DOI: 10.24996/ijs.2021.SI.1.22

ISSN: 0067-2904

MRI Probabilistic Neural Network Screening System: a benign and malignant recognition case study

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Abstract:
This work is aimed to design a system which is able to diagnose two types of tumors in a human brain (benign and malignant), using curvelet transform and probabilistic neural network. Our proposed method follows an approach in which the stages are preprocessing using Gaussian filter, segmentation using fuzzy c-means and feature extraction using curvelet transform. These features are trained and tested the probabilistic neural network. Curvelet transform is to extract the feature of MRI images. The proposed screening technique has successfully detected the brain cancer from MRI images of an almost 100% recognition rate accuracy.

Keywords: Benign Tumor, Brain tumor, Curvelet Transform, Malignant Tumor, Neural Network.

Introduction:

The Human brain is the most amazing and complex thing known in the world [1]. The brain is just like any other organ of the body exposed to many diseases including tumors. Brain tumors are one of dangerous diseases in the world. The detection and determination of the tumor type at early stage is very important for the cure of the patient [2]. Magnetic Resonance Imaging (MRI) is one of the essential tools in biological and medical research [3]. Artificial Neural Network (ANN) is a mathematical model that is inspired by the way biological nervous systems such as brain [4]. A brain tumor is an abnormal growth of cells within the brain. Some important researches in this field were done by: Dipanshu N. Masalkar and Shitole A.S., in 2014 [5] investigated brain tumor detection and classification using ANN. This system consists of several steps including image preprocessing using Gaussian filter, image segmentation by threshold based segmentation method, feature extraction using GLCM, dimensionality reduction.

Naveena H S et al., in 2015[6] exploited the capability of ANN for classification of MRI images to either cancerous or non-cancerous tumor. Segmentation is obtained by K-means clustering algorithm. Then, gray level co-occurrence matrix (GLCM) was used for feature extraction of segmented image. Finally, classification of brain tumors were carried out by Back propagation neural network (BPNN) and Probabilistic Neural Network (PNN) with the system accuracy of 79.02% while 97.25 % respectively.

N.D. Pergad and Kshitija V. Shingare in 2015 [7] designed a system for brain tumor extraction. This system consists of preprocessing for removing noise, then feature extraction. Image classification is achieved by Probabilistic Neural Network (PNN) with accuracy of 88.2%.

Vinayadth V. Kohir and Sahebgoud H. Karradi, in 2015 [8] presented Back Propagation Networks (BPNs) and Probabilistic Neural Network (PNN) for classification of brain tumor. Otsu's method of

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thresholding is used for detection of tumor in the brain MRI images. Feature extraction step is achieved using gray level co-occurrence matrix (GLCM). This work is aimed to design a system which is able to diagnose two types of tumors in a human brain (benign and malignant), using curvelet transform and probabilistic neural network.

Proposed Work

The methodology of the MRI brain image classification is as follow:

1. Preprocessing using Gaussian filter.
2. Segmentation by FCM algorithm.
3. Feature extraction using Curvelet Transform.
4. Classification using probabilistic neural network.

The dataset has 40 images: 20 images are benign, 20 malignant (cancerous) l images. The size of benign and malignant images used for classification is 256×256. These images were collected from al Kadhmiya teaching hospital and internet. Flowchart of the system algorithm is sketched in Figure-1

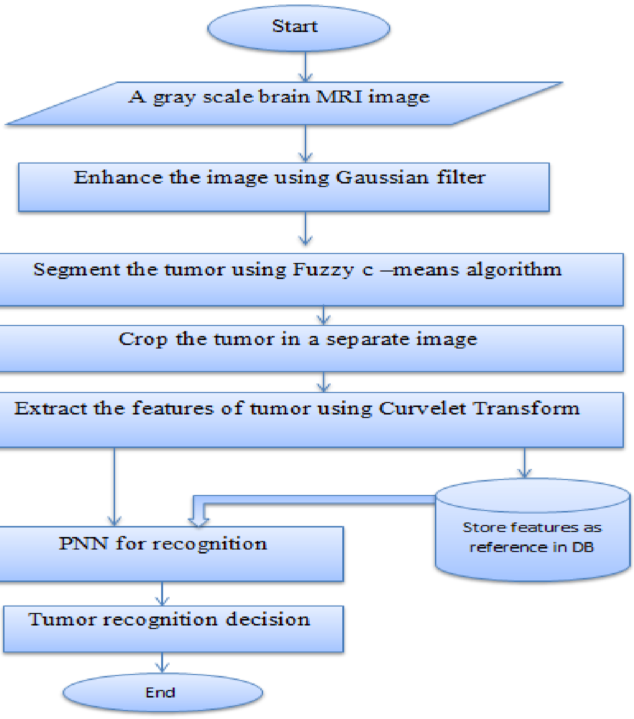

Figure 1- low chart of the system algorithm

Preprocessing:

