

A
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On
A NEW APPROACH FOR MRI IMAGE CLASSIFICATION

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Submitted By

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July 2014

Date: _____

I hereby declare that work presented in this dissertation entitled “**A New approach for MRI image classification**” has been carried out by me under the guidance of Mr. M.S. Choudhary, Associate Professor, Department of Electronics & Communication Engineering, Delhi Technological University, Delhi and hereby submitted for the partial fulfillment for award of degree of Master of Technology in Signal Processing & Digital Design at Electronics & Communication Department, Delhi Technological University, Delhi.

I further undertake that the work embodied in this major project has not been submitted for award of any other degree elsewhere.

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ABSTRACT

Magnetic Resonance (MR) Imaging has come up as widely accepted and revolutionary innovation in field of brain imaging. MRI is an imaging technique used in medical science to view the internal structures of the body in detail & having incomparable role of importance in brain imaging. MRI is a powerful tool to provide detail and reliable information about human brain, so it proved very helpful in the study of human brain. Here a work is done by simulating a method in MATLAB using artificial neural network to automatically classify brain MRI images. The proposed method for the classification of MRI Brain images consists of various stages namely Pre-processing, Feature extraction, Dimensionality reduction and Classification. Here for improving the MRI image quality, pre-processing is employed in MATLAB using `imadjust` function. The features are extracted using discrete wavelet transform. In Wavelet Transform, different frequencies are examined with different resolutions. Due to this reason, DWT is widely used for feature extraction. Then the features are reduced using kernel principal component analysis (KPCA). Two commonly used kernels are the polynomial kernel and Gaussian kernel. In this project, we are using polynomial kernel in which order of polynomial are varying ($p=2, 3, 4$) for achieving good classification rate. In last stage artificial neural network (ANN) is used as a multi class classification technique to classify between normal or abnormal (brain tumor infected) MRI images. The simulation results show that we obtain good classification rate from proposed method.

Keywords- Magnetic Resonance Imaging, wavelet transform, Kernel principal component analysis (KPCA), neural network

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CHAPTER 1

INTRODUCTION

To cure human brain diseases it is a pre-requisite to identify brain disease with high accuracy. To fill this gap, the process of automated classification of different brain images has been gone through various phases of advancement and improvements. A single inaccurate result could lead towards high risk for human life. It is a well known fact that double reading of brain images improves results but it is not cost effective. Brain disease diagnosis process improvement further advocates requirement of effective and accurate methods for classification. Earlier methods of diagnosis involved medical associates to analyse brain images on the basis of various parameters. In process of advancement, involvement of medical associates is replaced by robust automated diagnostic systems. This process improvement resulted in capability to monitor large number of patients continuously without much human interaction in process.

In our work, we have thrown light upon how we can use known features like pixel intensity for automated classification of MRI images. Absence of unanimously accepted and recognised processes to diagnose brain disease, highlights clear requirement of research to develop process of automated brain disease detection. BPN is still not applied with full capacity in classification of MRI brain images. Manual Classification and clustering techniques are not reliable and cost effective. So it is required to completely understand clustering and identification techniques for further improvements in this domain of medical science.

In recent years, Magnetic Resonance Imaging has come up as widely accepted and revolutionary innovation in field of brain imaging. It is recognised as a mile stone in evolution of diagnosis techniques of brain diseases. MRI is a powerful tool to provide detail and reliable information about human brain, so it proved very helpful in the study of human brain. Magnetic resonance imaging (MRI) acts as vital role in field of human brain due to its incomparable property.

1.1 Magnetic Resonance Imaging

MR image is effective instrument which give more correct information than the other imaging techniques like X ray, ultrasonic and CT images. MRI is an imaging technique used in medical science to view the internal structures of the body in detail & having incomparable role of importance in brain imaging. MRI gives good distinguish between the various soft tissues of the body. So in this way MRI can be used to take the image of different body's parts like brain, muscles, the heart etc. First property of MRI techniques is that it is used in non-invasively form. Secondly it is chosen than other imaging methods because it does not involve any ionizing radiation.

By help of magnetic field, radio waves, and a computer, Magnetic resonance imaging (MRI), nuclear magnetic resonance imaging (NMRI), or magnetic resonance tomography (MRT) are used to view the images of body structure. It visualizes internal structures of the body in detail. MRI uses the property of nuclear magnetic resonance (NMR).

