

Automatic classification of MR Brain Images using Artificial Neural Network

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Abstract — The automatic classification of MR brain images using artificial neural network is an important step in the medical image analysis. Magnetic resonance imaging (MRI) is an efficacious tool in the course of human brains. This project extracting the features of human brain and diagnose the normal and abnormal brain. This methodology involves two phases, feature extraction and classification. The feature extraction is done by Gray Level Correlation Matrix (GLCM). The key objective includes scheme the dissimilar features for a given image. Digital image has numerous features where a feature is a typical that can detention a definite visual property of an image any globally for the entire image, or nearby for objects or areas. A main function in dissimilar image requests is Feature abstraction. There are dissimilar procedures to abstract texture features such as Structural, Statistical methods. Feature abstraction is a main function in several image processing requests. A feature is an image representative that can capture definite visual properties of the image. Texture is an significant feature of numerous image types, which is the design of information or preparation of the structure found in a picture. Texture features are used in dissimilar requests such as image processing, remote sensing and content-based image recovery. These features can be removed in numerous ways. The utmost common way is using a Gray Level Co-occurrence Matrix (GLCM). GLCM covers the second-order arithmetical material of adjacent pixels of an image. Textural belongings can be considered from GLCM to recognize the details about the image content. In the classification stage, classification is done by feed forward artificial neural network. The feature then derived which can automatically deduce the normal and abnormal image. The classification is achieved with the success of more than 90%. The result illustrates the accurate classification of the human brain related to the other techniques.

Keywords—Magnetic resonance imaging (MRI), Grey Level Co-occurrence Matrix (GLCM), Feed forward artificial neural network.

I. INTRODUCTION

Brain is the commanding part of the human body and which is responsible for controlling the whole body. The magnetic resonance imaging (MRI) is the frequently chosen technique used for the diagnosis of brain related ailment and injuries. It is often used in the field of medical imaging where the soft tissue outlining is required. Magnetic resonance (MR) imaging was introduced into scientific medicine and has ever since unspecified an unparalleled role of significance in brain imaging [7]. Magnetic resonance imaging is an advanced medical imaging technique that has proven to be an efficient tool in the revise of the human brain. The information that MR images afford about the soft tissue anatomy has considerably improved the quality of brain pathology diagnosis and treatment. The key benefit of MR imaging is that it is a non-

invasive technique [10]. The use of computer technology in medical decision support is now prevalent and invasive across a extensive range of medical area such as cancer do research, gastroenterology, heart diseases, brain tumors, etc. Fully automatic normal and a pathological brain, distressed from brain lesion classification can be attained from magnetic resonance images, which is a great significance in the research and clinical studies.

There are several techniques to classify the brain images. Recent effort has revealed that the classification of human brain in magnetic resonance (MR) images is achievable via managed techniques such as artificial neural networks and support vector machine (SVM), and unsubstantiated classification techniques such as self-organization map (SOM) and fuzzy c -means. Other managed classification techniques, such as k -nearest neighbor (k -NN) which can be used to categorize the normal/pathological T1 and T2-weighted MRI images [11, 14]. In this study, we used supervised machine learning algorithms (FP-ANN) to attain the classification of images underneath two categories, either normal or a pathological brain. Most experts prefer MRI and CT scanning for diagnose. Computer Tomography (CT) scanning uses the ionizing radiation whereas MRI uses the magnetic field to diagnose. Particularly, it uses the magnetic field, radio waves and field gradients to generate the images inside the body. It gives the better and accurate result than CT.

Feature abstraction contains shortening the amount of properties required to define a huge set of data precisely. When execution examination of compound data one of the main difficulties stems from the amount of variables involved. Examination with a huge amount of variables usually needs a large quantity of memory and calculation power or a organization algorithm which over fits the exercise sample and simplifies poorly to new samples. Feature abstraction is a general term for approaches of building combinations of the variables to get round these glitches while still describing the data with sufficient correctness. Texture tangible or visual distinctive of a surface. Texture examination aims in finding a exclusive way of expressing the underlying features of textures and characterize them in some simpler but unique form, so that they can be used for strong, accurate classification and segmentation of objects. Though texture acting a significant role in image examination and pattern appreciation, only a few constructions implement on-board textural feature abstraction. In this paper, Gray level co-occurrence matrix is expressed to gain statistical texture features. A amount of texture features may be removed from the GLCM. Only four second order features namely energy, correlation, contrast, and entropy are computed. These four measures deliver high judgment correctness required for gesture picture approximation.

