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# Brain cancer detection using Curvelet Transform and Neural Network

Dr. Talib M. Jawad Abbas, Mays Yousif

**Abstract :** In past few years, Cancer is one of the worst diseases in the world causing death of many people. MRI is one of the widely used imaging technique for detection and classification of brain tumors. Typical structure for this proposed system consists of four stages:The initial stage in the proposed system is the pre-processing using Gaussian filter. FCM has been employed in the second stage for images segmentation. The third stage is the feature extraction of MRI images using Curvelet Transform. The fourth stage is classification that classified the tumor of MRI images using Artificial Neural Network to benign and malignant. The recognition rate of this system is 95%.

**Index Terms—**Brain cancer, Curvelet Transform , Neural Network, Benign Tumor , Malignant Tumor

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### 1. 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 deadly 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 an information processing paradigm, mathematical model that is inspired by the way biological nervous systems such as brain [4]. A brain tumor, defined as an abnormal growth of cells within the brain. One of the most important researches in this field were done by:

S. Prabha and M. Sasikala, in 2013 [5] proposed a system for classification of MRI images into benign tumor and malignant tumor using Fuzzy c-means (FCM) algorithm. Curvelet transform is used for feature extraction from region of interest. Co-occurrence matrix is formed for each sub-band of Curvelet Transform to calculate texture feature of images such as energy and entropy. Said Charfi et al. ,in 2014 [6]proposed a technique for classification of MRI images. this work consists of several steps including image segmentation using histogram dependent thresholding, feature extraction by Discrete Wavelet Transform (DWT), Principle Component Analysis (PCA) is used for the purpose of reduction the wavelet coefficients and finally Back Propagation Neural Network (BPNN) is used for classification of MRI images into benign and malignant tumor. The classification accuracy of the proposed system is 90%.Rajeshwar Nalbalwar et al., in 2014 [7] proposed system to detect tumor and classify the type of tumor using ANN. This work consists of three stages including tumorsegmentation by Thresholding method, feature extraction of images using Gray level co-occurrence matrix (GLCM), and classification of MRI images using Back propagation neural network.

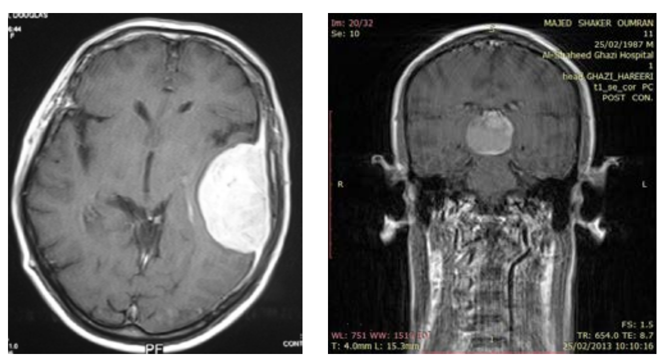
This work is aimed to design a system which is able to diagnose two types of tumors in a human brain (benign and malignant), by using the MRI images.

### 2. 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 back propagation neural network

The proposed system is implemented on a real human brain dataset. The input dataset consists in 40 images: 20 images are benign, 20 malignant (cancerous) l images. These benign and malignant images used for classification, are 256×256 sizes and acquired at several positions of the trans axial planes. These images were collected from al kadhmiya teaching hospital and interne



(a) Benign tumor (b) malignant tumor

Figure 1: MRI images

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### 2.1 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.2-D Gaussian distributions with standard deviation forpixel (x,y) is given by:

$$G(x,y)=\frac{1}{2\pi\sigma^2}\exp\frac{-x^2+y^2}{2\sigma^2} \quad (1)$$

The degree of blurring is controlled by blurring coefficient ( $\sigma$ ), as well as the size of the kernel used (squares with an odd number of pixels; e.g. 3×3, 5×5 pixels, so that the pixel being acted upon is in the middle) [8,9].

### 2.2 Segmentation

In this stage, segmentation is used to segment MRI images by using fuzzy c-means algorithm. FCM is one of the most widely used clustering algorithm for brain image segmentation. 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 [10,11]. The cluster centers and membership functions are updated iteratively [11].

$$v_i=\frac{\sum_{j=1}^{n}\mu_{ij}{}^{m}x_j}{\sum_{j=1}^{n}\mu_{ij}{}^{m}} \quad (2)$$

$$\mu_{ij}=\sum_{k=1}^{c}\left(\frac{x_j-v_i}{x_j-v_k}\right)^{\frac{-2}{m-1}} \quad (3)$$

The membership functions are subject to the following constraints:

$$\sum_{i=1}^{c}\mu_{ij}=1;0\le\mu_{ij}\le1;0<\sum_{j=1}^{n}\mu_{ij}<n \quad (4)$$

Where

$\mu_{ij}$ is the membership function of pixel$x_j$ in the ith cluster.

$c$ is the number of clusters.

$n$ is the number of pixels in the image.

$v_i$ is the center of the ith cluster.

$\left\|x_j-v_i\right\|$ is the Euclidean distance between $x_j$ and $v_i$.

( $m$ >1) is a weighting factor that controls the fuzziness of the resultant

Segmentation.

