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Detecting Brain Tumor using Neural Networks

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Abstract: ***The goal of this paper is to detect the brain tumor using neural networks. Image processing techniques play an important role in the diagnostics and detection of diseases and monitoring the patients having these diseases. A new method for Brain Tumor Analysis using Probabilistic Neural Network with Discrete Cosine Transformation is proposed. The conventional method tomography and magnetic resonance brain images analysis and tumor detection is human inspection. Operator assisted classification methods are impractical for large amounts of data and are also non reproducible. Computerized tomography and Magnetic Resonance images contain a noise caused by operator performance which can lead to serious inaccuracies in classification. The use of Neural Network technique shows great potential in the field of medical diagnosis. Hence in this probabilistic neural network and discrete cosine transformwas applied for brain tumor classification. Evaluation was performed on image database of 15 brain tumor images. The proposed method gives fast and better recognition rate when compared to previous classifier. The main advantage of this method is its high speed processing capability and low computational requirements.***

Keywords: Brain tumor detection, DCT, Brain tumor, Probabilistic Neural Network (PNN), Fuzzy c-Means (FCM).

I. INTRODUCTION

A brain tumor is an intracranial solid neoplasm or abnormal growth of cells within the brain or the central spinal canal. Brain tumor is one of the most common and deadly diseases in the world. Detection of the brain tumor in its early stage is the key of its cure. There are many different types of brain tumors that make the decision very complicated. So classification of brain tumor is very important, in order to classify which type of brain tumor really suffered by patient. A good classification process leads to the right decision and provide good and right treatment. Treatments of various types of brain tumor are mostly depending on types of brain tumor. Treatment may different for each type, and usually determined by:

A. Age, overall health, and medical history
B. Type, location, and size of the tumor
C. Extent of the condition
D. Tolerance for specific medications, procedures, or therapies
E. Expectations for the course of the condition
F. Opinion and preferences

Classification of tumor is to identify what type of tumor it is. The conventional methods, which are present in diagnosis, are Biopsy, Human inspection, Expert opinion and etc. The biopsy method takes around ten to fifteen days of time to give a result about tumor. The human prediction is not always correct, sometimes it becomes wrong but a computer cannot. The expert, himself cannot take the decision rather he refers to another expert to give his opinion, this process continues for long time[1].

In general, early stage brain tumor diagnose mainly includes Computed Tomography (CT) scan, Magnetic Resonance Imaging (MRl) scan, Nerve test, Biopsy etc[2]. At present with the rapid growth of the Artificial Intelligence (AI) development in Biomedicine, computer aided diagnosis attracts more and more attention. In this based on the power of Probabilistic Neural Network (PNN), a computer aided brain tumor classification method is proposed. It utilized the feed-forward neural network to identify which type of brain tumor suffered by patient regarding to the image of brain tumor from the Magnetic Resonance Imaging (MRl) and Computed Tomography (CT) scan as inputs for the network.

In detecting the brain tumor type of each patient, doctor usually refer MRl image and make the report about the MRl analysis of the patient. This method will help doctor in diagnosing brain tumor patients. With the existence of proposed system, doctor can train the system with some known data and then, use this system to generate the MRl report of the patient after testing the data.

In any classification system Dimensionality Reduction and Feature Extraction are very important aspects[5]. Images though small in size are having large dimensionality this leads to very large computational time, complexity and memory occupation. The performance of any classifier mainly depends on high discriminatory features of the images. In the proposed method we used Discrete Cosine Transform for both dimensionality reduction and feature extraction.

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II. RELEVENCE

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 originated, and whether they are cancerous (malignant) or not (benign)[9][12].

1) *Benign:* The least aggressive type of brain tumor is often called a benign brain tumor. They originate from cells within or surrounding the brain, do not contain cancer cells, grow slowly, and typically have clear borders that do not spread into other tissue.
2) *Malignant:* Malignant brain tumors contain cancer cells and often do not have clear borders. They are considered to be life threatening because they grow rapidly and invade surrounding brain tissue.
3) *Primary:* Tumors that start in cells of the brain are called primary brain tumors. Primary brain tumors may spread to other parts of the brain or to the spine, but rarely to other organs.
4) *Metastatic:* Metastatic or secondary brain tumors begin in another part of the body and then spread to the brain. These tumors are more common than primary brain tumors and are named by the location in which they begin[9].