The involvement of this paper is the addition of an efficient feature extraction tool and a robust classifier to perform a accurate

automated MR normal or a pathological brain images classification. The classification is achieved with the success of more than 90%. The result illustrates the accurate classification of the human brain related to the other techniques.

The rest of this paper is organized as follows. Sector 2, presents the proposed technique, utilized in this exertion for feature extraction. In sector 3, the artificial neural networks algorithm is obtained for classification principle. Sector 4 experimentally demonstrates the performance of the proposed methods. At last, sectors 5 illustrate the winding up of this paper.

II. PROPOSED TECHNIQUE

Image features symbolizes the distinctive appearances of the object or an image. The purpose of feature extraction in this study is to reduce the original data set to represent the image in its compact and unique form of single values. This feature extraction process is done through two steps. Initially the wavelet coefficients are extracted through the discrete wavelet transform algorithm and if they wanted it can be reducing dimension, of them required features are selected by using the principal component analysis algorithm. After the feature extraction the extracted feature is given as an input to the classifier. The classification process has done by the feed forward artificial neural network. This proposed technique is illustrated in the Fig. 1.

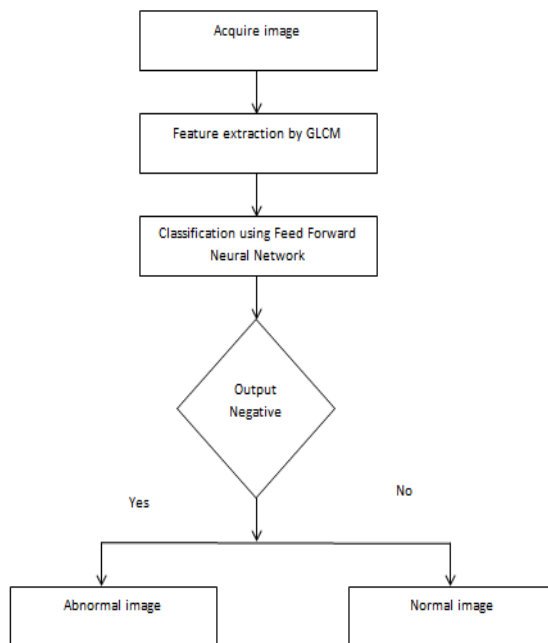


Fig.1. Method of proposed technique

A. Feature abstraction using GLCM

In arithmetical texture analysis, texture features are calculated from the arithmetical distribution of experimental groupings of strengths at stated positions comparative to each other in the image. According to the number of strength points (pixels) in each grouping, data are classified into first-order, second-order and higher-order data. Basically, texture demonstration methods can be classified into two classes [3],

1. Statistical and
2. Structural.

The Gray Level Concurrence Matrix (GLCM) technique is a way of removing second order arithmetical texture features. The method has been used in a amount of applications, Third and higher order textures study the associations among three or more pixels. These are hypothetically thinkable but not usually applied due to scheming time and interpretation strain. Gray-level co-occurrence matrix (GLCM) is the arithmetical method of examining the textures that studies the spatial connection of the pixels [5]. A GLCM is a matrix somewhere the figure of rows and columns is equivalent to the number of gray levels, G , in the image. The matrix component $P(i, j | \Delta x, \Delta y)$ is the comparative occurrence with which two pixels, divided by a pixel distance $(\Delta x, \Delta y)$, happen within a given region, one with strength 'i' and the other with strength 'j'. The matrix element $P(i, j | d, \theta)$ comprises the second order numerical probability values for changes among gray levels 'i' and 'j' at a specific dislocation distance d and at a particular angle (θ) . Using a huge number of strength levels G implies storage a lot of brief data, i.e. a $G \times G$ matrix for each mixture of $(\Delta x, \Delta y)$ or (d, θ) . Due to their huge dimensionality, the GLCM's are identical sensitive to the size of the texture examples on which they are assessed. Thus, the figure of gray levels is often condensed.