In this stage, we try to analysis the image which perform noise reduction and image enhancement techniques to enhance the image quality. Gaussian filter was used in this stage, it is a linear filter. It suppresses high frequency details such as noise and edges, while preserving the low frequency components of the image. This filter blurs everything which is smaller than the features of the image [9, 10].

Segmentation:

In this stage, MRI images are segmented by fuzzy c-means algorithm (FCM). Fuzzy c-means retain more information than hard segmentation method, it has also robust characteristics for ambiguity. In FCM algorithm, each pixel will have different values of membership on each cluster instead of belonging to one cluster. Each data point corresponding to each cluster has a membership basis on the distance between the data and the cluster center. The membership and the cluster centers are updated simultaneously after each iteration [11,12].

The cluster centers and membership functions are updated iteratively [12].

$$v_i = \frac{\sum_{j=1}^{n} \mu_{ij}^{\,m} x_j}{\sum_{j=1}^{n} \mu_{ij}^{\,m}}$$

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

The membership functions, μ_{ij} ,for C number of clusters, n number of pixels in the image and vi center of the ith cluster are constrained by:

$$\sum_{i=1}^{c} \mu_{ij} = 1; 0 \le \mu_{ij} \le 1; 0 < \sum_{j=1}^{n} \mu_{ij} < n$$

Where: $\left\| x_j - v_i \right\|$ is the Euclidean distance

(μ_{ij} >1) is a weighting factor that controls the fuzziness of the resultant segmentation.

By minimizing the objective function Figure-2, FCM attempts to find clusters in the data. The equation of objective function is shown below:

$$J_m = \sum_{j=1}^{n} \sum_{i=1}^{c} \mu_{ij}{}^{m} \left\| x_j - v_i \right\|^2$$

Where J_m is the objective function that reduces at each iteration [12].

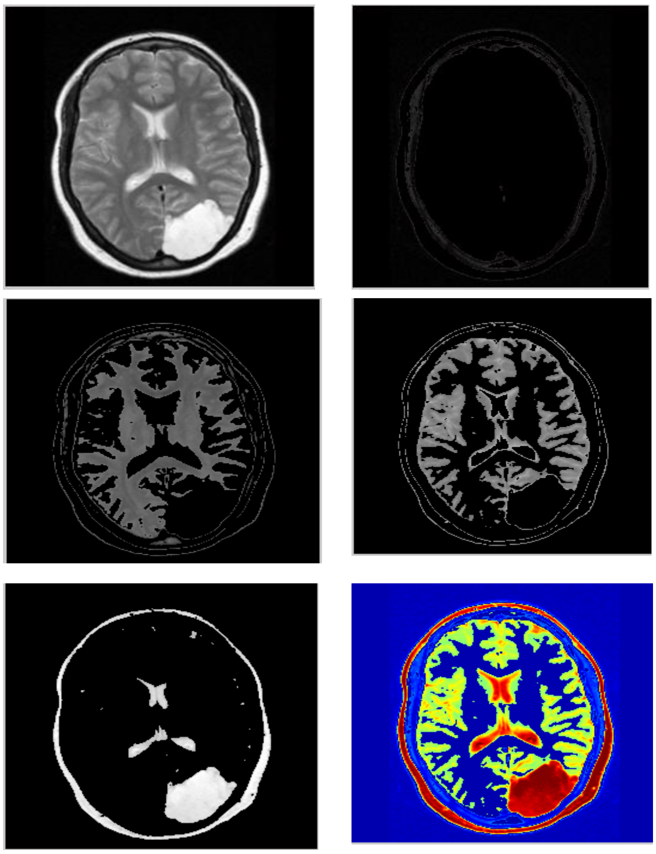

Figure 2-Result of Fuzzy C-means

Feature Extraction using Curvelet Transform:

The curvelet transform is designed to overcome the limitations of Gabor filters and wavelet transform [13].

