DETECTION OF BRAIN TUMOR USING BACK-PROPAGATION AND PROBABILISTIC NEURAL NETWORK

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Abstract- Brain tumor is one of the major causes of death among people. There are over one hundred twenty types of brain and central nervous system tumors. It is evident that the chances of survival can be increased if the tumor is detected and classified correctly at its early stage. Magnetic resonance (MR) imaging is currently an indispensable diagnostic imaging technique in the study of the human brain. A brain tumor, defined as an abnormal growth of cells within the brain or the central spinal canal. So tumor detection needs to be fast and more accurate enough as the patient cannot recover if the damage is more than 50%. For detecting this tumor CT or MRI scan is done. This CT or MRI scan images are taken for this project to process it. This work presents the artificial neural network approach namely Back propagation network (BPNs) and probabilistic neural network (PNN). It is used to classify the type of tumor in CT or MRI images of different patients with Astrocytoma type of brain tumor. In this, image segmentation is done by the Otsu's method of thresholding which is used to detect the tumor in the brain MRI images. The Gray Level Co-occurrence Matrix (GLCM) is used to achieve the feature extraction. The whole system worked in two modes firstly Training/Learning mode and secondly Testing/Recognition mode finally gets a classified output

Keywords- BPNN, GLCM, MRI, PNN, Otsu's Method

I. INTRODUCTION

A. Overview of Brain Tumor

A brain tumor is defined as the growth of abnormal cells in the tissues of the brain. Brain tumors can be benign (noncancerous) or malignant (cancerous). In contrast to normal cells, cancer cells result from uncontrolled cell growth and can grow into adjacent tissue. Although benign tumors can become large and press on healthy organs and tissue, which can potentially affect their functioning, they rarely invade other tissue. Primary brain tumors start from the brain itself, while secondary brain tumors (i.e. metastatic tumors) originate from other parts in the body. Non-invasive imaging methods, e.g. magnetic resonance imaging (MRI), computed tomography (CT) and positron emission tomography (PET), that could diagnose a brain tumor, would avoid unnecessary surgery. MRI represents an interesting approach for the anatomical assessment of brain tumors since it provides superior soft tissue contrast and high-resolution information.

B. Treatment

Treatment of brain tumors depends on a number of factors such as the type, location and size of the tumor. Other factors that are taken into account are the age and general health of the patient. Several types of treatment including surgery, radiotherapy, chemotherapy, and currently developed innovative targeted therapies. In many cases combination therapy is used. If the location of a brain tumor is accessible for surgery, the neurosurgeon may remove as much as possible of the tumor. Removal of even a portion of the brain tumor may help to reduce signs of elevated intracranial pressure. In addition, surgery can reduce the amount of tumor that needs to be treated by radiation or chemotherapy.

C. Detection of Tumor

A scan is the first step to identify if a brain tumor is present and to locate exactly where it is growing. A scan creates computerized image of the brain and spinal cord by examining it from different angles. Some scans used a contrast agent to allow the doctor to see the difference between normal and abnormal tissue. Many diagnostic imaging techniques can be performed for early detection of tumors such as Computed Tomography (CT), Position Emission Tomography (PET) and Magnetic Resonance Image (MRI). Compared all other imaging techniques MRI is efficient in the application of brain tumor detection and identification, due to high contrast of soft tissue high spatial resolution and since it does not produce harmful radiation and is an non-invasive technique. Although MRI seems to be efficient in producing information regarding location and size of tumor. Many researchers have used classification techniques for MRI data analysis such as Baye's-nerarest classifier; Artificial Neural Network based approach and Support Vector Machine's as a classification technique. These systems are complex, time consumes is comparatively more and accuracy is low. Due to these reasons the combination of Otsu's method of thresholding is used for image segmentation and ANNs like Back-Propagation and Probabilistic Neural networks are used as classifier.

