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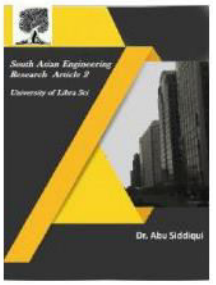

SEGMENTATION, DETECTION AND CLASSIFICATION OF BRAIN TUMOR MRI IMAGES USING ANN

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ABSTRACT

Too many people are being faced with the ruinous diagnosis each year and also tumors are main cause of death in children and young people. Tumors are very similar to healthy cells and they will grow rapidly. We have to detect the brain tumor as its early stage itself otherwise this may cause of death of patient. Then medical imaging plays major role in diagnosis of tumor. It is in this regard a new segmentation method which combines Otsu thresholding and region-based segmentation methods is presented. Detection of brain tumor is done by the new segmentation process which is a combination of two segmentation processes Otsu's method and region based method. The segmented images were given to a artificial neural network to classify whether the image has a tumor. The proposed Otsu-region based segmentation method is highly efficient (up to 98%), in detecting the defected areas in brain MRI images.

Keywords: Tumor, MRI, Segmentation, Otsu-region segmentation, GLCM, probabilistic neural network, back-propagation neural network

1. INTRODUCTION

The brain, its structure, and the role that each part plays in our everyday thoughts and behaviors is remarkable. These are some reasons why a tumor in the brain is so complex. There are one hundred and twenty types of brain and central nervous system tumors. Tumor is an uncontrolled or abnormal growth tissue in any part of the body. These cells are look like healthy and normal cells. A brain tumor is an abnormal growth of tissue in the brain or central spine that can disrupt proper brain function. Doctors refer to a tumor based on where the tumor cells began, and whether they are cancerous (malignant) or not (benign). Tumor cells will look like normal cells in early stages and they will rapidly grow in body. A scan creates computerized images of the brain and spinal cord by examining it from different angles. Some scans use a contrast agent (or a dye) to allow the doctor to see the difference between normal and abnormal tissue which are shown in fig1.

Many diagnostic imaging techniques can be performed for the early detection of brain tumors such as

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Computed Tomography (CT), Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI). Compared to all other imaging techniques, MRI is efficient in the application of brain tumor detection and identification, due to the high contrast of soft tissues, high spatial resolution and since it does not produce any harmful radiation, and is a non-invasive technique [4, 5]. Although MRI seems to be efficient in providing information regarding the location and size of tumors. Many researchers have used different classification techniques for MRI data analysis, such as Bayes classifier-nearest classifier, artificial neural network (ANN) based approach, and support vector machines (SVMs) as a classification scheme [2]. In these classification techniques designing the system is complex, time consumption is comparatively more and accuracy is low. Due to these reasons Otsu-region based method of segmentation is used for image segmentation and artificial neural networks like back-propagation and probabilistic neural networks are used as classifier.

The objective of this paper is to present a system as a diagnostic tool for identification of tumor cancer appearing in brain. This project also proposed brain cancer / tumor classification from MRI data by means of texture analysis based on gray level co-occurrence matrix (GLCM) to train the artificial neural networks (back propagation neural network used here). For this first segment the input image using image processing techniques like clustering methods. In this we are using Otsu's method of segmentation. The segmented image will undergo feature extraction; this will further process in two stages of classifier. We describe the modes of this technique in two stages: the Training/Learning and Testing/Classification. Back propagation network (BPN) and probabilistic neural network (PNN) based classifier are used to classify the type of tumor in MRI image as normal or abnormal brain images which are shown in the Fig1.

1.1 Magnetic Resonance Imaging

Medical imaging is the technique and process of creating visual representations of an internal body for clinical analysis and medical intervention, as well as visual representation of the function of some organs or tissues. It has many techniques to get medical images. Examples: CT-scanning, ECG, X-ray scanning and MRI. CT (computed tomography) is a special type of X-ray scanning. X-ray and CT-scanning both will use the X-rays and these rays will have ionizing radiations. Due to this some illness and problems will appear in human body. Where as in MRI uses strong magnetic field does not uses the ionizing radiations and it will give better images compare to other scanning techniques. So, in this we are using MRI scanning technique.