The MRI scanner contains a tube bounded by large circular magnets. The patient is laid on a bed which is movable. Then patient is inserted into the magnet. An intense magnetic field is produced by magnets. This magnetic field aligns the magnetization of few atomic nuclei in the body, after that radio wave is applied. Then, different types of protons in body start to spin, and they produce a signal which is observed by MRI scanner's receiver. This observed signal is recorded and processed digitally with help of computer. An image is generated of the scanned area of the body. We can obtain 2D images or 3D volumes in any orientation by changing the direction of gradients of magnetic field.

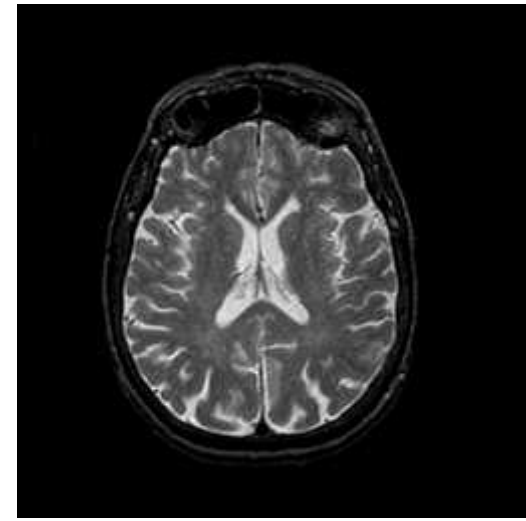
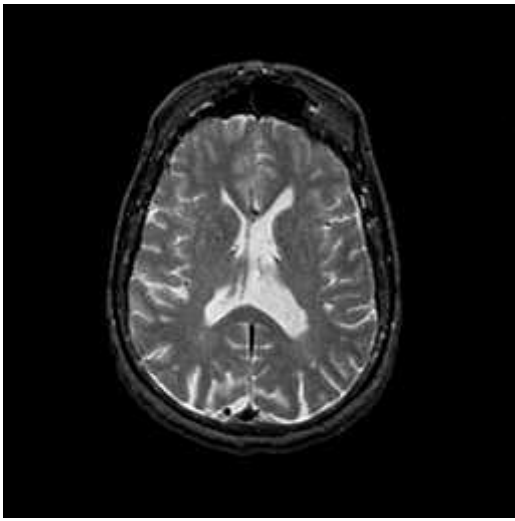
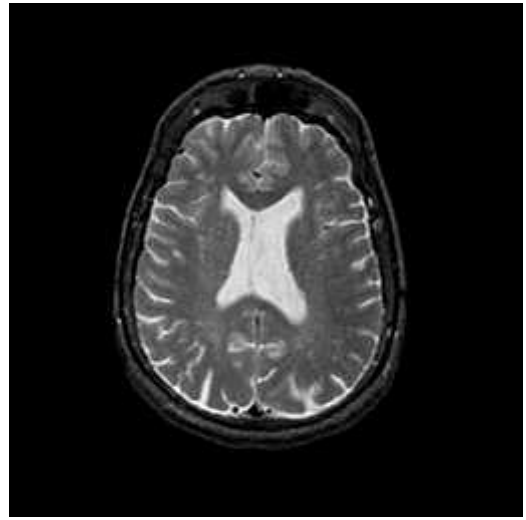
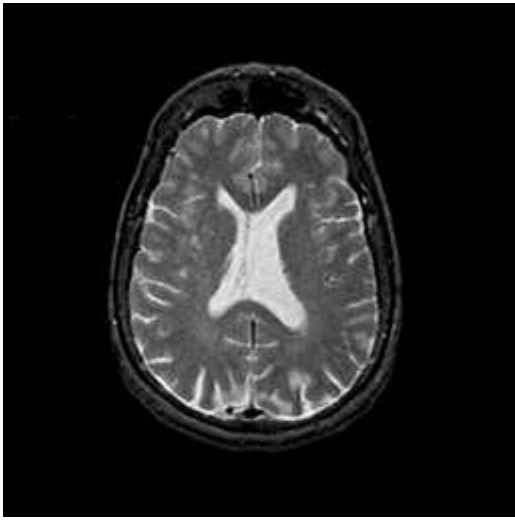
Firstly brain is placed in a magnetic field. Due to magnetic field, the hydrogen nuclei are aligned in the direction of the magnetic field. Every H_2 nucleus in the brain can be viewed as a vector where the vector's strength and direction are strength and direction of the magnetic field of the hydrogen nucleus. The vector which is represented here is regarded as the Magnetic Dipole Moment (MDM). Then the RF pulses are sent from scanner for measuring the MRI signal. Initially, main magnetic field is applied in z-direction. When RF pulse is applied, then MDM.s is moved to x-y plane. Now RF pulse is removed, then all MDM.s tip to its original state. So RF pulse transfers its energy to the system. After removing RF pulse, this energy is released during MDM.s returning to its original lower state. This released energy is known as relaxation. During this period, it is signal that is measured during MRI.