GLCM matrix preparation can be described with the sample for four different gray levels. Now one pixel counterbalance is used (a orientation pixel and its instantaneous neighbour). If the window is huge enough, using a larger counterbalance is possible. The topmost left cell will be occupied with the figure of times the mixture 0,0 arises, i.e. how many countless time within the image zone a pixel with grey level 0 (neighbour pixel) decreases to the right of alternative pixel with grey level 0(reference pixel). Texture is a modification and dissimilarity of data in small scale. Texture examination computes sensitive potentials such as rough, smooth or silky as a purpose of the spatial variation in pixel strengths. At the first step, we measured and planned histogram of images, but could not attain useful material because positional material was not measured. So we decided to use Graycomatrix and extract features from that.

GLCM computes the possibility of a pixel with the gray-level rate i happening in a detailed spatial association to a pixel with the value j . The figure of gray levels in the image governs the size of the GLCM. So, we require 256×256 matrices. We measured angle and distance as the key two parameters in our study. Although there is a role in Matlab Image Processing toolbox that calculates four limitations Contrast, Correlation, Energy, and Homogeneity [11, 6], the paper by Haralick suggests a few more

parameters that are also computed. It is easy to add new features created on the GLCM by this code.

Gray Level Co-Occurrence Matrix (GLCM) has showed to be a common arithmetical technique of removing textural feature from images. Affording to co-occurrence matrix, Haralick defines fourteen textural features restrained from the possibility matrix to abstract the appearances of texture data of remote sensing

Images. In these paper four important features, contrast, Correlation, Entropy, and the homogeneity [4, 15] are nominated for execution using Xilinx ISE 13.4.

3.1. Homogeneity

It yields a value that procedures the familiarity of the partition of elements in the GLCM to the GLCM transverse

$$\text{Homogeneity} = \sum_{i,j} \frac{p(i,j)}{1+|i-j|}$$

Where i, j are the three-dimensional coordinates of the function p(i, j), Ng is gray quality.

3.2. Contrast

It yields a amount of the power alteration between a pixel and its neighbor ended the whole image.

$$\text{Contrast} = \sum_{i,j} |i-j|^2 p(i,j)$$

IDM mass value is the converse of the Contrast weight.

3.3. Entropy

Entropy demonstrates the number of information of the image that is required for the image density. Entropy calculates the loss of information or communication in a transmitted signal and also processes the image information.

$$\text{Entropy} = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} -P_{ij} * \log P_{ij}$$

3.4. Correlation

Correlation processes the linear reliance of grey levels of adjacent pixels. Digital Image Correlation is an visual technique that pays chasing & image recording techniques for correct 2D and 3D dimensions of variations in images. This is frequently used to amount distortion, dislocation, strain and optical flow, but it is extensively applied in numerous areas of science and engineering.

One very mutual request is for calculating the gesture of an optical mouse.

$$\text{Correlation} = \frac{\sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} (i,j)p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$$

The preparation and abstraction of the four given image features are removed using matlab for scheming GLCM as image cannot be straight given as input. All the texture features are actual numbers. Actual numbers cannot be showed using waveforms which display only bits as outputs. So bits are changed to real numbers using “\$bitstoreal” facility. Hence the actual number output will be showed in the console space. As the delay assumed is 10ns, till 10ns the 64 inputs and after 10ns the inputs will be allocated. The latter one is the output which is the texture feature.

| | | | | | | | |
|----|-----|------|------|------|------|----|---|
| 75 | 23 | 0 | 0 | 0 | 0 | 0 | 0 |
| 23 | 275 | 84 | 17 | 1 | 0 | 0 | 0 |
| 0 | 94 | 1393 | 336 | 61 | 7 | 0 | 0 |
| 0 | 8 | 328 | 3455 | 491 | 60 | 1 | 0 |
| 0 | 0 | 57 | 519 | 4133 | 350 | 5 | 0 |
| 0 | 0 | 5 | 58 | 309 | 4039 | 12 | 0 |
| 0 | 0 | 0 | 0 | 0 | 19 | 18 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Grey level correlation matrix

III. SUPERVISED LEARNING CLASSIFIERS

A. Artificial Neural Network Based Classifier

An ANN is a numerical representation consisting of a number of highly consistent processing elements ordered into layers, geometry and functionality of which have been looked like to that of the human brain. The ANN may be observed as a massively similar distributed processor which has a natural tendency for storing empirical knowledge and making it accessible for use. Classification difficult can be solved ANN accurately and in a non-linear method [1, 9], An ANN is a naturally stimulated computational model collected of various dispensation elements called artificial neurons. Neurons are coupled with coefficients or weights which builds the neural network’s arrangement. The dispensation elements have weights, transfer function and yields for dispensation information.