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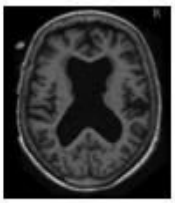
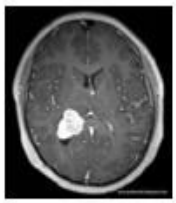

Figure1. normal and abnormal images

1.2. Image Segmentation

Image segmentation is process of dividing the image into multiple objectives. Or image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels also known as super pixels).The goal of segmentation is to simplify and enhance the representation of an image into something that is more meaningful and easier to analyze. [7] Different types of segmentation techniques are shown in table 1.

Practical Applications of Image segmentation are content-based image retrieval, machine vision, medical imaging (locate tumors and other pathologies measure tissues volume surgery planning), object detection, recognition tasks, traffic control systems.

2. Gray-level Co-occurrence Matrix (GLCM)

A statistical approach that can well describe second-order statistics of a texture image is a co-occurrence matrix. Gray level co-occurrence matrix (GLCM) was firstly introduced by Haralick. A co-occurrence occurrence matrix, also referred to as a co, also referred to as a co-occurrence occurrence distribution, is defined over an, is defined over an image to be the distribution of to be the distribution of co-occurring values at a occurring values at a given offset given offset Or Represents the distance and angular spatial Represents the distance and angular spatial relationship over an image sub relationship over an image sub-region of specific region of specific size.

The GLCM is created from a gray-scale image. The GLCM is calculates how often a pixel The GLCM is calculates how often a pixel with gray with gray-level (grayscale intensity or level (grayscale intensity or Tone) value i occurs either horizontally, vertically, or diagonally to adjacent pixels vertically, or diagonally to adjacent pixels with the value j .In our proposed system MRI image can be decomposed into patterns with regular textures. So we should be able to represent these regular texture regions by using co-occurrence matrices. To do so, we utilize the co-occurrence matrices in angles of 0^0,45^0, 90^0 and 135^0 [6, 10]. The example for the GLCM is shown below. Consider the image (below left). If we use the position operator 1 pixel to the right and 1 pixel down then we get the gray-level co-occurrence matrix (below right)

$$P = \frac{1}{16}\begin{bmatrix} 4 & 2 & 1 \\ 2 & 3 & 2 \\ 0 & 2 & 0 \end{bmatrix}$$

$$\begin{matrix} 0 & 0 & 0 & 1 & 2 \\ 1 & 1 & 0 & 1 & 1 \\ 2 & 2 & 1 & 0 & 0 \\ 1 & 1 & 0 & 2 & 0 \\ 0 & 1 & 0 & 2 & 0 \\ 0 & 0 & 1 & 0 & 1 \end{matrix}$$

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Where an entry P_ij is a count of the number of times that $F = (x, y) = i$ and $F(x + 1, y + 1) = j$. For example, the first entry comes from the fact that 4 times a 0 appears below and to the right of another 0.The factor 1/16 is because there are 16 pairs entering into this matrix, so this normalizes the matrix entries to be estimates of the co-occurrence probabilities. For statistical confidence in