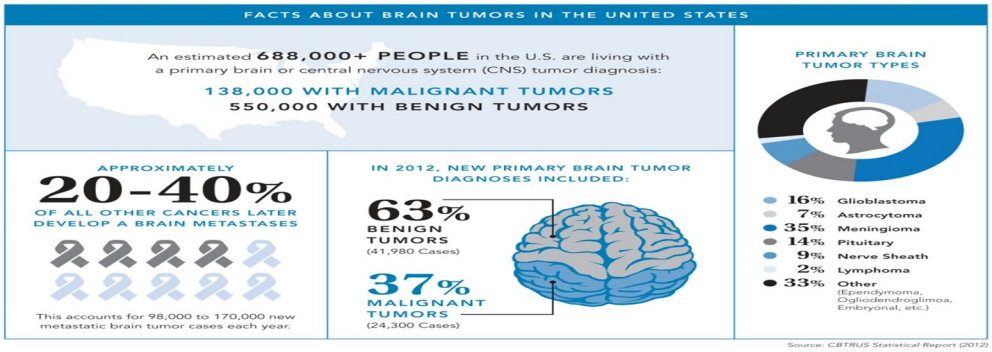


Figure 2.1: Facts about Brain tumor

III. EXISTING TECHNIQUES

A. *Brain Tumor classification using Biopsy method*

A surgical procedure to remove a small sample of tissue from the tumor. So the cells can be examined under a microscope. The biopsy method takes around ten to fifteen days of time to give a result about tumor. The human prediction is not always correct, sometimes it becomes wrong but a computer cannot. The expert, himself cannot take the decision rather he refers to another expert to give his opinion, this process continues for long time[1][2][9]. There are two kinds of biopsy procedures:Open Biopsy: done during a craniotomy. To remove a tumor or a piece of tissue from the brain.Closed Biopsy: when a needle is used to access and remove a small selection of tumor tissue from an area that is difficult to reach.Disadvantages:Examined under a microscope,Time consuming,Inaccurate

B. *Brain Tumor classification using K means Clustering*

The methodology consists of three steps: enhancement, segmentation and classification. To improve the quality of images and limit the risk of distinct regions fusion in the segmentation phase an enhancement process is applied. We adopt mathematical morphology to increase the contrast in MRI images. Then we apply Wavelet Transform in the segmentation process to decompose MRI images. At last, the k-means algorithm is implemented to extract the suspicious regions or tumors[13].

C. *Disadvantages in the Existing Systems*

1) Impractical for large amounts of data and non reproducible.
2) Difficult to get accurate results
3) Medical Resonance images contain a noise caused by operator performance which can lead to serious inaccuracies classification.
4) Images though small in size are having large dimensionality:
5) very large computational time
6) complexity
7) memory occupation\

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IV. PROPOSED METHOD

Brain Tumor Classification using Probabilistic Neural Network with Discrete Cosine Transform

1) Dimensionality reduction and Feature extraction using the Discrete Cosine Transform
2) Classification using Probabilistic Neural Network (PNN).

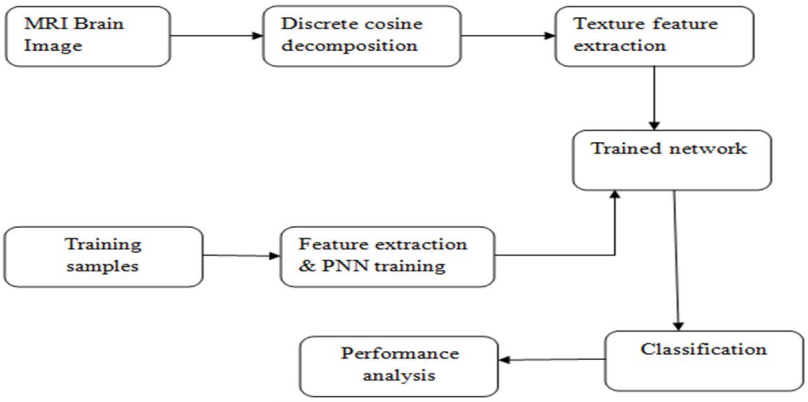


Figure 4.1: Block diagram

The system is designed for Brain Tumor Analysis using Probabilistic Neural Network with Discrete Cosine Transform and these modules follows different methodologies to produce result.The MRI image module includes the dimensionality reduction and feature extraction using the discrete cosine transform and classification using probabilistic neural network.The brain tumor region is segmented by using discrete cosine transform.Database will be created for non knowledge based image classification and this having same set of normal and abnormal image for training process.The neural network will used as an image classifier and before that it will be trained GLCM features of reference image and target vectors for image classification.The trained network will classify the image into normal, benign or malignant image according input image feature vectors.This module will be classified the input image into normal, benign or malignant images effectively.