Classification: PNN had been proposed for classification of data [14].

PNN has three layers. The first layer is the input layer which is the first distributed of the training patterns. The second layer is the pattern layer. The third layer is the summation layer that is applying a nonlinear operation on the dot product[15].

Result and Discussion

The PNN is a supervised neural network. Because of its robustness, it is widely used in pattern classification tasks. The PNN classifier is belonging to the class of radial basis function. For the PNN classifier, the important issue is to determine the optimal smoothing parameter σ. There is no common method available to determine σ; trial and error was used for computation of smoothing parameter. Training can be viewed as determining the best smoothing parameter σ for a set of training vectors. In this work, the PNN classifiers are trained with different smoothing parameter values from 0.1 to 3. To train the PNN, training data set was applied, and to verify the accuracy of the proposed classifier, testing data set was applied. Besides, the performance of the system has been evaluated according to three measures: Accuracy, Sensitivity, and Specificity.

In this proposed system, 20 MRI images are used for training and 20 MRI images for testing. At the end, trained network was obtained, if any benign or malignant images were test, the network gives good results.

The standard deviation of a sub-band at scale and orientation can be shown as [16]:

$$\sigma_{jl} = \frac{\sqrt{\Sigma_x \Sigma_y \left(\left|\text{curvelet}_{jl}(x,y)\right| - \mu_{jl}\right)^2}}{\text{MxN}} \quad (8)$$

Entropy is a measure of gray level distribution randomness [17].

$$\text{Entropy} = -\sum_{x=1}^{N}\sum_{y=1}^{N} \left|\text{curvelet}_{jl}(x,y)\right| \log_2 \left|\text{curvelet}_{jl}(x,y)\right| \quad (9)$$

Table 1-result of PNN

40 images	Correctly classified	Incorrectly classified	Accuracy
Benign	20	0	98%
Malignant	19	1	

The performance of this method Figure-3 gives high accuracy when comparing with the other algorithms used in the references [6-8].

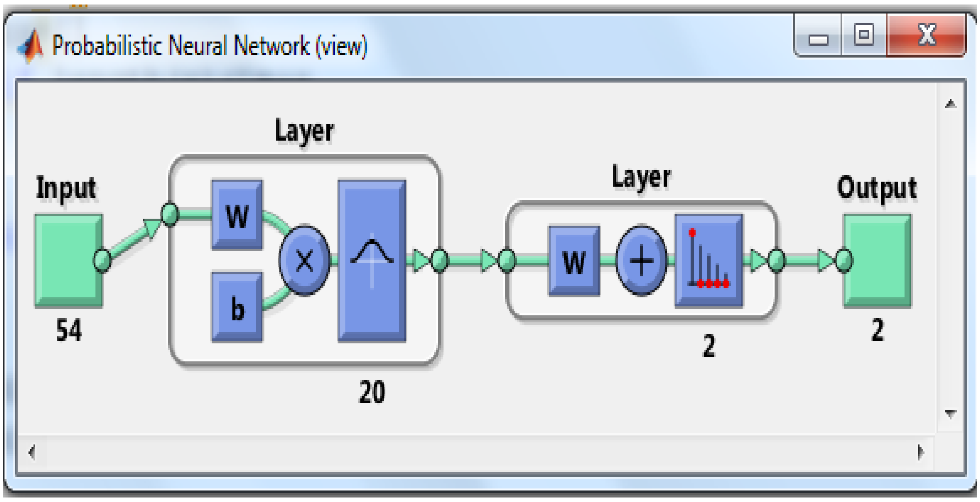

Figure 3-Probabilistic Neural Network Training

Conclusion

The proposed screening technique has successfully detected the brain cancer from MRI images of an almost 100% recognition rate because of the preprocessing, segmentation and feature extraction to train and test the probabilistic neural network.

Future Work

The future work will be filtered using an implementable filter [18,19] extended the presented 2D model [1] to be developed for a 3D grayscale edge filtering model [20]. Consequently, the new filtering multidimensional model may be efficiently implemented in a reconfigurable hardware of ACIC or FPGA[21-23].

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