The main objective of this work is to present a system as a diagnostic tool for detection of tumor appearing in brain. This project also proposed brain tumor classification from MRI data by means of texture analysis based on GLCM to train the ANNs. For this first segment the input image using image processing techniques like Otsu's threshold method. The segmented image will undergo feature extraction; this will further process in two stages of classifier. In this Back-Propagation and Probabilistic Neural network based classifier is used to detect and identify the brain tumor in MRI image as normal or abnormal brain images which are shown in figure 1 and 2.

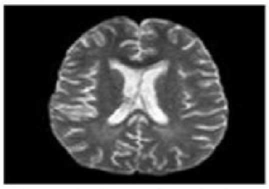


Figure 1. Normal brain image

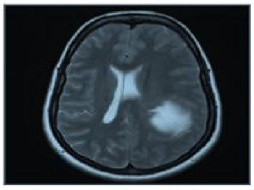


Figure 2. Abnormal brain image

II. MAGNETIC RESONANCE IMAGING

An MRI scanner uses a strong magnetic field and radio waves to create pictures of the tissues and other structures inside the brain, on a computer. The magnetic field aligns the protons (positively charged particles) in hydrogen atoms, like tiny magnets. Short bursts of radio waves are then sent to knock the protons out of position, and as they realign, (relaxation time), they emit radio signals which are detected by a receiving device in the scanner. The signals emitted from different tissues vary, and can, therefore, be distinguished in the computer picture. An MRI scanner can create clear detailed pictures of the structure of the brain and detect any abnormalities or tumors. Sometimes a dye, or tracer, such as gadolinium may be introduced via a vein in the arm, to improve contrast in the image. Images can be enhanced by differences in the strength of the nuclear magnetic resonance signal recovered from different locations in the brain.

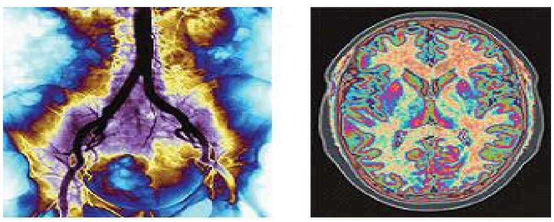


Figure 3. Digitally enhanced MRI images of the brain

The process of having a scan is painless and safe, there is no exposure to radiation, but occasionally, a patient may have a reaction to the tracer dye. Pregnant mothers are not recommended to undertake the procedure unless there is no alternative, since it is not known whether the effects of a strong magnetic field may affect the developing baby.

The scanner is a large tunnel surrounded by a circular magnet; the patient lies on a couch which slides into the tunnel. It is quite noisy so the patient is given headphones with music of their choice, and has to keep still for 15 to 40 minutes as the tiny radio wave signals are picked up by the computer. It is entirely painless, but children may require a general anaesthetic to keep them still for long enough. The radiographer will need to know if the patient has any metal in their body such as a metal skull plate, inner ear implants, pacemaker, artificial joints, or screws or pins holding bone fracture repairs. The patient may resume normal activities immediately after the scan, and the radiologist studies the pictures and sends a report to the doctor.

MRI is a medical imaging technique used in radiology to investigate the anatomy and function of the body in both health and disease. MRI scanners use strong magnetic fields and radio waves to form images of the body. The technique is widely used in hospitals for medical diagnosis, staging of disease and for follow-up without exposure to ionizing radiation. MRI has a wide range of applications in medical diagnosis and there are estimated to be over 25,000 scanners in use worldwide. MRI has an impact on diagnosis and treatment in many specialties although the effect on improved health outcomes is uncertain. Since MRI does not use any ionizing radiation its use is recommended in preference to CT when either modality could yield the same information.