a) *Input Image:* In imaging science, image processing is any form of signal processing for which the input is an image, such as a photograph or video frame(MRI,CT)[9].
b) *Fast Discrete Cosine Decomposition:* Discrete Cosine Transform is a discrete sinusoidal unitary transform consists of a set of basis vectors that are sampled cosine functions. The DCT has the property that, for a typical image, most of the visually significant information is concentrated in just a few coefficients. These coefficients can be used as a type of signatures that are useful for face recognition tasks [3],[4]. The DCT of an M x N gray scale matrix of the face image f (x, y) is defined as follows: $T(u,v) = \sum\sum f(x,y)\alpha(u)\alpha(v)\cos((2x+1)u\prod/2M)\cos((2y+1)v\prod/2N)$ The values T (u, v) are the DCT coefficients. This technique is efficient for small square inputs such as image blocks of 8 x8 pixels.
c) *Texture Feature Analysis:* Texture is that innate property of all surfaces that describes visual patterns, each having properties of homogeneity. It contains important information about the structural arrangement of the surface, such as; clouds, leaves, bricks, fabric, etc. It also describes the relationship of the surface to the surrounding environment. In short, it is a feature that describes the distinctive physical composition of a surface.[15].Texture properties include: Coarseness, Contrast, Directionality, Line-likeness, Regularity, Roughness. Texture is one of the most important defining features of an image. It is characterized by the spatial distribution of gray levels in a neighborhood[6]. In order to capture the spatial dependence of gray-level values, which contribute to the perception of texture, a two-dimensional dependence texture analysis matrix is taken into consideration. This two-dimensional matrix is obtained by decoding the image file; jpeg, bmp, etc.

A. GLCM Feature Extraction

1) *Co-occurrence Matrix:* A Co-Occurrence Matrix (COM) is square matrices of relative frequencies with which two neighboring pixels separated by distance d at orientation occur in the image, one with gray level i and the other with gray level j .A COM is therefore a square matrix that has the size of the largest pixel value in the image and presents the relative frequency distributions of gray levels and describe how often one gray level will appear in a specified spatial.

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There are 14 features that may be extracted from COM matrix but usually 4 or 5 features are more interested ones. Here 2 textural features were calculated from the COM for direction h values of 0^o and a distance d of 1. The co-occurrence features energy and entropy which can easily differentiate non-homogeneous region from homogeneous region are considered. Energy is called Angular Second Moment.

It is a measure the homogeneousness of the image and can be calculated from the normalized COM. It is a suitable measure for detection of disorder in texture image. Higher values for this feature mean that less changes in the image amplitude or intensity result in a much sparser COM. The energy is formulated by the following equation. It is widely used in medical image segmentation; method first select a seed point, then turn the similar pixels around the seed pixel into the seed area. It is simple, especially for a small segmentation structure.

The following figure 5.2 shows how gray-co-matrix calculates several values in the GLCM of the 4-by-5 image I. Element(1,1) in the GLCM contains the value 1 because there is only one instance in the image where two, horizontally adjacent pixels have the values 1 and 1.Element (1, 2) in the GLCM contains the value 2 because there are two instances in the image where two, horizontally adjacent pixels have the values 1 and 2. Graycomatrix continues this processing to fill in all the values in the GLCM.

Graycomatrix calculates the GLCM from a scaled version of the image. By default, if I a binary image, graycomatrix scales the image to two gray-levels. If I is an intensity image, graycomatrix scales the image to eight gray-levels. You can specify the number of gray-levels graycomatrix uses to scale the image by using the 'Num-Levels' parameter, and the way that graycomatrix scales the values using the 'Gray-Limits' parameter.