These signals are received by a computer that analyzes and converts them into an image of the part of the body being examined. This image appears on a viewing monitor.

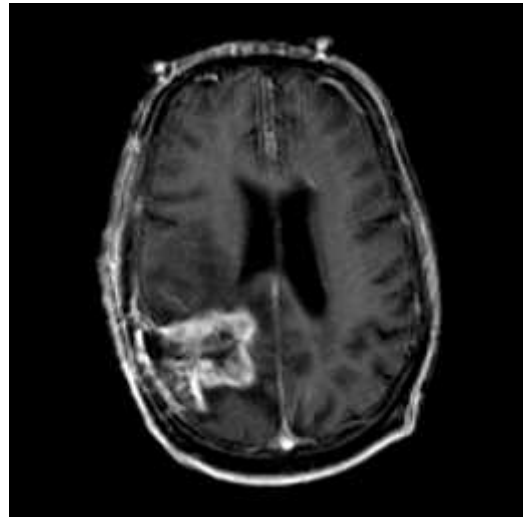
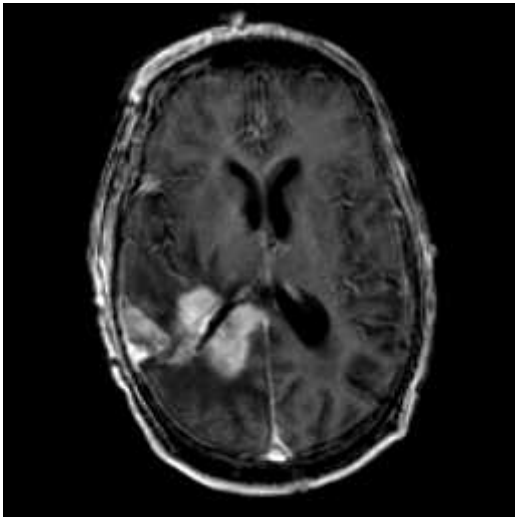
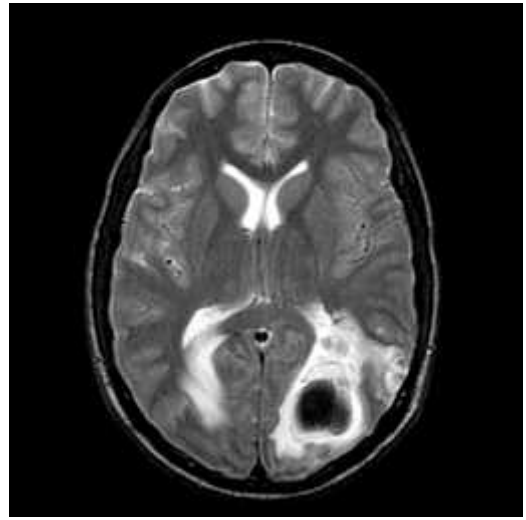
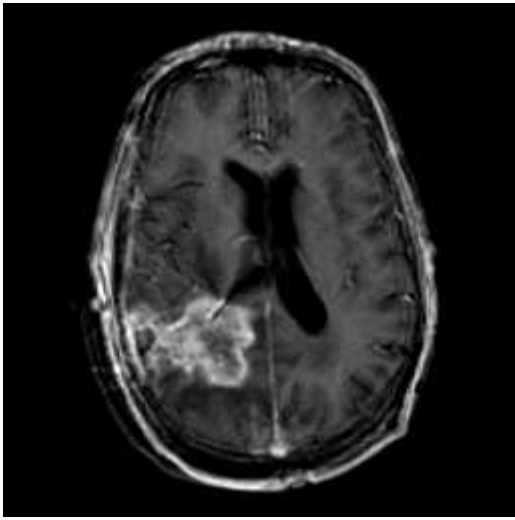
Magnetic resonance imaging (MRI) gives better result for examining organs or soft tissue as compare to computed tomography (CT) because images of soft tissues and organs in CT are vague due to bones. MRI does not involve any ionizing radiation. In MRI, the strong magnet is used, so due to this reason, we cannot take MRI on patients with implanted pacemakers, intracranial aneurysm clips, cochlear implants etc.