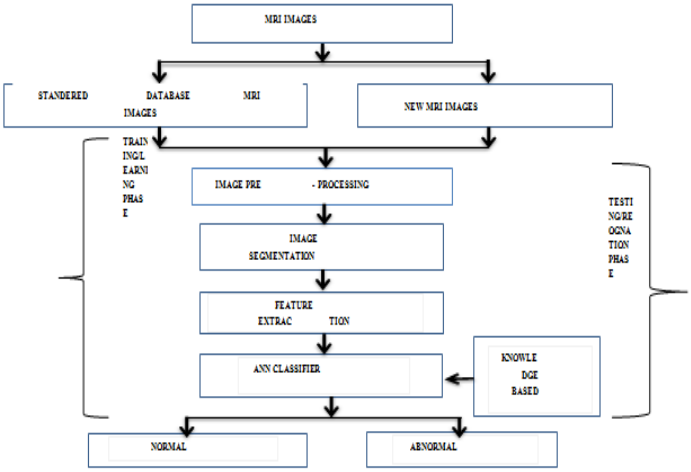

Figure 2: Proposed Methodology

the estimation of the joint probability distribution, the matrix must contain a reasonably large average occupancy level. Achieved either by (a) restricting the number of amplitude quantization levels (causes loss of accuracy for low-amplitude texture), or (b) using large measurement window. (Causes errors if texture changes over the large window). Typical compromise: 16 gray levels and window size of 30 or 50 pixels on each side. Now we can analyze P: maximum probability entry element difference moment of order k. Using GLCM we can find Texture features which are shown in table 2.

Table 2: Computation of Texture features

ENERGY	$F_1 = \sum_{i,j=0}^{N-1} P^2(i,j)$
CONTRAST	$F_2 = \sum_{i,j=0}^{N-1} P(i,j) * \|i,j\|^2$
HOMOGENITY	$F_3 = \sum_{i,j=0}^{N-1} \frac{P(i,j)}{1+(i-j)^2}$
DISSIMILARITY	$F_4 = \sum_{i,j=0}^{N-1} P(i,j) * \|(i,j)\|$
ENTROPY	$F_5 = \sum_{i,j=0}^{N-1} P(i,j) * [-\ln P(i,j)]$
MAXIMUM PROBABILITY	$F_6 = \max_{i,j} P(i,j)$
INVERSE	$F_7 = \sum_{i,j=0}^{N-1} \frac{P(i,j)}{(i-j)^2}$

Table 3: Values of Texture Features

Texture Features	Training	Testing
Energy	0.8501	0.8361
Contrast	0.7365	0.7165
Homogeneity	0.5280	0.5851
Dissimilarity	1.7076	0.7861
Entropy	0.2439	0.3981
Maximum Probability	0.9695	0.9502
Inverse	0.9849	0.9753

3. Proposed Methodology

The method used for detection and classify the brain tumor is shown in Figure 2. This paper shows the new approach to detect and classify the MRI images by adaptive segmentation method like Otsu-region based method. The segmentation process will detect whether the tumor is present or not. After segmentation texture features are calculated by using GLCM in different directions (i,e. 0^0,45^0, 90^0 and 135^0). Then using artificial neural networks (Back-propagation and Probabilistic neural networks). Depend on the future extraction and segmentation process tumor is classified into different astrocytoma types of tumors. The necessary steps of method is as follows:

Image segmentation using image processing techniques (Otsu-region based method) perform for the input image.

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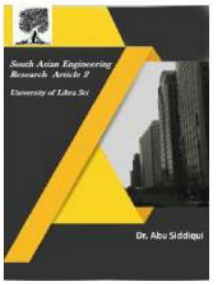

- Texture Features extraction using GLCM Matrix in different Direction (i.e. at 0^0,45^0, 90^0 and $135^{0)}$ [11, 10].
- Train a neural network on different image samples for certain class.
- Test unknown image sample by calculate the texture features by GLCM and used a neural network to detect it and to classify the different types of cancers [8].

The proposed method consists of two phases:

- Training/Learning Phase
- Testing/Recognition Phase

3.1 Training/Learning Phase

In Learning/Training Phase the ANN is trained for recognition of different Astrocytoma types of brain cancer. The known MRI images are first processed through segmentation using pre-processing and various image processing steps such as Histogram Equalization, Thresholding, and morphological operation etc. and then textural features are extracted using Gray Level Co-occurrence Matrix. The features extracted are used in the Knowledge Base which helps in successful classification of unknown Images. These features are normalized in the range -1 to 1 and given as an input to Back Propagation Neural Network (BPN) Based Classifier. In case of Probabilistic Neural Network these features are directly given as an input to PNN based classifier. The features such as angular second moment (ASM) or energy, contrast, inverse difference moment (IDM) or homogeneity, dissimilarity, entropy, maximum probability and inverse for each type of MRI image that was trained for the neural network is shown in table 3.