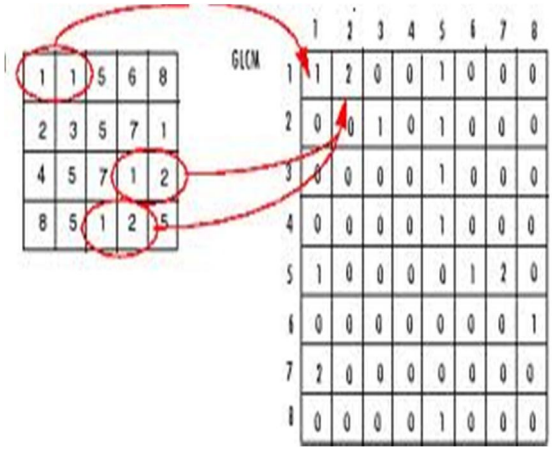


Figure 5.2: Co-occurrence Matrix

To create a GLCM, use the graycomatrix function. The graycomatrix function creates a gray-level co-occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value *j*. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial relationships between the two pixels. Each element *(i,j)* in the resultant glcm is simply the sum of the number of times that the pixel with value *i* occurred in the specified spatial relationship to a pixel with value j in the input image[14].

Because the processing required to calculate a GLCM for the full dynamic range of an image is prohibitive, graycomatrix scales the input image. By default,graycomatrix uses scaling to reduce the number of intensity values in grayscale image from 256 to eight. The number of gray levels determines the size of the GLCM. To control the number of gray levels in the GLCM and the scaling of intensity values, using the NumLevels and the Gray Limits parameters of the graycomatrix function.The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image. For example, if most of the entries in the GLCM are concentrated along the diagonal, the texture is coarse with respect to the specified offset.

To illustrate, the following figure 5.2 shows how graycomatrix calculates the first three values in a GLCM. In the output GLCM, element (1, 1) contains the value 1because there is only one instance in the input image where two horizontally adjacent pixels have the values 1 and 1, respectively. Glcm (1, 2) contains the value 2because there are two instances where two horizontally adjacent pixels have the values 1 and 2. Element (1, 3) in the GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3. Graycomatrix continues processing the input image, scanning the image for other pixel pairs *(i,j)* and recording the sums in the corresponding elements of the GLCM.

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B. Texture Feature Extraction[14]

1) ***Energy:*** It is a gray-scale image texture measure of homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture. Uniformity (or) Angular Second Moment, returns the sum of squared elements in the gray level co-occurrence matrix. Its range is [0 1].

$E=\sum_x\sum_y p(x,y)^2$;p(x,y) is the GLCM

2) *Contrast:* Contrast is the main diagonal near the moment of inertia, which measure the value of the matrix is distributed and images of local changes in number, reflecting the image clarity and texture of shadow depth.Also measures the local variation in the gray level co-occurrence matrix. It returns measure of intensity between pixel and its neighbour over the whole image.Range is $[0,size(GLCM,1)-1)^2]$.

Contrast $I = \sum \sum (x-y)^2 p(x,y)$

Correlation Coefficient:Measures the joint probability occurrence of the specified pixel pairs.Also measures the degree of correlation a pixel has to its neighbor over the whole image. Its range is [-1 1].

$Correlation=sum(sum((x- \mu x)(y-\mu y)p(x , y)/\sigma_x\sigma_y))$

3) *Homogeneity:* Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. The Inverse Differential Moment, returns a value that measures the closeness of the distribution of elements in gray level co-occurrence matrix to the gray level co-occurrence matrix diagonal. Its range is [0 1].

Homogenity = sum(sum(p(x , y)/(1 + [x-y])))

Entropy: or Disorder. It measures image texture randomness, when the space co-occurrence matrix for all values are equal, it achieved the minimum value.

$S = -\sum_x \sum_y p(x,y) \log p(x,y)$

Where, P(x,y) is the probability of finding a pixel with gray level x at a distanceand angle from a pixel with gray level y, and μ and σ are the mean and standard deviations of respectively. These statistical features can be further fed to the PNN classifier for training and testing the performance of the classifier in classifying the brain MR images into normal, benign and malignant brain tumors.

C. Architecture of Probabilistic Neural Networks (PNN)

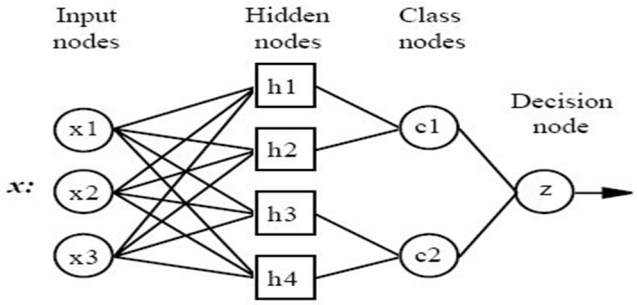


Figure 5.5:Architecture of a PNN

Probabilistic Neural Network is a type of Radial Basis Function (RBF) network, which is suitable for pattern classification. The fundamental architecture has three layers, an input layer, a pattern layer, and an output layer[7][8].