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

$$J_m=\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}{}^{m}\left\|x_j-v_i\right\|^2 \quad (5)$$

Where $J_m$ is the objective function that reduces at each iteration [11].

### 2.3 Feature Extraction using Curvelet Transform

The curvelet transform is a multi-scale geometrical transform with frame elements given by scale, location and orientation parameters. It has not only the time-frequency localization properties of wavelet but also shows a very high degree of directionality. The Curvelet transform is designed to overcome the limitations of Gabor filters and wavelet transform.

Curvelet transform has been developed to obtain complete coverage of the spectral domain and to capture more orientation information. With curvelet transform, there is no loss of information because the curvelet transform covers the whole frequency spectrum. The discrete ridgelet transform is the first approach of the curvelet transform. Since 1999, ridgelet based curvelet transform is an effective tool in image de-noising, image decomposition, texture classification, image de-convolution, astronomical imaging and contrast enhancement,but it is not effective as it uses complex ridgelet transform.

In 2005, Unequally-Spaced Fast Fourier Transform (USFFT) and wrapping based fast curvelet transform are two new forms of Curvelet Transform based on different operations of Fourier samples proposed by Candès et al.Curvelet have both variable length and width and represent more anisotropy whereas ridgelet have variable width and fixed length which is equal to the size of the image [12].

Wrapping based curvelet transform is faster in computation time and more robust than ridgelet and USFFT based curvelet transform. In this work, we used discrete curvelet transform based on wrapping Fourier samples [12,13]. The 2-D discrete Curvelet Transform is expressed as:

$$C^D(j,l,k) = \sum_{0 \le x < M, 0 \le y < N} g[x,y] . \varphi^D{}_{j,l,k} \quad (6)$$

Where $g[x,y]$, $0 \le x < M, 0 \le y < N$ is the 2-D input image, $C^D(j,l,k)$ are the discrete curvelet coefficients, $\varphi^D{}_{j,l,k}$ is the curvelet basis function.

$j$ is the scale, $l \in [0, 2\pi]$ is the orientation and $k \in R$ is the location [12].

Curvelet transform captures the curved edges in the frequency domain effectively. It implements parabolic scaling law on the sub-band. Curvelet shows an oscillating behavior in the direction perpendicular to their orientation in frequency domain.Wrapping based curvelet transform has pyramid structure consisting of multiple orientations at each scale in the frequency domain. Each sub band has different orientations and positions [13].

The architecture of FDCT via wrapping is as follows:

1. Fourier samples $\hat{f}$ is obtained by applying 2-D FFT on the image.
2. For each scale $j$ and angle $l$, the product $\tilde{U}_{j,l} . \hat{f}$ is obtained. where is $\tilde{U}_{j,l}$ the parabolic window (curvelet window) which is basically computed in the frequency domain.
3. The product wraps around the origin and obtain

$$\tilde{f}_{j,l}[n_1,n_2] = W\left(\tilde{U}_{j,l} . \tilde{f}\right)_{[n_1,n_2]} \quad (7)$$

Where $0 \le n_1 < L_{1,j}$ and $0 \le n_2 < L_{2,j}$ are the range of $n_1$ and $n_2$ respectively. $L_{1,j}$, $L_{2,j}$ are dimensions of the rectangle.

With the help of inverse 2-D FFT to each $\hat{f}_{j,l}$, the discrete curvelet coefficients $C^D(j,l,k)$ are obtained [12].

### 2.4 Classification

ANN is a model for one of the most important features of the human brain in the biological neural system. This feature is the ***ability to learn***that shows parallel intellectual development of human. Human learns how to read, write, speech, understand, recognize and distinguish pattern by means of examples. So, ANN are trained in the same way. It is trained rather than programmed [14]. Back propagation is one of the Neural Network models that is widely used in all fields. The back-propagation algorithm is organized in layered feed-forward that send their signals 'forward' and propagate the errors of signal backwards. The input layer receives the inputs signals and the neuron in the output layer gives the output of the network. As well as one or more intermediate hidden layers are also used. Back propagation algorithm is a supervised learning which means that both the input and outputs of the network are provided, and then the error is calculated. Error is the difference between actual output and the expected result. The goal of back propagation is to reduce this error. Finally, ANN learns the data. The training process begins with initial random numbers of weight. The weight is adjusted after each trial until the error will be minimal [14].

