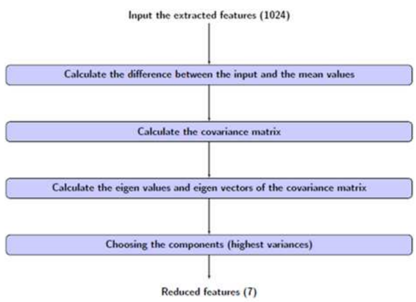

Fig. 4: Steps involved in PCA.

5. Classification:

Classification analyses the numerical properties of image features and organizes the data into different categories. In this proposed system, RBFN is used to classify MRI images into normal or abnormal.

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5.1 RBFN:

RBF neural network is based on supervised learning. Figure 5 shows the typical architecture of an RBF Network. It consists of an input vector, a layer of RBF neurons, and an output layer with one node per category or class of data.

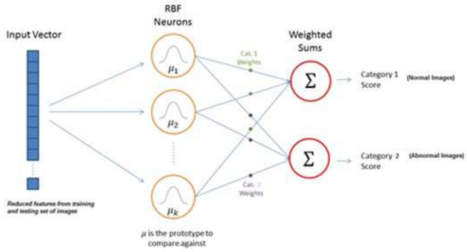
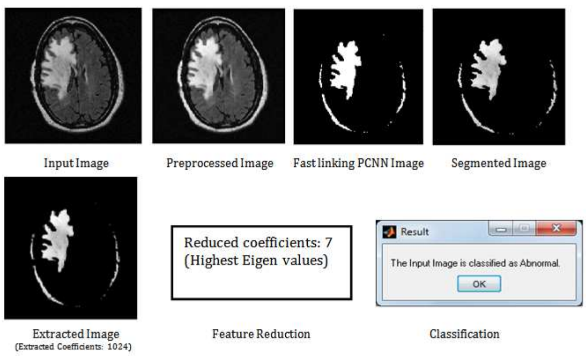


Fig. 5: RBF Network Architecture.

In this module, the wavelet co-efficients from feature reduction module are the inputs to the network. Each RBF neuron stores a "prototype" vector which is just one of the vectors from the training set. Each RBF neuron compares the input vector to its prototype, and outputs a value between 0and 1 which is a measure of similarity. If the input is equal to the prototype, then the output of that RBF neuron will be 1. As the distance between the input and prototype grows, the response falls off exponentially towards 0. The shape of the RBF neurons response is a bell curve, as illustrated in the network architecture. The output of the network consists of a set of nodes, one per category that we are trying to classify. Each output node computes a sort of score for the associated category. Typically, a classification decision is made by assigning the input to the category with the highest score. The score is computed by taking a weighted sum of the activation values from every RBF neuron. Each output node is computing the score for a different category; every output node has its own set of weights. The output node will typically give a positive weight to the RBF neurons that belong to its category, and a negative weight to the others. This network, classifies MRI images into two categories: normal and abnormal.

Results:

The input data set consists of 127 (axial, T2 FLAIR weighted) MRI brain images of size 256 x 256 pixels each. The input image format is in dcm. The MRI image slices were grouped into two classes, namely normal and abnormal depending on the tumor present in the slice. These two different sets are grouped and used for classification. The system was implemented using Matlab 2010a and was tested and evaluated for different set of images by randomly selecting images from the input dataset images.



Figures 6 and 7 show the segmented images using PCNN and Fast linking PCNN algorithm. By using Fast linking PCNN algorithm, it has been proved that the number of iterations is minimized to produce the satisfactory segmentation results.

The performance of the proposed system was evaluated using accuracy measure. The proposed system was evaluated with the dataset which contains 127 images for training as well as testing purpose. These include 10 normal and 117 abnormal brain MR images. The average classification accuracy rate is 91.4% for various tests with randomly selecting images from the dataset. The accuracy rate is calculated using the following Equation (7).

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \qquad (7)$$

Where True Positive (TP), True Negative (TN), False Positive (FP) and False Negative(FN).

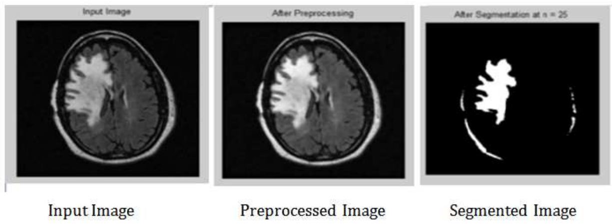


Fig. 6: Segmentation using PCNN.

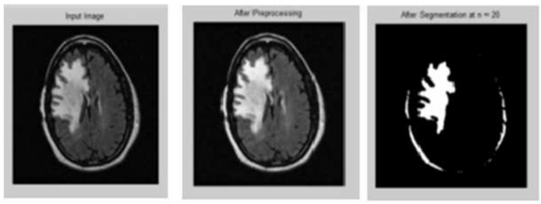


Fig. 7: Segmentation using Fast Linking PCNN.

Table 1: Performance of RBFN.

Test No	Total No. of Images (Training and Testing)	Test Results
Test 1	35	TP: 31TN:1 FP:0 FN:3
Test 2	50	TP:40 TN:5 FP:1 FN: 4
Test 3	70	TP:60TN:5 FP:1 FN: 4

Conclusion:

In this paper, we studied the existing techniques for automatic classification of brain images and proposed a hybrid technique with a goal of reducing the computational cost involved without compromising on the accuracy in the diagnosis. The proposed system was evaluated with a real human brain dataset and the results were analyzed. The results clearly prove that fast linking PCNN algorithm requires minimum number of iterations to produce the satisfactory results compared to PCNN and the RBFN classifier produced high accuracy detection rate. And hence we are able to conclude that our proposed hybrid technique provides high accuracy with less computational cost compared to other brain MR image classification systems.

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