3.2 Testing/Recognition Phase

The second stage is recognition/testing phase. To test unknown MRI image sample and classify, two steps are performed, the first one is segmented the image and calculate the GLCM for each input MRI image. The obtained GLCM is used to extract features depending on equations which shown in figure 3. The second step is train the above features with the desired values of neural networks to determine the MRI image belong to which grade of astrocytoma type of brain tumor. After training the unknown images will send to testing phase and tumors will detected by segmentation process and classified by BPNN and PNN classifier [5, 8]. The taken decision is made by back-propagation neural network (BPN) based classifier and probabilistic neural network (PNN) based classifier.

4 Image segmentation By Otsu-region Based Method

The Otsu-method is named by Nobuyuki Otsu in 1979 is used to automatically clustering based image thresholding. In this paper, the image segmentation is done by Otsu-method and region based method to locate and detect the tumor in MRI image of patient. So, it can collectively called as Otsu-region based method of segmentation. Firstly segmentation is done by Otsu-method and the process as follows: The

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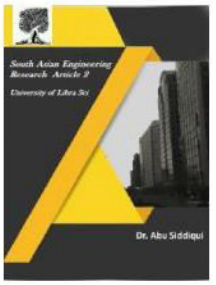

algorithm assumes that the image contains two classes of pixels following bi-modal histogram (foreground pixels and background pixels), it then calculates the optimum threshold separating the two classes so that their intra-class variance is minimal, or equivalently, so that their inter-class variance is maximal. Consequently, Otsu's method is roughly a one-dimensional, discrete analog of Fisher's Discriminant Analysis. Otsu's method is also directly related to the Jenks optimization method. Where q_1 and q_2 are define the estimates of class probabilities as

$$q_1 = \sum_{i=1}^{t} P(i) \quad \text{And} \quad q_2 = \sum_{i=t+1}^{L} P(i) \tag{1}$$

Sigma's are individual class variances and are defined as

$$\sigma_1^2(t) = \sum_{i=1}^{t} [i - \mu_1^2(t)]^2 \frac{P(i)}{q_1(t)} \tag{2}$$

$$\sigma_2^2(t) = \sum_{i=t+1}^{L} [i - \mu_2^2(t)]^2 \frac{P(i)}{q_2(t)} \tag{3}$$

Where $\mu_1(t)$ and $\mu_2(t)$ are class means

$$\mu_1(t) = \sum_{i=1}^{t} \frac{iP(i)}{q_1(t)} \tag{4}$$

$$\mu_2(t) = \sum_{i=t+1}^{L} \frac{iP(i)}{q_2(t)} \tag{5}$$

Here P represents the image histogram. The problem of minimizing within class variance can be expressed as maximization of problem of the between class variance. It can be written as difference of total variance and within class variance:

$$\sigma_b^2(t) = \sigma^2 - \sigma_w^2(t) = q_1(t)[1 - q_1(t)][\mu_1(t) - \mu_2^2(t)]^2 \tag{6}$$

Finally, this expression can safely maximized and the solution is t that maximizing $\sigma_b^2(t)$. Algorithm of the Otsu's Method: For each case potential threshold T,

- Compute histogram and probabilities of each intensity level.
- Set up initial $q_i = 0$ and $\mu_i = 0$.
- Step through all possible thresholds maximum intensity.
- Update q_i and μ_i.
- Compute $\sigma_b^2(t)$.
- Desired threshold corresponds to the maximum.