Fig 1.1 MRI machine



(a) Normal MRI images



(b) Abnormal MRI images (Brain tumour)

The brain MRI images may contain both normal and defective abnormal slices. Normal and abnormal brain image (brain tumor) are determined by its symmetry at the axial and coronal images. Asymmetry beyond a certain degree is a sure indication of the diseased brain and this has been exploited for initial classification at a gross level. Therefore, further examination involving MRI brain classification on the images is required.

1.1.1 MRI Analysis using Image Processing

Firstly MRI image are obtained by MRI machine to detect normal brain image or abnormal brain image. For this algorithms are to be developed so that the normal & abnormal MRI brain images can be classified by machine or computer. The following image processing techniques are taken place for analyzing the MRI image.

A) Pre-processing of MRI images

Due to data acquisition scanner problems, some MRI images are darker rather than others. For improving the quality of image, image enhancement techniques are employed. Intensity adjustment is one of the methods of image enhancement technique in which the intensity value of original image are mapped into a new range of intensity value. Here for improving the MRI image quality, we are using gamma correction which is implemented in MATLAB using `imadjust` function.

B) Features extraction

The most commonly used technique is Wavelet Transform. In Wavelet Transform, different frequencies are examined with different resolutions because it is based on multi-resolution technique. Wavelets are short time localized waves with zero average value. By using Wavelet Transform, we can obtain time and frequency version of signal. Wavelet transform gives better result as compare to FT or SIFT. Due to above properties of Wavelet is used for feature extraction from MRI image.

C) Features Reduction

There are different methods for feature reduction by which dominant features are chosen.

- a) Principal Component Analysis
- b) Kernel Principal Component Analysis
- c) Singular Value Decomposition
- d) Linear Discriminant Analysis

In this project, for feature reduction Kernel principal component analysis is used by which dominant features are chosen. Commonly used kernels are Gaussian or polynomial. In this project, polynomial kernel is used in which we are changing the power of kernel for getting accurate classification rate.

D) Classification

In Classification section, principal feature are chosen from Kernel Principal Component analysis are applied to classifier for training and classification. Different methods are used for classification:

- a) Artificial Neural Network (A.N.N)
- b) k-Nearest Neighbors (k-NN)
- c) Maximum Likelihood
- d) SVM classifier
- e) Parzen Window Method
- f) FCM

In this project, artificial neural network is used for training the network.

1.2 Thesis Objective

In this thesis, our goal is to achieve higher classification rate in order to diagnosis normal images from those with brain abnormality like brain tumor. Firstly, features are extracted using discrete wavelet transformation. Wavelets seem to be a suitable tool for this task, because they allow analysis of images at various levels of resolution. Secondly, kernel principal component analysis (KPCA) is used for reducing the feature vector dimension and also increasing discrimination between classes. Kernel Principal Component analysis is appealing since it effectively reduces the dimensionality of the data and therefore reduces the computational cost of analyzing new data. Finally, pattern recognition method (ANN) is used for classification. The results indicate classification of data. In our work, the database contains different images. We use artificial neural network as a classifier. The number of features obtained by KPCA for maximum classification rate is less and we obtain better classification rate. However, DWT, KPCA, and classifiers are commonly used steps in pattern recognition problems.