A three layer neural network was shaped with five hundred nodes inside the 1st (input) layer, 1 to fifty nodes in the hidden layer, and 1 node as output layer. We diverse the diversity of nodes within the hidden layer in a very replication so as to work out the finest diversity of hidden nodes [2, 8]. This was to keep away from over fitting or under fitting the information. Owing to hardware boundaries, ten nodes in the hidden layer were chosen to run the final replication. Figure 2 shows the approach of the Feed Forward Neural networks employed in this analysis.

The 500 information points which are extracted from all subjects were then used as inputs of the neural networks. The output node resulted in any 0 or one, for control or patient information severally. Given that the nodes in the input layer might immerse up values from an huge vary, a transfer function was used to modify information 1st, before sending it to the hidden layer, and then was changed with another transfer work before causing it to the output layer. In this work, a tan sigmoid transfer function was used among the input and hidden layer, and a log sigmoid function was used among the hidden layer and the output layer.

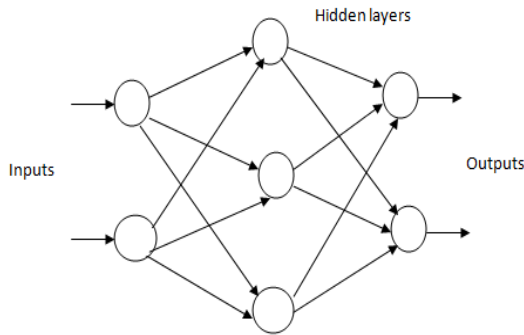


Fig.2. Feed forward neural network

The weights in the hidden node wanted to be set persecution “training” information. Therefore, subjects were separated into training and testing datasets. Away from the 69 subjects, a pair of random patients and 2 random controls was selected as “test data”, whereas the rest of the dataset was used for training. Coaching information was used to nourish into the neural networks as inputs and then express the output; the weights of the hidden nodes were planned using back propagation algorithm. 120 trials were performed on the same Neural Network, choosing sixty five subjects aimlessly at each time for preparation and four remaining subjects for testing to look out correctness of neural network prediction. The most often used learning algorithm in classification problems is the back-propagation algorithm [7]. Getting knowledge in a neural network involves alter the weights and biases of the network in sort to diminish a price function. The cost function consistently includes Associate in Nursing fault term active of however shut the network’s forecast area unit to the category labels for the examples within the training set. in addition, it may symbolize a complexness phrase that reacts a earlier distribution over the values that the parameters will get [12].

The activation function measured for each node in the network is the binary sigmoid function determined (with $s = 1$) as $output = 1 / (1 + e^{-x})$, where x is the sum of the weighted inputs to that exacting node. This is a frequent function used in several BPN. This function restricts the output of all nodes in the network to be between 0 and 1. Note down all neural networks are

fundamentally trained till the error for all training iteration stopped diminishing.

Fig.3 illustrates the plan of the particular network for the forecast of stroke unwellness. The complete set of final data (20 inputs) is given to the basic network, in which the final designation corresponds to output units. The net inputs and outputs of the j hidden layer neurons may be considered as follows

$$net_j^h = \sum_{i=1}^{N+1} W_{ji} x_i$$

$$y_j = f(net_j^h)$$

Analyze the lattice inputs and outputs of the k output layer neurons are

$$net_k^o = \sum_{j=1}^{J+1} V_{jk} y_j$$

$$Z_k = f(net_k^o)$$

Revise the weights in the output layer (for all k, j pairs)

$$V_{kj} \leftarrow V_{kj} + C\lambda(d_k - Z_k)Z_k(1 - Z_k)y_j$$

Revise the weights in the hidden layer (for all i, j pairs)

$$W_{ij} \leftarrow W_{ij} + C\lambda^2 y_j (1 - y_j) x_i \left(\sum_{k=1}^k (d_k - z_k) z_k (1 - z_k) v_{ik} \right)$$

Revise the error term

$$E \leftarrow E + \sum_{k=1}^k (d_k - z_k)^2$$

And do again from Step 1 until all input patterns have been obtained. If E is below some predefined acceptance level, then stop. Or else, reset $E = 0$, and do again from Step 1 for another epoch.