4.1 Advantages

- Speed: Because Otsu's threshold operates on histogram its quite fast.
- Easy of coding: Approximately eighty lines of very easy stuff.

4.2 Disadvantages

- Assumption of uniform illumination.
- It does not use any object structure or spatial coherence.
- The non-local version assumes uniform statistics

After doing the Otsu-method of segmentation considering the clusters the region based image segmentation has to be done. Due to this we can identify accurate location and present scenario of tumor in which state is present. This method will give the fast and accurate results.

5. Artificial Neural Networks

Artificial neural networks (ANNs) or connectionist systems are a computational model used in machine learning, computer science and other

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research disciplines, which is based on a large collection of connected simple units called artificial neurons, loosely analogous to axons in a biological brain[1, 6, 7].In this paper, Back-propagation neural network and Probabilistic neural networks are used as classifier.

- Back-Propagation Neural Network: The backward propagation of errors or back-propagation, is a common method of training artificial neural networks and used in conjunction with an optimization method such as gradient descent. The algorithm repeats a two phase cycle, propagation and weight update. Back propagation is a supervised learning method[3].In supervised learning, each input vector needs a corresponding target vector. Input vector and target vector are presented in training of the network. The output vector which is result of the network is compared with the target output vector then an error signal is generated by the network. This error signal is used for adjustment of weights until the actual output matches the target output. Algorithm stages for BPN are initialization of weights, feed forward, back propagation of Error and Updation of weights and biases.
- Probabilistic Neural Network: A probabilistic neural network (PNN) is a feed forward neural network, which is widely used in classification and pattern recognition problems[3].The PNN algorithm, the parent probability distribution function (PDF) of each class is approximated by a Parzen window and a non-parametric function. Then, using PDF of each class, the class probability of a new input data is estimated and Bayes rule is then employed to allocate the class with highest posterior probability to new input data. When an input is presented, the first layer computes distances from the input vector to the training input vectors and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities. PNN is a fast training process and an inherently parallel structure that is guaranteed to converge to an optimal Classifier as the size of the representative training set increases and training samples can be added or removed without extensive retraining.

6. Experimental Results And Discussion

A total of 50 .jpg images are used in the simulation and testing of the system. Out of 48 images [1, 2, 3, 4,....., 18] are with tumor shown in fig3 and [19, 20, 21,...., 50] are normal images shown in fig.4. These images are collected from the Basaveshwara Hospital and Medical Science Gulbarga. Using these data created the 11 groups of images which having disease and normal images for

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testing as discussed in the following sections. Considering an example of 1.jpg for testing the results are shown in fig5, and texture features are shown in Table 3. Total average Accuracy of Back-Propagation Neural Network Classifier is 83.3% which is shown in the Table 4 and Table 5.

Total average accuracy of the Probabilistic Neural Network Classifier is 96.26% which is shown in Table 6 and Table 7.

Total average accuracy of PNN =96.26Observing all the above results the PNN accuracy is more than the BPNN. PNN is a Bayes optimal classifier and learns better than BPNN with the limited set of data. Hence, PNN accuracy is more.