1.3 Thesis Outline

This thesis is organized as follows. In Chapter 1, some overview of thesis is outlined in this section. In Chapter 2, literature reviews related to this project are discussed here. Chapter 3 includes the introduction to MRI. In this section the working of MRI which is based on physics mechanism has been discussed here. In chapter 4, methodology of proposed work is discussed. The various techniques of image processing are used for MRI analysis. For features extraction, wavelet Transform is discussed. Features reduction is done using polynomial kernel principal component analysis & for classification Artificial Neural Network is discussed. Chapter 5 presents the simulation result of Neural Network. Lastly, the conclusion of this project and the scope for the future work are covered in Chapter 6.

CHAPTER 2

LITERATURE SURVEY

For this study, journals, articles, books and other related sources that can be related with this topic are discussed. The use of all these sources is to elaborate the idea and concepts. Literature reviews also give the skills to criticize and evaluate the original source articles to retrieve the important point to this study. The process of collecting data and managing the data to the information that relates to the study is one of the ways to have a deeper understanding about the study of research conducted.

2.1 Related Works

This section will present some approaches that have been developed and used in MRI images.

Madhubanti Maitra , Amitava Chatterjee and Fumitoshi Matsuno (2008) [11] has presented, “A Novel Scheme for Feature Extraction and Classification of Magnetic Resonance Brain Images Based on Slantlet Transform and Support Vector Machine”. In this paper, a new method is developed for MRI brain image classification in which Slantlet Transform is used for feature extraction to give superior time localization. Now feature extracted by this method is applied to SVM classifier to train the network for classification whether MRI brain image belongs to normal or abnormal brain image. This proposed method gives 100% classification rate.

N. Hema Rajini, R.Bhavani (2011) [12] published a paper on “Classification of MRI Brain Images using k-Nearest Neighbor and Artificial Neural Network”. MRI gives good distinguish between the various soft tissues of the body. So MRI images are used for diagnosis of brain disease. The methodology of this paper consists of following stages, feature extraction, feature reduction and classification. In the first stage, the features are extracted by discrete wavelet transformation (DWT) from MRI images and then PCA is used for reducing the features which is extracted by DWT. In the classification stage, the classification of MRI image whether it belongs to normal or abnormal brain image are done by the feed forward back propagation artificial neural network (FP-ANN) and k-nearest neighbor (k-NN). The feed forward back propagation artificial neural network (FP-ANN) has

given 90% classification rate and k-nearest neighbor (k-NN) has given 99% classification rate.

Xunheng Wang, Yun Jiao, Zuhong Lu (2011) [13] presents a paper on, “Discriminative Analysis of Resting-state Brain Functional Connectivity patterns of Attention-Deficit Hyperactivity Disorder using Kernel Principal Component Analysis”. The simulation result shows that SVM based Kernel Principal Component Analysis gives accurate classification rate of 81%. KPCA improves the performance of system.

Mohd Fauzi Othman and Mohd Ariffanan Mohd Basri (2011) [14] presents, “Probabilistic Neural Network for Brain Tumor Classification”. Here, Probabilistic Neural Network is used for classification of MRI brain images. Two steps are involved for classification : feature extraction and classification. PCA is used for extraction of the features from MRI image. At last, the features are employed to Probabilistic Neural Network for detection of brain tumor. The simulation results show that workable range for classification accuracy is from 100% to 73% for different value of spread factor.

M. Shasidhar, V.Sudheer Raja, B. Vijay Kumar (2011) [15] develops a method for , “MRI Brain Image Segmentation using Modified Fuzzy C-Means Clustering Algorithm”. Fuzzy C-Means Clustering Algorithm is used in this paper which gives the best segmentation efficiency. The main disadvantage of using this method is large computation time for convergence. The results give better result of the modified FCM algorithm in comparison to conventional FCM algorithm.

Noramalina Abdullah, Lee Wee Chuen, Umi Kalthum Ngah, Khairul Azman Ahmad (2011) [16] has presented a paper on “Improvement of MRI Brain Classification using Principal Component Analysis”. MRI gives good distinguish between the various soft tissues of the body. So in this way MRI can be used to take the image of different body’s parts like brain, muscles, the heart etc. First property of MRI techniques is that it is used in non-invasively form .Secondly it is chosen than other imaging methods because it does not involve any ionizing radiation. Due to above property of MRI, MRI scanner is used to analyze the brain disease. In this paper, simulations results with or without using PCA are compared in form of classification accuracy. If PCA is used as feature reduction techniques

then it will give 85% classification accuracy otherwise it will give 65% classification accuracy.