D. All PNN Networks have four Layers

1) *Input Layer:* There is one neuron in the input layer for each predictor variable. In the case of categorical variables, *N*-1 neurons are used where *N* is the number of categories. The input neurons (or processing before the input layer) standardize the range of the values by subtracting the median and dividing by the interquartile range. The input neurons then feed the values to each of the neurons in the hidden layer.

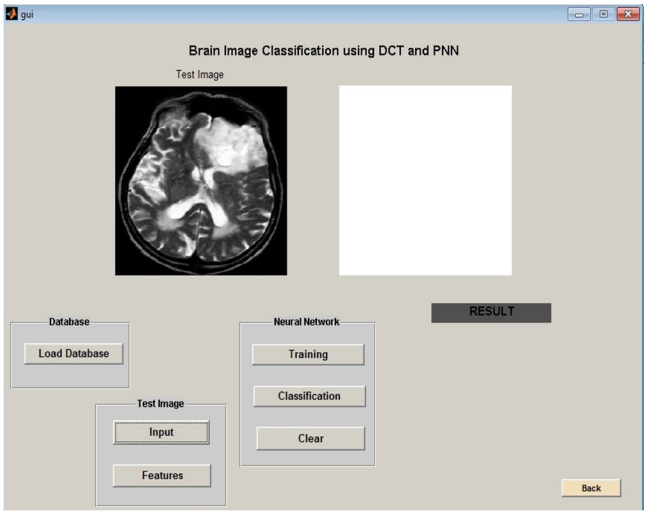
2) *Hidden Layer:* This layer has one neuron for each case in the training data set. The neuron stores the values of the predictor variables for the case along with the target value. When presented with the *x* vector of input values from the input layer, a hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the RBF kernel function using the sigma value(s). The resulting value is passed to the neurons in the pattern layer.

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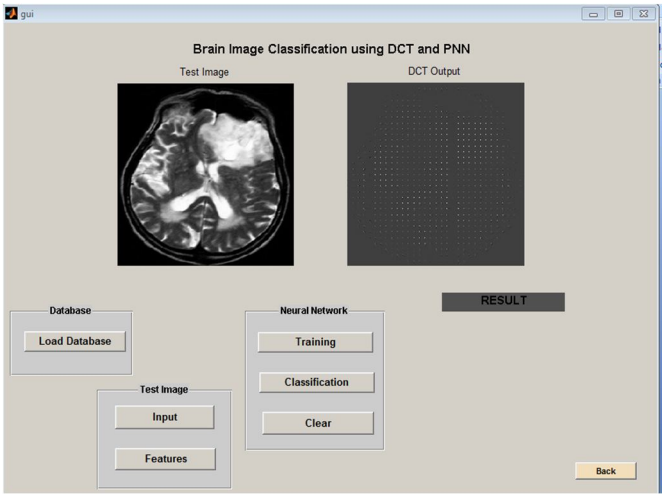
3) *Pattern layer / Summation Layer:* The pattern layer constitutes a neural implementation of a Bayes classifier, where the class dependent Probability Oensity Functions (POF) are approximated using a Parzen estimator[6]. Parzen estimator determines the POF by minimizing the expected risk in classifying the training set incorrectly. Using the Parzen estimator, the classification gets closer to the true underlying class density functions as the number of training sampies increases. The pattern layer consists of a processing element corresponding to each input vector in the training set. Each output class should consist of equal number of processing elements otherwise a few classes may be inclined falsely leading to poor classification results. Each processing element in the pattern layer is trained once. An element is trained to return a high output value when an input vector matches the training vector. In order to obtain more generalization a smoothing factor is included while training the network. The pattern layer classifies the input vectors based on competition, where only the highest match to an input vector wins and generates an output. Hence only one classification category is generated for any given input vector. If there is no relation between input patterns and the patterns programmed into the pattern layer, then no output is generated.
4) *Decision Layer:* The decision layer is different for PNN networks. For PNN networks, the decision layer compares the weighted votes for each target category accumulated in the pattern layer and uses the largest vote to predict the target category.