Figure 4. Clinical MRI scanner

III. PROPOSED METHODOLOGY

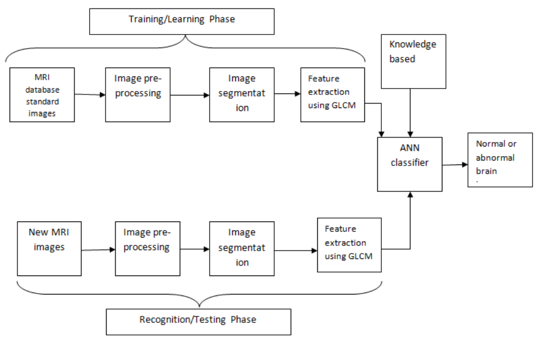


Figure 5. Proposed System for Detection of Brain Cancer

The method used for MRI brain tumor image detection is shown in Fig. 5. This paper introduces a new approach of brain cancer classification for astrocytoma type brain detection which is a part of image processing using Gray level co-occurrence matrix (GLCM). The easiest way in this work is a classification of any MRI images of patients into patterns using adaptive segmentation (i.e. using image processing technique such as Otsu's method thresholding) with the use of their textures features in different direction (i.e. 0º, 45º, 90º and 135º) of GLCM matrix to train the artificial neural networks (back propagation neural network and probabilistic neural network used here). This association obtains a good result.

In this work extracting the texture feature for unknown image sample and let the neural detect the type of this image or the type of brain tumor using a neural network and the approach applied for different MRI images. We propose a brain tumor detection method based on Gray level co-occurrence matrix (GLCM) with a neural network to recognize a certain class. The necessary steps are allocated below.

- Image segmentation using image processing techniques (Otsu's method) perform for the input image.
- Texture Features extraction using GLCM Matrix in different Direction (i.e. at 0º, 45º, 90º and 135º).
- Train a neural network on different image samples for certain class (i.e. gradeI, gradeII, gradeIII and gradeIV).
- Test unknown image sample by calculate the texture features by GLCM and used a neural network to detect it.

The proposed system consists of two stages as below:
A. Learning/Training Phase
B. Recognition/Testing Phase

A. Learning/Training 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 tab.

B. Recognition/Testing: 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. The taken decision is made by back-propagation neural network (BPN) based classifier and probabilistic neural network (PNN) based classifier.

IV. SEGMENTATION USING OTSU'S METHOD

Image segmentation is the division of an image into regions or categories, which correspond to different objects or parts of objects. Every pixel in an image is allocated to one of a number of these categories. A good segmentation is typically one in which:

- pixels in the same category have similar grey scale of multivariate values and form a connected region,
- Neighbouring pixels which are in different categories have dissimilar values.

In the image processing, Otsu's Thresholding method (1979) is used for automatic binarization level decision, based on the shape of the histogram. The algorithm assumes that the image is composed of two basic classes; foreground and background. It then computes an optimal threshold value that minimizes weighted within class variances of these two classes. It is mathematically proven that minimizing the between class variance.

Otsu's threshold is used in many applications from medical imaging to low level computer vision. Otsu's method is aimed in finding the optimal value for the global thresholding. It is based on the interclass variance maximization. Well thresholded classes have well discriminated intensity values.

Where q1 and q2 represent the estimate of class probabilities defined as:

$$q_1(t) = \sum_{i=1}^{t} P(i)$$

And

$$q_2(t) = \sum_{i=t+1}^{I} P(i)$$

Sigma's are the individual class variances defined as:

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

and

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

Class means:

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

and

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

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

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

Finally, this expression can safely be maximized and the solution is t that is maximizing $\boldsymbol{\sigma_b^2(t)}$.

Figure 4.4 shows the example for image segmentation using Otsu's method of thresholding and global thresholding method technique.

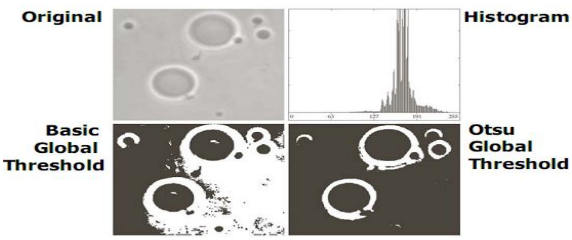


Figure 6. Optimal global thresholding using Otsu's method

Algorithm of the Otsu's Method:
For each case potential threshold T,

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

Advantages of Otsu's Method:

- Speed: Because Otsu's threshold operates on histogram its quite fast.

