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) 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

**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].

\[
\mu_{ij} = \frac{\sum_{k=1}^{n} \mu_{ij}^m \times x_k}{\sum_{j=1}^{n} \mu_{ij}^m}
\]
The membership functions, \( \mu_{ij} \), for \( C \) number of clusters, \( n \) number of pixels in the image and \( v_i \) center of the \( i \)th cluster are constrained by:
\[
\sum_{i=1}^{C} \mu_{ij} = 1; 0 \leq \mu_{ij} \leq 1; 0 < \sum_{j=1}^{n} \mu_{ij} < n
\]
Where: \( \| x_j - v_i \| \) is the Euclidean distance and \( ( \mu_{ij} > 1) \) 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:
\[
J_m = \sum_{j=1}^{n} \sum_{i=1}^{C} \mu_{ij}^m \| x_j - v_i \|^2
\]
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 $\sigma$. There is no common method available to determine $\sigma$; trial and error was used for computation of smoothing parameter. Training can be viewed as determining the best smoothing parameter $\sigma$ 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]:

$$
\sigma_{jl} = \sqrt{\frac{\sum_{x} \sum_{y} \left[\text{curvelet}_{jl}(x,y) - \mu_{jl}\right]^2}{M \times N}}
$$

(8)

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

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

(9)

**Table 1**-result of PNN

|        | 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].

![Probabilistic Neural Network](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].
References

1. Hasan S, Yousif M. and Al-Talib TM. 2018. Brain tumor classification using Probabilistic Neural Network. *Journal of Fundamental and Applied Sciences*. 2018; 10(4S): 667-70.

2. Schaap K. 2015. Working with MRI: An investigation of occupational exposure to strong static magnetic fields and associated symptoms. Utrecht University; 2015 Jun 30.

3. Maind SB. and Wankar P. 2014. Research paper on basic of artificial neural network. *International Journal on Recent and Innovation Trends in Computing and Communication*. 2014 Jan; 2(1): 96-100.

4. Masalkar DN. and Shitole AS. 2014. Advance Method for Brain Tumor Classification. *International Journal on Recent and Innovation Trends in Computing and Communication*. 2014; 2(5): 1255-9.

5. Naveena HS., Shreedhara KS. and Mohamed R. 2015. Detection and Classification of Brain Tumor using BPN and PNN Artificial Neural Network Algorithms. *International Journal of Computer Science and Mobile Computing*. IJCSMC,. 2015 Apr; 782-9.

6. Pergad N. and Shingare K. 2015. Brain MRI Image Classification Using Probabilistic Neural Network and Tumor Detection Using Image Segmentation'. *International Journal of Advanced Research in Computer Engineering & Technology* (IJARCE). 2015; 4(6).

7. Kohir V. and Karradi S. 2016. Detection Of Brain Tumor Using Back-Propagation And Probabilistic Neural Network. InProceedings of 19th IRF International Conference, India 2015.

8. Abuazoum MS. Efficient Analysis of Medical Image De-noising for MRI and Ultrasound Images (Doctoral dissertation, Universiti Tun Hussein Onn Malaysia).

9. Padmavathi K, Thangadurai R. The Role of Image Enhancement in Citrus Canker Disease Detection. *International Journal Of Advanced Computer Science And Applications*. 2016 Sep 1; 7(9): 293-6.

10. Selvaraj D. and Dhanasekaran R. 2013. MRI brain image segmentation techniques-A review. *Indian Journal of Computer Science and Engineering* (IJCSE). 2013 Oct; 4(5): 364-81.

11. Kaus MR, Warfield SK, Nabavi A, Black PM, Jolesz FA, Kikinis R. 2001. Automated segmentation of MR images of brain tumors. *Radiology*. 2001 Feb; 218(2): 586-91.

12. Rahulkar AD., Jadhav DV. and Holambe RS. 2010. Fast discrete curvelet transform based anisotropic feature extraction for iris recognition. Ictact Journal on Image and Video Processing. 2010 Nov.

13. Specht DF. 1988. Probabilistic neural networks for classification, mapping, or associative memory. In *IEEE international conference on neural networks* 1988 Jul 24, 1(24): 525-532.

14. Anderson D, McNeill G. 1992. Artificial neural networks technology. *Kaman Sciences Corporation*. 1992 Aug 20; 258(6): 1-83

15. Sumana IJ. 2008. Image retrieval using discrete curvelet transform. Monash University; Nov.

16. Nayak GR. and Verma MT. 2014. Brain Cancer Classification Using Back Propagation Neural Network And Principle Component Analysis. *International Journal of Technical Research and Applications*. 2014 Jul; 2(4): 26-31.S.

17. Charfi S, Lahmyed R. and Rangarajan L. 2014. A novel approach for brain tumor detection using neural network. *International Journal of Research in Engineering and Technology*. 2014; 2: 93-104.

18. Hasan S., Boussakta S., Yakovlev A. 2010. Improved parameterized efficient FPGA implementations of parallel 1-D filtering algorithms using Xilinx System Generator. In The 10th *IEEE International Symposium on Signal Processing and Information Technology* 2010 Dec 15 (pp. 382-387). IEEE.

19. Hasan S, Boussakta S. and Yakovlev A. 2011. Parameterized FPGA-based architecture for parallel 1-D filtering algorithms. InInternational Workshop on Systems, Signal Processing and their Applications, WOSSPA 2011 May 9 (pp. 171-174). IEEE.

20. Hasan S. Performance-vetted 3-D MAC processors for parallel volumetric convolution algorithm: A 256× 256× 20 MRI filtering case study. In 2016 Al-Sadeq International Conference on Multidisciplinary in IT and Communication Science and Applications (AIC-MITCSA) 2016 May 9 (pp. 1-6). IEEE.
21. Humaidi AJ, Hassan S and Fadhel MA. Rapidly-fabricated nightly-detected lane system: An FPGA implemented architecture. *The Asian International Journal of Life Sciences*. 2018; 16(1): 343-355.

22. Humaidi AJ, Hassan S and Fadhel MA. 2018. FPGA-based lane-detection architecture for autonomous vehicles: A real-time design and development. *The Asian International Journal of Life Sciences*. 2018; 16(1): 223-237.

23. Humaidi AJ, Hasan S, Al-Jodah AA. 2018. Design of Second Order Sliding Mode for Glucose Regulation Systems with Disturbance. *International Journal of Engineering & Technology*. 2018; 7(2.28): 243-7.