V.P.Gladis Pushpa Rathi1 and Dr.S.Palani (2012) [19] published a paper on “A novel approach for feature extraction and selection on MRI images for brain tumor classification” in which new approach is developed for feature selection and extraction. This new method extracts the combination of features like intensity, texture, shape based features. It classifies the brain disease like brain tumor in form of white matter, gray matter, CSF, abnormal and normal area. After feature selections, features are reduced by PCA and Linear Discriminant Analysis. In the last, the reduced features are applied to SVM classifier. This new approach for feature selection gives good classification accuracy.

Amer Al-Badarneh, Hassan Najadat (2012) [20] present “A Classifier to Detect Tumor Disease in MRI Brain Images”. In the conventional methods, tumor detection is done by manually. Recently, automatic methods are developed for classification. In this paper, neural network (NN) and K-Nearest Neighbor (K-NN) are given for tumor detection. The simulation result shows that K-NN gives 100% classification accuracy and NN gives 98.92% classification rate.

S.N.Deepa & B.Aruna Devi (2012) [21] has presented a paper on “Artificial Neural Networks design for Classification of Brain Tumour” in which Back propagation neural network (BPN) and Radial Basis Function Neural network (RBFN) are used for classification brain MRI either cancerous or noncancerous tumour. In this method texture features are extracted from MRI image. Then these features are applied to BPN and RBFN. The simulation results show that RBFN gives 85.71% classification rate.

Devi Sarwinda, Aniasi M. Arymurthy (2013) [26] has proposed an approach for feature selection using Kernel PCA for Alzheimer’s disease detection with 3D MR images of brain in which Kernel PCA is used to select the features that produced by an extraction feature method, i.e. complete local binary pattern from three orthogonal planes. The proposed approach is used to detect Alzheimer’s disease using 3D Magnetic Resonance Images (MRI) of brain. A support vector machine classifier is adapted to discriminant normal from Alzheimer’s, normal from mild cognitive impairment (MCI) and MCI from Alzheimer’s. The

experimental results show our proposed method achieves an accuracy of 100% for classification of Alzheimer's and normal.

Walaa Hussein Ibrahim, Ahmed Abdel Rhman Ahmed Osman and Yusra Ibrahim Mohamed (2013) [27] published a paper on "MRI Brain Image Classification Using Neural Networks". Neural Network technique is used for classification of MRI brain image. The methodology of this work consists of following stages, preprocessing, feature reduction, and classification. Firstly, we obtain MRI image from MRI scanner and is converted into suitable form for processing. In the second stage we have obtained the dimensionally reduction using principles component analysis (PCA). Then in the classification stage the Back-Propagation Neural Network has been used as a classifier for classification of abnormal MRI brain images.

D. Sridhar and Murali Krishna (2013) [28] has proposed a new approach "Brain Tumor Classification Using Discrete Cosine Transform and Probabilistic Neural Network". Decision making was performed in two steps, i) Dimensionality reduction and Feature extraction using the Discrete Cosine Transform and ii) classification using Probabilistic Neural Network (PNN). It provides fast and better classification rate as compare to other techniques. This method requires low computation & provides high processing speed.

V. Amsaveni and N. Albert Singh (2013) [29] have developed a new method for, "Detection of Brain Tumor using Neural Network". Here the computer based method is suggested for detection of abnormal brain. In this paper, it consists of following stages, preprocessing, feature extraction, and classification. The texture features are extracted in this paper by using Gabor filter. The features which are extracted by Gabor filter are applied to Artificial Neural Network classifier to train the network and detect the brain disease. This method gives the 89.9% classification accuracy for detection of brain tumor.

Ms. Suchita Goswami and Mr. Lalit kumar P Bhaiya (2013) [30] has proposed a new approach, "Brain Tumour Detection using Unsupervised Learning Neural Network". In this paper, unsupervised Learning Neural Network is suggested for classification of Brain MRI images. Firstly, the preprocessing of MRI images is done which includes histogram equalization, thresholding, edge detection and noise filtering. In second step, Independent Component Analysis (ICA) is used to extract the features from MRI images. In third step

these are applied to Self organized map (SOM) for classification of MRI images. At last k-mean clustering are used for segmenting different brain into different tissue.