Block diagram of the proposed system is shown in figure 2

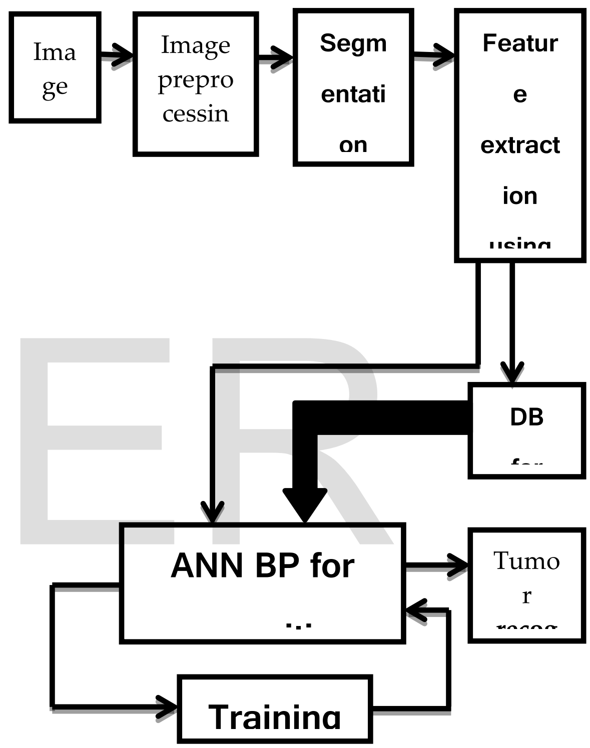


Figure 2: block diagram of the proposed system

### 3. Result and discussion

In the proposed algorithm, classification of brain tumor has done with BPNN. It classified MRI input image into benign or malignant tumor. BPNN designed with the number of hidden layers and output layers with different transfer function and learning rule. The transfer function of hidden layer is sigmoid function while the transfer function in output layer is pure-line. The learning rule at hidden layers and output layer is Levenberg-marqua. It is easy to verify the result of BPNN which gives accurate result by considering the condition like True Positive, False Positive, True Negative and False Negative. The system has two operational phases, training phase and testing phase.

In training phase of this algorithm, the weight of each neural network neuron is adjusted such that the network should be capable of accurately recognizing differentclasses of images. The testing phase starts by taking the training images and testing images for each class and passing each one of them to calculate output of neural network. In this work, forty MRI image were used, 20 MRI images for training and 20 for testing. The result of back propagation neural network gives two groups according to the features extractor into benign and malignant tumor. In this work, feature vector using curvelet transform consist of mean, standa

The standard deviation of a sub-band at scale $j$ and orientation $l$ can be shown as [13]:

$$\sigma_{jl} = \frac{\sqrt{\Sigma_x \Sigma_y \left(\left|curvelet_{jl}(\mu x, y)\right| - {}_{jl}\right)^2}}{MxN} \quad (9)$$

Entropy is a measure of gray level distribution randomness [15].

$$Entropy = -\sum_{x=1}^{N}\sum_{y=1}^{N}\left|curvelet_{jl}(x,y)\right| log_2 \left|curvelet_{jl}\right. \quad (10)$$

The performance of classification algorithm is evaluated by computing the percentages of Sensitivity, Specificity and Accuracy, the respective definition are as follows [6]:

SE=TP/(TP+FN) *100(11)

SP=TN/(TN+FP)*100 (12)

AC=(TP+TN)/(TP+TN+FP+FN)*100 (13)

Where,

True Positive (TP): Correctly classified positive cases.

True Negative (TN): Correctly classified negative cases.

False Positive (FP): Wrongly classified negative cases.

False Negative (FN): Wrongly classified positive cases.

| No. of images | Accuracy | Sensitivity | Specifity |
|---|---|---|---|
| 40 | 95% | 95% | 95% |

Table 1: Result of BPNN

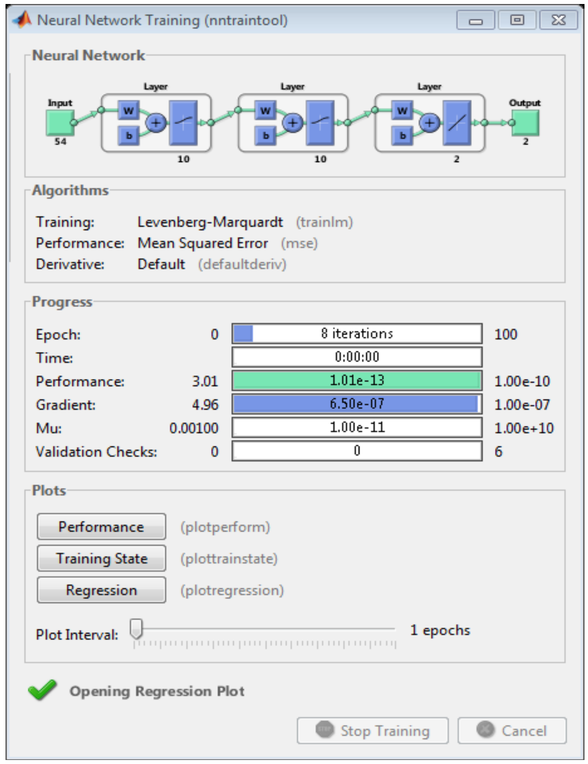


Figure 3: training of BPNN



## 4. Conclusion and future work

Brain cancer is the most dangerous diseases, so early detection of this diseases is necessary. But the detection of brain cancer is most difficult task. Our proposed method follows an approach in which the stages are preprocessing, segmentation, feature extraction, and then these features are used to train and test the neural network. Curvelet transform is used to extract the feature of MRI images. From the results, the proposed technique successfully detects the brain cancer from MRI images. Our proposed method gives 95% accuracy. If it is detected correctly in early
stages then it increases the key of survival. In future, this technique can be used in the detection of other types of tumor

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