Easy of coding: Approximately eighty lines of very easy stuff.
Disadvantages of Otsu's Method:

Assumption of uniform illumination.
It does not use any object structure or spatial coherence.

The non-local version assumes uniform statistics.

V. GRAY LEVEL CO-OCCURANCE 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 gray-level co-occurrence matrix (GLCM) is essentially a two-dimensional histogram. The GLCM method considers the spatial relationship between pixels of different gray levels [3]. The method calculates a GLCM by calculating how often a pixel with a certain intensity i occurs in relation with another pixel j at a certain distance d and orientation [3]. A co-occurrence matrix is specified by the relative frequencies P (i, j, d,). A co-occurrence matrix is therefore a function of distance d, angle and grayscales i and j. The calculation of the GLCM of an segmented image is as shown in figure 5.1.

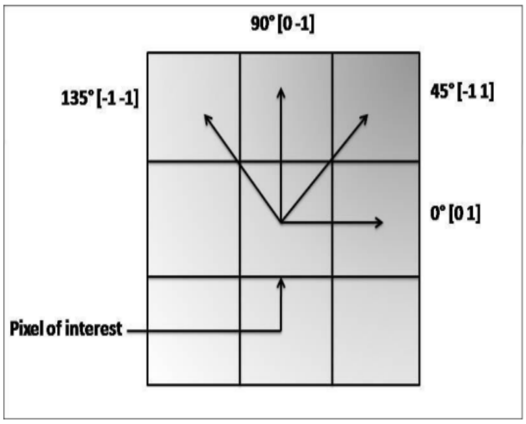


Figure 7. Direction for generation of GLCM

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°, 45°, 90°, and 135°.

VI. TEXTURE FEATURES

Generally texture is a feature used in the analysis and interpretation of images. Texture is described by a set of local statistical properties of pixel intensities. When the GLCM is generated, the textures feature could be computed from the GLCM. The seven common textures features discussed here are angular second moment (ASM) or energy, contrast, inverse difference moment (IDM) or homogeneity, dissimilarity, entropy, maximum probability and inverse. Energy is also known as uniformity of ASM (angular second moment) which is the sum of squared elements from the GLCM [10]. Contrast is used to measure the local variations. Homogeneity is to measure the distribution of elements in the GLCM with respect to the diagonal. Entropy measures the statistical randomness. The seven common textures features are shown in figure 3. All these features are extracted using GLCM methods at four directions (i.e. 0º, 45º, 90º and 135º) for every feature. The computation of the texture features are given in the below table 1.

Table 1. Computation of texture features

Energy	$F1 = \sum_{i,j=0}^{N-1} Pi,j2$
Contrast	$F2 = \sum_{i,j=0}^{N-1} P(i,j) * (i,j)2$
Homogeneity	$F3 = \sum_{i,j=0}^{N-1} \frac{P(i,j)}{1+(i-j)2}$
Dissimilarity	$F4 = \sum_{i,j=0}^{N-1} P(i,j) * \lvert(i,j)\rvert$
Entropy	$F5 = \sum_{i,j=0}^{N-1} P(i,j) * [-\ln(P(i,j))]$
Maximum probability	$F6 = \max i,j \; P(i,j)$
Inverse	$F7 = \sum_{i,j=0}^{N-1} \frac{P(i,j)}{(i-j)2}$

VI. ARTIFICIAL NEURAL NETWORKS

A. Back-Propagation Neural Network (BPNN)

Back propagation is a supervised learning method. 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 (i.e. actual output) 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.