V. RESULTS AND DISCUSSIONS

After studying various MRI images, many cancerous and non-cancerous tumors were detected by carrying out the above procedure. The outputs are given below:

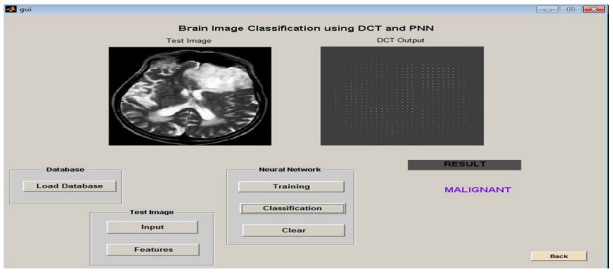


This image shows the input image of a MRI brain image. After that loading the database image. Apply DCT to the database image. After resizing the inputimageapply DCT equation.Then extracted the five features.



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After that calculate Euclidian distance. Then PNN training carried out. After the training process classify the input image into normal,benign or malignant image according input image feature vectors.



For a malignant image,

```
User selected F:\thesis\1 full code\FULL CODE\TestImages\new12.jpg
Features of Test Image
Energy    Contrast    Correlation    Homogenity    Entropy
  1.0e+003 *

    0.0004    1.6041    0.0001    0.0007    0.0039

Features of database Image
  1.0e+003 *

  Columns 1 through 9

    0.0004    0.0005    0.0003    0.0003    0.0003    0.0002    0.0004    0.0006    0.0002
    1.2742    0.8500    2.1873    1.8666    2.0201    1.8710    1.0079    1.4892    1.6481
    0.0002    0.0001    0.0002    0.0001    0.0002    0.0002    0.0001    0.0001    0.0002
    0.0007    0.0008    0.0006    0.0006    0.0006    0.0005    0.0008    0.0008    0.0006
    0.0037    0.0031    0.0050    0.0045    0.0051    0.0053    0.0032    0.0022    0.0047

  Columns 10 through 15

    0.0004    0.0004    0.0004    0.0004    0.0004    0.0005
    0.9858    1.9303    1.9198    1.6669    1.6041    1.0865
    0.0001    0.0001    0.0001    0.0001    0.0001    0.0002
    0.0008    0.0007    0.0007    0.0007    0.0007    0.0008
    0.0031    0.0040    0.0038    0.0033    0.0039    0.0031

     1     1     1     1     1     2     2     2     2     2     3     3     3     3     3
```

For a benign image,

```
User selected F:\thesis\1 full code\FULL CODE\TestImages\test4.JPG
Features of Test Image
Energy    Contrast    Correlation    Homogenity    Entropy
  1.0e+003 *

    0.0004    1.0079    0.0001    0.0008    0.0032

Features of database Image
  1.0e+003 *

  Columns 1 through 9

    0.0004    0.0005    0.0003    0.0003    0.0003    0.0002    0.0004    0.0006    0.0002
    1.2742    0.8500    2.1873    1.8666    2.0201    1.8710    1.0079    1.4892    1.6481
    0.0002    0.0001    0.0002    0.0001    0.0002    0.0002    0.0001    0.0001    0.0002
    0.0007    0.0008    0.0006    0.0006    0.0006    0.0005    0.0008    0.0008    0.0006
    0.0037    0.0031    0.0050    0.0045    0.0051    0.0053    0.0032    0.0022    0.0047

  Columns 10 through 15

    0.0004    0.0004    0.0004    0.0004    0.0004    0.0005
    0.9858    1.9303    1.9198    1.6669    1.6041    1.0865
    0.0001    0.0001    0.0001    0.0001    0.0001    0.0002
    0.0008    0.0007    0.0007    0.0007    0.0007    0.0008
    0.0031    0.0040    0.0038    0.0033    0.0039    0.0031

     1     1     1     1     1     2     2     2     2     2     3     3     3     3     3
```