Hari Babu Nandpuru, Dr. S. S. Salankar and Prof. V. R. Bora (2014) [31] have presented a paper on, "MRI Brain Cancer Classification Using Support Vector Machine". This research paper proposes an intelligent classification technique to recognize normal and abnormal MRI brain image. Magnetic resonance imaging (MRI) is commonly used techniques for analyzing human brain. In this paper feature extraction from MRI Images will be carried out by gray scale, symmetrical and texture features. The main goal is to give excellent classification rate for classification of MRI brain cancer using SVM.

CHAPTER 3

THE BASICS OF MRI

MR image is effective instrument which give more correct information than the other imaging techniques like X ray, ultrasonic and CT images. MRI is an imaging technique used in medical science to view the internal structures of the body in detail & having incomparable role of importance in brain imaging. Magnetic resonance imaging (MRI) acts as vital role in field of human brain due to its incomparable property. MRI gives good distinguish between the various soft tissues of the body. So in this way MRI can be used to take the image of different body's parts like brain, muscles, the heart etc. First property of MRI techniques is that it is used in non-invasively form .Secondly it is chosen than other imaging methods because it does not involve any ionizing radiation.

By help of magnetic field, radio waves, and a computer, Magnetic resonance imaging (MRI), nuclear magnetic resonance imaging (NMRI), or magnetic resonance tomography (MRT) is used to view the images of body structure. It visualizes internal structures of the body in detail. MRI uses the property of nuclear magnetic resonance (NMR).

MRI scanner is shown in a fig. 3.1.The MRI scanner contains a tube bounded by large circular magnets. The patient is laid on a bed which is movable. Then patient is inserted into the magnet. An intense magnetic field is produced by magnets. This magnetic field aligns the magnetization of few atomic nuclei in the body, after that radio wave is applied. Then, different types of protons in body start to spin, and they produce a signal which is observed by MRI scanner's receiver. This observed signal is recorded and processed digitally with help of computer. An image is generated of the scanned area of the body. We can obtain 2D images or 3D volumes in any orientation by changing the direction of gradients of magnetic field. Magnetic resonance imaging (MRI) gives better result for examining organs or soft tissue as compare to computed tomography (CT) because images of soft tissues and organs in CT are vague due to bones.MRI does not involve any ionizing radiation. In MRI, the strong magnet is used, so due to this reason, we cannot take MRI on patients with implanted pacemakers, intracranial aneurysm clips, cochlear implants etc.

3.1 The brain in a magnetic field

Firstly we measure an MRI signal in which brain is placed in a magnetic field. Due to magnetic field, the atoms nuclei are aligned in the direction of the magnetic field. All electrically charged nuclei start to rotate around their axis. The brain contains different types of nuclei. The hydrogen nucleus is most commonly measured in MRI due to large quantity of hydrogen nuclei in the human brain [7]. If the hydrogen nucleus is measured in MRI, then it gives a strong MRI signal. H_2 nuclei are positively charged particles that revolve around their axis. A magnetic field is produced if an electrically charged particles move.