Table 4: Detection of Tumor Using BPNN

Experiment numbers	Images numbers	Correctly Detected images	Incorrectly detected images	Accuracy %
1	1,2,3,4,.....,18	1 ,2,4,5,6,8,9,10, 11 ,12,14,15,16, 17	3,7,13,18	77.7
2	1,2,3,4,5,6, ...15	1 ,2,4,5,6,8,9,10, 11 ,12,14, 15	3,7,13	80
3	1,2,3,.....,11 ,13,15,17,18	1 ,2,4,5,6,8,9,10, 11 ,15, 17	3,7,13,18	76.6
4	1,2,3,4,5,6,8,10 12,14,16,18,13,15	1 ,2,4,5,6,10,12,14, 15 , 16	3,13,18	80
5	17,1,16,15,14,18,12, 11,10,8,6,7,13,2,4	17 ,1,16,15,14,12, 11 ,10,8,6,2, 4	18,7,13	80
6	1,2,18,4,5,6,7,9,10, 11,12,14,16,17,8	1 ,2,4,5,6,9,10,11, 12 ,14,16,17, 8	7,18	83.6
7	18,16,3,4,1,9,10,6, 15,17,11,12,2,5,14	16 ,4,1,9,6,15,17, 12,2,5,14,10,11	3,18	83.6
8	10,11,12,13,14,15, 16,17,18,1,2,4,6,8,5	10 ,11,12,14,15,16, 17 ,1,2,4,6,8, 5	13,18	83.6
9	1,2,3,6,7,9,11,13,14 15,1,6,17,8,10	1,2,6,9,11,14,15,1, 617 ,8, 10	3,13,7	80
10	3,6,9,12,15,14,2,4, 16,8,10,7,13,17,11	6 9,12,15,14,2,4,16, 8 ,10,17, 11	3,13,7	80

Table 5: Combination of With Tumor and Normal Images

Experiment numbers	Images numbers	Correctly Detected images	Incorrectly detected images	Accuracy %
11	1,2,3,4,5,6,7, ...,48,49,50	1,2,4,5,6,78,9,10,11,12,14,15,16,17, 19,20,21,23,24,25,26,27,28,29,31,...,50	3,7,13,18,22,30	83.3

Table 6: Detection of Tumor Using PNN

Experiment numbers	Images numbers	Correctly Detected images	Incorrectly detected images	Accuracy %
1	1,2,3,4,5,6, ...,18	1 ,2,4,5,6,8,9,10, 11 ,12,14,15,16, 17	18	94.4
2	1,2,3,4,5,6, ...15	1 ,2,4,5,6,8,9,10, 11 ,12,14, 15	0	100
3	1,2,3,.....,11 ,13,15,17,18	1 ,2,4,5,6,8,9,10, 11 ,15, 17	18	93.3
4	1,2,3,4,5,6,8,10 12,14,16,18,13,15	1 ,2,4,5,6,10,12,14, 15 , 16	18	93.3
5	17,1,16,15,14,18,12, 11,10,8,6,7,13,2,4	17 ,1,16,15,14,12, 11 ,10,8,6,2, 4	18	93.3
6	1,2,13,4,5,6,7,9,10, 11,12,14,16,17,8	1 ,2,4,5,6,9,10,11, 12 ,14,16,17, 8	0	100
7	18,16,3,4,1,9,10,6, 15,17,11,12,2,5,14	16 ,4,1,9,6,15,17, 12 ,2,5,14,10,11	18	93.3
8	10,11,12,13,14,15, 16,17,18,1,2,4,6,8,5	10 ,11,12,14,15,16, 17 ,1,2,4,6,8, 5	18	93.3
9	1,2,3,6,7,9,11,13,14 15,1,6,17,8,10	1 ,2,6,9,11,14,15,1, 6 17 ,8, 10	0	100
10	3,6,9,12,15,14,2,4, 16,8,10,7,13,17,11	6 ,9,12,15,14,2,4,16, 8 ,10,17, 11	0	100

Table 7: Combination of With Tumor and Normal Images

Experiment numbers	Images numbers	Correctly Detected images	Incorrectly detected images	Accuracy %
11	1,2,3,4,5,6,7, ...,48,49,50	1,2,4,5,6,78,9,10,11,12,14,15,16,17,19 ,20,21,23,24,25,26,27,28,29,31,...,50	18	98