For a normal image

```
User selected F:\thesis\1 full code\FULL CODE\TestImages\new6.jpg
Features of Test Image
Energy    Contrast    Correlation    Homogenity    Entropy
  1.0e+003 *

    0.0003    2.0856    0.0001    0.0007    0.0035

Features of database Image
  1.0e+003 *

  Columns 1 through 9

    0.0004    0.0005    0.0003    0.0003    0.0003    0.0002    0.0004    0.0006    0.0002
    1.2742    0.8500    2.1873    1.8666    2.0201    1.8710    1.0079    1.4892    1.6481
    0.0002    0.0001    0.0002    0.0001    0.0002    0.0002    0.0001    0.0001    0.0002
    0.0007    0.0008    0.0006    0.0006    0.0006    0.0005    0.0008    0.0008    0.0006
    0.0037    0.0031    0.0050    0.0045    0.0051    0.0053    0.0032    0.0022    0.0047

  Columns 10 through 15

    0.0004    0.0004    0.0004    0.0004    0.0004    0.0005
    0.9858    1.9303    1.9198    1.6669    1.6041    1.0865
    0.0001    0.0001    0.0001    0.0001    0.0001    0.0002
    0.0008    0.0007    0.0007    0.0007    0.0007    0.0008
    0.0031    0.0040    0.0038    0.0033    0.0039    0.0031

     1     1     1     1     1     2     2     2     2     2     3     3     3     3     3
```

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VI. PERFORMANCE ANALYSIS

The performance of classifier can be evaluated through following parameters,

1) Sensitivity: It measures the proportion of actual positives which are correctly identified

Sensitivity = Tp. / (Tp + Fn)

Where,

Tp = True Positive: Abnormality correctly classified as Abnormal

Fn = False negative: Abnormality incorrectly classified as normal

2) Specificity: It measures the proportion of negatives which are correctly identified.

Specificity = Tn./(Fp + Tn)

Where,

Fp = False Positive: Normal incorrectly classified as Abnormal

Tn = True negative: Normal correctly classified as normal

3) Total accuracy: (Tp+Tn)./(Tp+Tn+Fp+Fn)

The network generates the performance metrics,

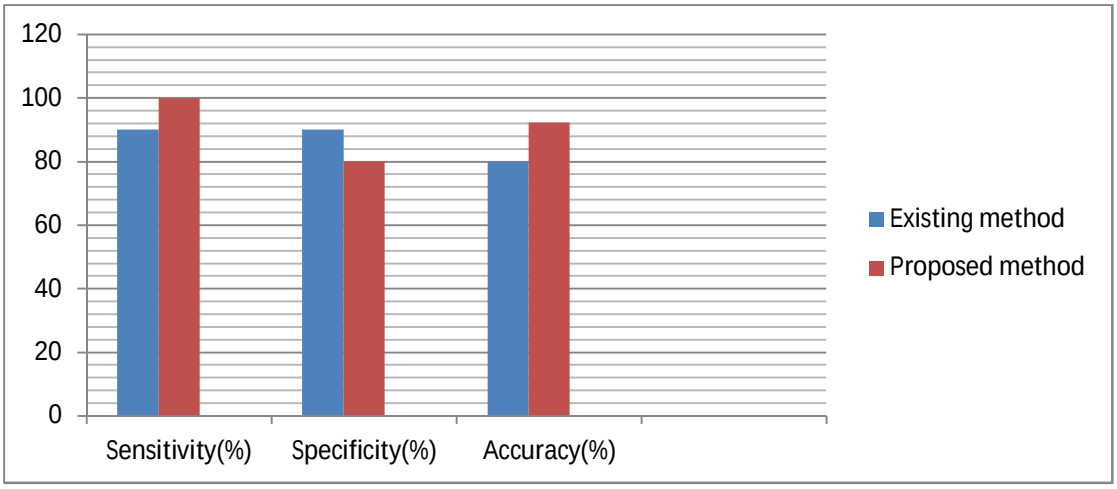
a) Sensitivity: 100%,

b) Specificity: 80%,

c) Accuracy: 92.3077%

VII. COMPARISON CHART

The following chart shows that performance comparisons between neural network classifiers existing system and proposed system.



VIII. CONCLUSION

This new method is a combination of Discrete Cosine Transform and Probabilistic Neural Network. By using these algorithms an efficient Brain Tumor Classification method was constructed with maximum accuracy of 92%. Simulation results using Brain Tumor databased emonstrated the ability of the proposed method for optimal feature extraction and efficient Brain Tumor classification. The ability of our proposed Brain Tumor Classification method is demonstrated on the basis of obtained results on Brain Tumor image database. For generalization, the proposed method should achieve 92% accuracy on other BrainTumor image databases and also on other combinations of training and test samples.