B. Probabilistic Neural Network (PNN)

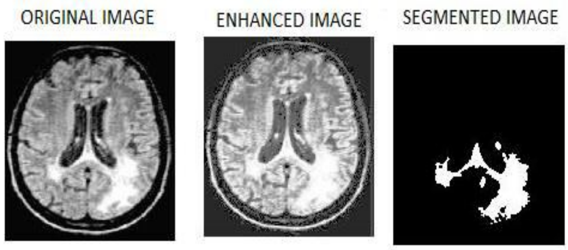
Probabilistic neural networks (PNN) are a kind of radial basis network suitable for classification problems. A PNN is primarily a classifier since it can map any input pattern to a number of classifications that is Probabilistic neural networks can be used for classification problems. When an input is 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.

A Probabilistic Neural Network (PNN) is defined as an implementation of statistical algorithm called Kernel discriminate analysis in which the operations are organized into multilayered feed forward network with four layers: input layer, pattern layer, summation layer and output layer. A PNN is predominantly a classifier since it can map any input pattern to a number of classifications. Among the main advantages that discriminate PNN is: Fast training process, an inherently parallel structure, 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. Accordingly, a PNN learns more quickly than many neural networks model and have had success on a variety of applications. Based on these facts and advantages, PNN can be viewed as a supervised neural network that is capable of using it in system classification and pattern recognition. The main objective of this paper is to describe the possible use of various PNN in solving some problems arising in signal processing and pattern recognition.

The main attention is devoted to application of PNN in various classification problems like: classification brain tissues in multiple sclerosis, classification image texture, classification of soil texture and EEG pattern classification. Experimental results have been carried out and it verify the ability of modified PNN in achieving good classification rate in compared with traditional PNN or back propagation neural network BPNN and PNN.

VII. EXPERIMENTAL RESULTS AND DISCUSSION

A total of 48 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 fig. 6.1 and [19, 20, 21……48] are normal images shown in fig. 6.2. These images are collected from the World Cancer Organization and Basaveshwara Hospital and Medical Science Gulbarga. Using these data created the 11 groups of images which having disease and normal images for testing as discussed in the following sections. Considering an example of 1.jpg for testing the results are shown in fig. 8, fig. 9 and fig. 10 and texture features are shown in table 2.



(a) (b) (c)

Figure 8. (a) Original MRI image (b) Enhanced image (c) Segmented image

Figure 9 Back- Propagation Neural Network Detection and identification

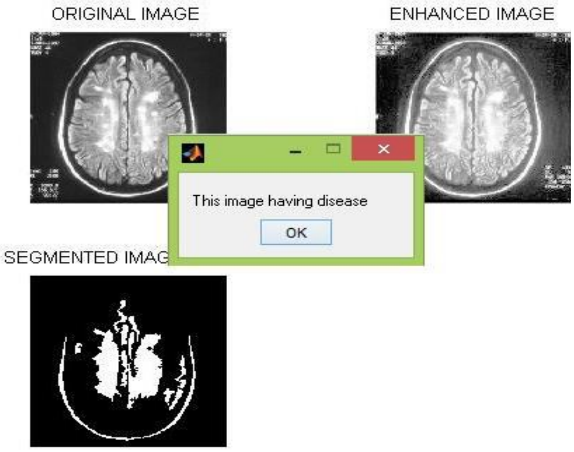


Figure 10 Probabilistic Neural Network Detection and Identification

Table 2. Texture features

Texture Features	Training	Testing
Energy	0.8501	0.8391
Contrast	0.7365	0.7165
Homogeneity	0.5280	0.5851
Dissimilarity	1.7076	2.7867
Entropy	0.2439	0.3981
Maximum Probability	0.9695	0.9502
Inverse	0.9849	0.9753