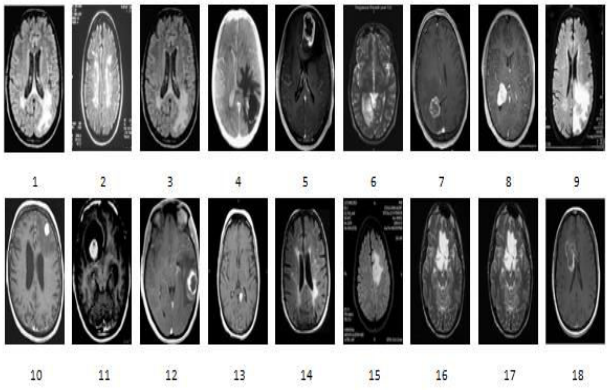

Figure 3: Brain MRI Images with Tumor

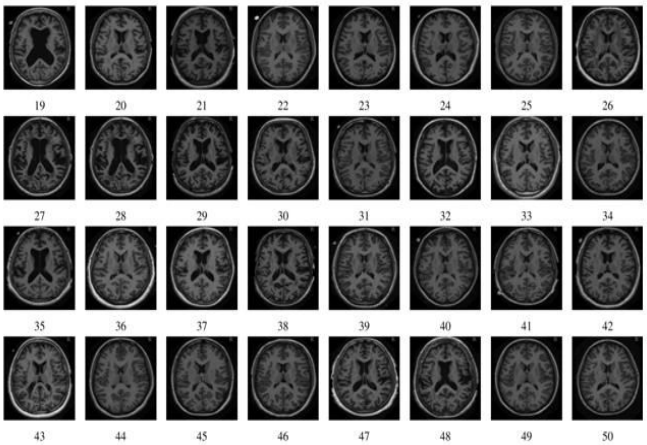

Figure 4: Brain MRI Images Without Tumor

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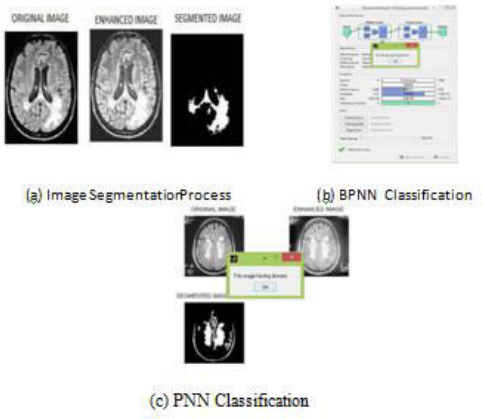

Figure 5: Detection and Segmentation of Brain MRI Images

7.Conclusions

The complete system worked in two stages firstly Training/Learning and secondly Testing/Recognition. The image processing tool such as Otsu-Region method of segmentation is performing on Training/Learning and Testing/Recognition phases. Texture features

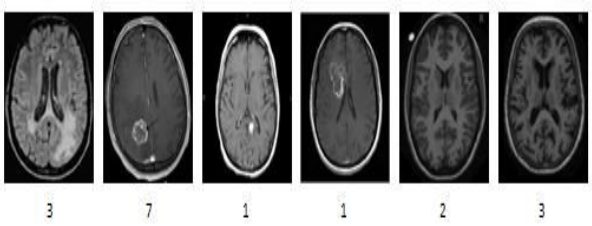

Figure 6: Incorrectly Detected MRI Images

are used in these phases of the Artificial Neural Network. Co-occurrence matrices at 0^0,45^0, 90^0 and 135^0 are calculated and Texture Features are extracted from the Gray-Level Co-Occurance (GLCM) matrices. The above process efficiently classifies the tumor types in brain MRI images With the BPNN accuracy is 83.3% and PNN accuracy is 96.26%The system has been designed has more accuracy and fast compared other classification and segmentation process.

8. Future Work

The system can be designed to classify other types of cancer. The further scope of the system is to improved ANN architecture by using other approach. The system can be designed by sing any segmentation techniques and combination two or more segmentation techniques to get exact location and conations of tumor and also use many classifier like SVM (support vector machine,) improve ANN as a classifiers and also use combination of SVM and ANN.

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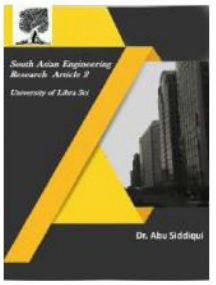

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