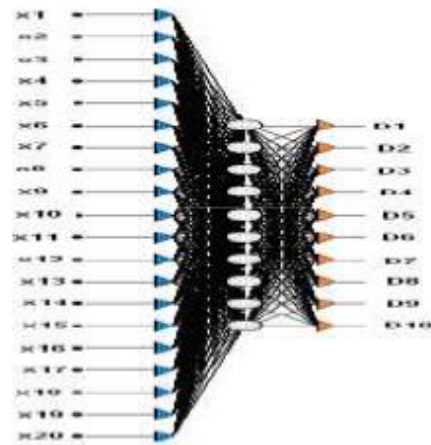


Fig.3. Back propagation neural network

IV. IMPLEMENTATION RESULTS

Different numerical actions have been used to examine the quantitative assessment of proposed technique and its performance evaluation with other proposed technique. The input dataset consists of axial, T1 and T2-weighted image, 256 x 256 pixel MR brain images (Fig. 4). The integer of MR brain images in the input dataset is 50 of which 25 are of normal brain images and 25 are of pathological brain images. The pathological brain image set consists of images of brain which is affected by brain lesion. The significant feature of a normal human brain is the regularity that it displays in the axial and coronal images. Irregularity in an axial MR brain image powerfully indicates irregularity. Hence regularity in axial MR images is a significant feature that wants to be measured in making a decision whether the MR image within reach is of a normal or an abnormal brain. A normal and a pathological T2-weighted MR brain image are illustrated in Fig. 4 a and b, correspondingly. The lack of regularity in an abnormal brain MR image is clearly observed in Fig. 4b. Irregularity beyond a definite degree is a sure suggestion of the diseased brain and this has been subjugated in our work for classification. Most of the experts chosen the accuracy measurement for performance evaluation [15].

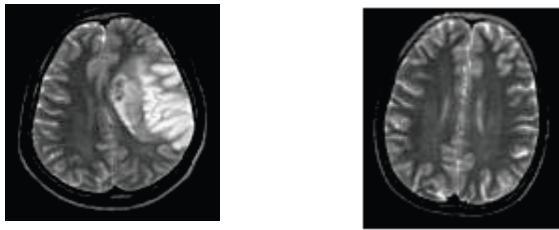


Fig.4. Axial T2-weighted MR brain images: (a) normal brain; (b) abnormal brain

We present the performance assessment methods used to estimate the proposed methods. To end with, we demonstrate the experimental consequences and study the performance of the proposed classifiers for the MRI dataset declared over. We estimate the performance of the proposed approach in terms of sensitivity (4), specificity (5) and accuracy (6). The three terms are described as follows.

Sensitivity (true positive fraction) is the prospect that a diagnostic test is optimistic, given that the person has the sickness,

$$Sensitivity = \frac{TP}{TP+FN}$$

Specificity (true negative fraction) is the prospect that a diagnostic test is pessimistic, given that the person does not have the sickness,

$$Specificity = \frac{TN}{TN+FP}$$

Accuracy is the prospects that a diagnostic test is properly achieved

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

where:

TP (True Positives) – properly classified positive cases,

TN (True Negative) – properly classified negative cases,

FP (False Positives) – imperfectly classified negative cases, and

FN (False Negative) – imperfectly classified positive cases.

TABLE I

CLASSIFICATION PERFORMANCE COMPARISON FOR BRAIN MR IMAGES

| Technique | Classification accuracy (%) |
|--|-----------------------------|
| DWT-SOM[2] | 94.00 |
| DWT-SVM with linear Kernel[2] | 96.15 |
| DWT-SVM with polynomial Kernel[2] | 98.00 |
| DWT-SVM with radial basis function based kernel[2] | 98.00 |
| Our proposed DWT-FP-ANN based classifier | 90.00 |

Table 2 describes the classification rates for the proposed method. In this study classifiers are used which is based on managed machine learning are obtained for MRI normal/pathological human brain classification. In the proposed approach using gray level correlation matrix.