Table 3. Detection of Brain Tumor using BPNN

Expt. number	Image numbers	Correctly detected Images	Incorrectly detected images	Accuracy %
1	1, 2,3…..18	1, 2,3…..18	3, 7,13, 18 =04	77.7
2	1,2,3…..12,13,14,15	1,2,3…..12,13,14,15	3,7,18 =03	80
3	1,3,5,7,9,11,13,15,17,18, 2,4,6,8,10	1,3,5,7,9,11,13,15,17,18,2,4,6,8,10	3,7,13,18 =04	76.6
4	2,4,6,8,10,12,14,16,18,1, 3,5,13,15,17	2,4,6,8,10,12,14,16,18, 1,3,5,13,15,17	18,13,7 =03	80
5	1,17,16,15,14,13,12,11, 10,8,6,7,3,2,4	1,17,16,15,14,12,11, 10,8,6,2,4	13,7,3 =03	80
6	1,2,18,4,5,6,7,9,10,11,12, 14,16,17,13,	1,2,8,4,5,6,9,10,11,12,14,16,17 =13	7,18 =02	83.6
7	18,6,3,4,1,9,10,7,13,15,16,17,11,12,2,5	6,4,1,9,10,15,16,17,11, 12,2,5 =11	3,7,13,18 =04	76.6.
8	10,11,12,13,14,15,16,17, 18,1,2,4,6,8,5	10,11,12,14,15,16,11,2, 4,6,8,5 =13	18,13 =02	83.6
9	1,2,3,6,7,9,11,13,14,15,16,17,8,10	1,2,6,7,9,11,14,15,16,17,10 ,8 =12	3,7,13 =03	80
10	3,6,9,12,15,14,2,4,6,8,10, 7,13,17,11	6,9,12,15,14,2,4,6,8, 10,17,11 =12	3,7,13 =03	80

Total average accuracy of the BPNN = 79.76%

Table 5.Detection of brain tumor using PNN

Expt. number	Image numbers	Correctly detected Images	Incorrectly detected images	Accuracy %
1	1, 2,3…..18	1,2,3,4,5,6,7,8,9,10,11 ,12,13,14,15,16,17	18	94.4
2	1,2,3…..12,13,14,15	1,2,3…..12,13,14,15 =14	--	100
3	1,3,5,7,9,11,13,15,17,18, 2,4,6,8,10	1,3,5,7,9,11,13,15,17, 2,4,6,8,10 =14	18	93.3
4	2,4,6,8,10,12,14,16,18,1, 3,5,13,15,17	2,4,6,8,10,12,14,16,1, 3,5 =14	18	93.3
5	1,17,16,15,14,13,12,11, 10,8,6,7,3,2	1,17,16,15,14,13,12,1 1,10,8,6,7,3,2 =15	--	100
6	1,2,18,4,5,6,7,9,10,11,12, 14,16,17,13	1,2,8,4,5,6,7,9,10,11,1 2,14,16,17	18	93.3
7	18,6,3,4,1,9,10,7,13,15,1 6,17,11,12,2,5		18	100
8	10,11,12,13,14,15,16,17, 18,1,2,4,6,8,5	10,11,12,13,14,15,16, 17,18,1,2,4,6,8,5	18	93.3
9	1,2,3,6,7,9,11,13,14,15,1 6,17,8,10	1,2,3,6,7,9,11,13,14,1 5,16,17,8,10	--	100
10	3,6,9,12,15,14,2,4,6,8,10, 7,13,17,11	3,6,9,12,15,2,4,6,8,10, 7,13,17,11	--	100

Observing all the above results the PNN accuracy is more than the BPNN. PNN is a Baye's optimal classifier and learns better than BPNN with the limited set of data. Hence, PNN accuracy is more.

CONCLUSION

Detection of Brain Cancer Using Artificial Neural Network approach namely, Back propagation network (BPNs) and Probabilistic neural network (PNN). The complete system worked in two stages firstly Training/Learning and secondly Testing/Recognition. The image processing tool such as Otsu's method of thresholding is performing on Training/Learning. Texture features are used in the Training/Learning of the Artificial Neural Network. Co-occurrence matrices at 0º, 45º, 90º and 135º are calculated and Gray Level Co-occurrence Matrix (GLCM) features are extracted from the matrices. The above process efficiently classifies the tumor types in brain MRI images. 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 has been designed has more accuracy and fast compared other classification and segmentation process.

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