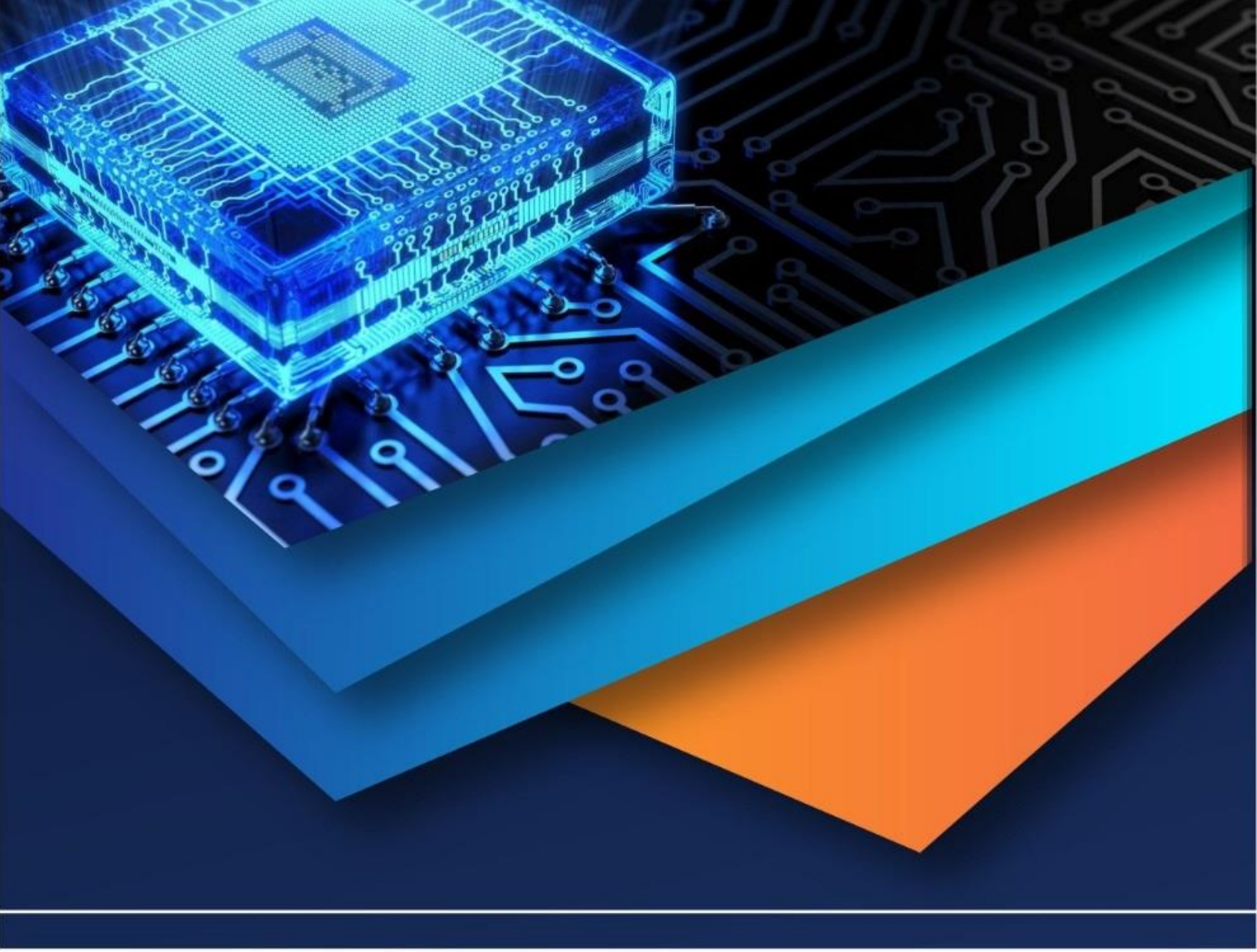
Here, probabilistic neural network was used for classification based on unsupervised leaning using statistical features and target vectors. In addition with, the statistical features are extracted from co-occurrence matrix of detailed coefficients of segmented images. These features are useful to train a neural network for an automatic classification process. Finally this system is very useful to diagnose the diseases from MRI images for early detection of tumor. The system can enhance with features of cosine transform and support vector machine classifier to increase the classification accuracy. An automated system for the detection of brain tumor has been developed.

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