TABLE II

CLASSIFICATION RATES FOR THE USED CLASSIFIERS

| Technique | Sensitivity (%) | Specificity (%) | Accuracy (%) |
|------------|-----------------|-----------------|--------------|
| DWT-FP-ANN | 94 | 90 | 90 |

So, the 3rd estimation component and all exhaustive components are used as the coefficients. Those coefficients are used for extracting the features. The feed forward artificial neural network classifier is used for MRI normal/pathological human brain classification.

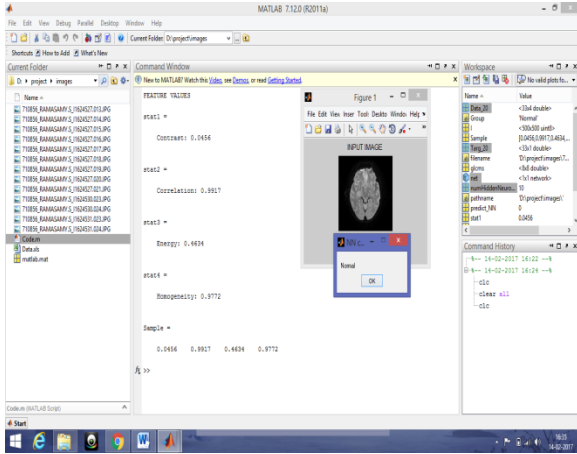


Fig.5a. GUI of the proposed technique

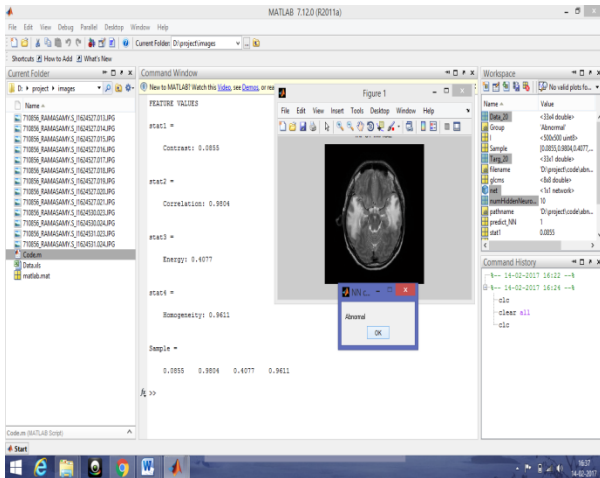


Fig.5b. GUI of the proposed technique

Feature Abstraction is a technique of catching visual contented of images for indexing & recovery. Original or low level image features can be any general features, such as abstraction of color, texture and shape or area specific features. This paper presents an application of gray level co-occurrence matrix (GLCM) to abstract second order arithmetical texture features for gesture approximation of images. The Four features specifically, Contrast, Correlation, Homogeneity, and Entropy are calculated using Xilinx FPGA. The results demonstration that these texture features need high perception correctness requires less calculation time and hence professionally used for real time applications.

V. CONCLUSIONS

We have developed a automatic classification of MR brain images diagnostic system with normal and abnormal classes using an artificial neural network. The medical decision making system was calculated by the Grey level cooccurrence matrix, and the supervised learning method (FP -ANN) that we have make a very talented results in classifying the healthy and brain patient having injury. The advantage of this system is to aid the physician to make the final decision without hesitation. According to the experimental consequences, the proposed approach is proficient for the classification of the human brain into normal and pathological. Classification percentage is more than 90% in case of feed forward artificial neural network. The results have been evaluated to the results accounted very lately based on the same T1 and T2-weighted MRI database. The similar approach can be reasonably extended to other types of MR images also. The declared consequences illustrates that this proposed method can make an exact and strong classifier. The classification performances of this work explain the benefits of this method which is it is fast, simple to work, non-invasive and reasonably priced.

REFERENCES

1. Nandhini.V, Karthick.G, MRI BRAIN TUMOR CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK, International Journal of Science and Engineering Research, Volume 3 Issue 4 April -2015
2. Kalpana U. Rathod, Prof. Y. D. Kapse, MATLAB BASED BRAIN TUMOUR EXTRACTION USING ARTIFICIAL NEURAL NETWORK , International Journal on Recent and Innovation Trends in Computing and Communication Volume: 4 Issue: 3, march-2016
3. Dr. C.Narasimham, Sowmya Y, Mounika B, CONTENT BASED IMAGE RETRIEVAL USING TEXTURE, International Journal of Engineering Applied Sciences and Technology, Vol. 1, Issue 4, ISSN No. 2455-2143, Pages 39-4, 2016
4. Khin Nyein Nyein Hlaing and Anilkumar Kothalil Gopalakrishnan, MYANMAR PAPER CURRENCY RECOGNITION USING GLCM AND K-NN, Second Asian Conference on Defence Technology, 2016
5. Kshitija V. Shingare1, N. D. Pergad2, AN EFFICIENT BRAIN IMAGE CLASSIFICATION USING PROBABILISTIC NEURAL NETWORK AND TUMOR DETECTION USING IMAGE PROCESSING, International Journal of Advanced Research in Computer and Communication Engineering Vol. 4, Issue 5, May2015
6. Vanita Mane, Nilambari Kulkarni, SOURCE CAMERA IDENTIFICATION USING GLCM, IEEE International Advance Computing Conference, 2015.
7. Ganesh Ram Nayak, Mr. Toran Verma, BRAIN CANCER CLASSIFICATION USING BACK PROPAGATION NEURAL NETWORK AND PRINCIPLE COMPONENT ANALYSIS, International Journal of Technical Research and Applications, Volume 2, Issue 4 (July-Aug 2014), PP. 26-31
8. Ms. Sangeetha C, Ms. Shahin A, BRAIN TUMOR SEGMENTATION USING ARTIFICIAL NEURAL

- NETWORK, International Research Journal of Engineering and Technology (IRJET), Volume: 02 Issue: 04, July-2015
9. Trongmun Jiralerspong, Sato Fumiya, Chao Liu and Jun Ishikawa, SPECTRAL ANALYSIS AND ARTIFICIAL NEURAL NETWORK BASED CLASSIFICATION OF THREE MENTAL STATES FOR BRAIN MACHINE INTERFACE APPLICATIONS, International Joint Conference on Neural Networks, 2016
 10. Tao Li, Wensheng Zhang, CLASSIFICATION OF BRAIN DISEASE FROM MAGNETIC RESONANCE IMAGES BASED ON MULTI-LEVEL BRAIN PARTITIONS, IEEE- 2016
 11. IR. Qayyum, 2K. Kamal, 3T. Zafar, 4S. Mathavan, WOOD DEFECTS CLASSIFICATION USING GLCM BASED FEATURES AND PSO TRAINED NEURAL NETWORK, National University of Sciences and Technology (NUST), 2016
 12. Rafael Sosa Perez, Angela Castañeda Oviedo, Juan Camarillo-Peñaranda and Gustavo Ramos, A NOVEL FAULT CLASSIFICATION METHOD USING WAVELET TRANSFORM AND ARTIFICIAL NEURAL NETWORKS, IEEE- 2016
 13. Rakesh Asery, Ramesh Kumar Sunkaria, Lakhn Dev Sharma, Aman Kumar, FOG DETECTION USING GLCM BASED FEATURES AND SVM, Conference on Advances in Signal Processing (CASP) Cummins College of Engineering for Women, Pune. Jun 9-11, 2016
 14. Tapas Si, Arunava De, Anup Kumar Bhattacharjee, ARTIFICIAL NEURAL NETWORK BASED LESION SEGMENTATION OF BRAIN MRI, Communications on Applied Electronics (CAE), Volume 4 - No. 5, February 2016
 15. Guang-Shuai Zhang, Zhihai Lu, Genlin Ji, Ping Sun, Jian-Fei YANG, Yudong Zhang Jianguo, AUTOMATED CLASSIFICATION OF BRAIN MR IMAGES BY WAVELET-ENERGY AND K-NEAREST NEIGHBORS ALGORITHM, Seventh International Symposium on Parallel Architectures, Algorithms and Programming, 2015