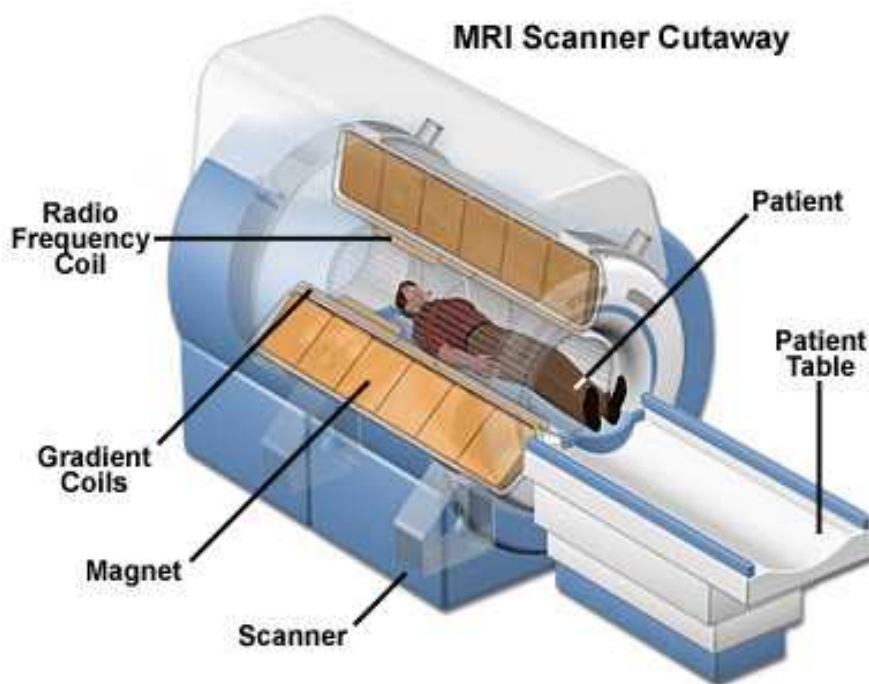


Fig.3.1 MRI Scanner

The produced magnetic field can be expressed in a vector form. A vector is representation of data in amplitude and direction form. Mostly, in mathematics, a vector is represented by an arrow. The arrow's length is defined by its amplitude and arrow's direction points the direction of given vector. In this way, every hydrogen nucleus can be represented as a vector which produces magnetic field. Similarly, every H_2 nucleus in the brain can be viewed as a vector where the vector's strength and direction are strength and direction of the magnetic field of the hydrogen nucleus. The vector which is represented here is regarded as the Magnetic Dipole Moment (MDM) [4] [7]. Before applying the magnetic field, the direction

of MDM.s of all hydrogen nucleus is in a random. Two things happen simultaneously when a magnetic field is applied in brain [7].

Firstly, after applying magnetic field, MDMs of H_2 nuclei are aligned in the same direction as in main magnetic field. Numbers of MDMs of H_2 nuclei that is aligned in direction of magnetic field depends upon strength of magnetic field. No. of MDMs of H_2 nuclei that are in direction of magnetic field are directly proportional to applied magnetic field.

Secondly, the MDM.s of H_2 nuclei starts to precess after locating brain in magnetic field. Brain have different kinds of MDMs of nuclei .So for particular magnetic field, frequency of precession the MDM of a H_2 nucleus is different from the MDM of other nuclei like sodium nuclei. The frequency of precession is also changed by changing the strength of magnetic field [4].

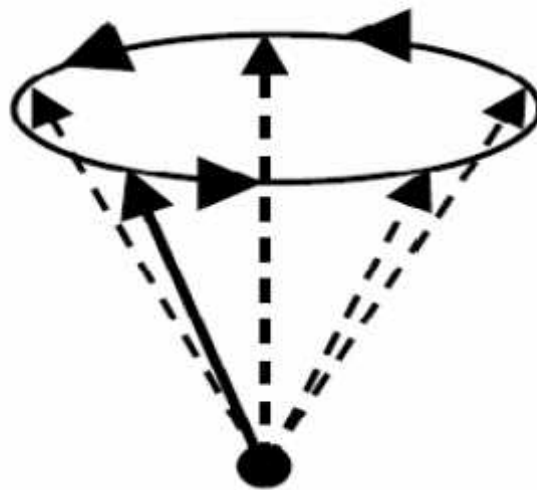


Fig. 3.2 Precession of the MDM

3.2 Effect of radiofrequency pulse

The RF pulse is used for measuring the MRI signal. The RF pulse is generally an electromagnetic wave .If RF pulse is applied perpendicular to the main magnetic field, and then it is known as a 90^0 RF-pulse.

This 90^0 RF-pulse is used to tip the MDM.s of the hydrogen nuclei. Let assume that main magnetic field is applied in z direction. Then 90^0 RF pulse is applied to tip MDM.s of H_2 nuclei in x-y plane. This will be applicable if the frequency of both RF- pulse and precession

of the MDM.s are same. For a given magnetic field, each MDM.s of H_2 nuclei have its specific frequency of precession. Now 90° RF pulse is removed, then MDM.s is returned to its original direction, it is called as relaxation [7].

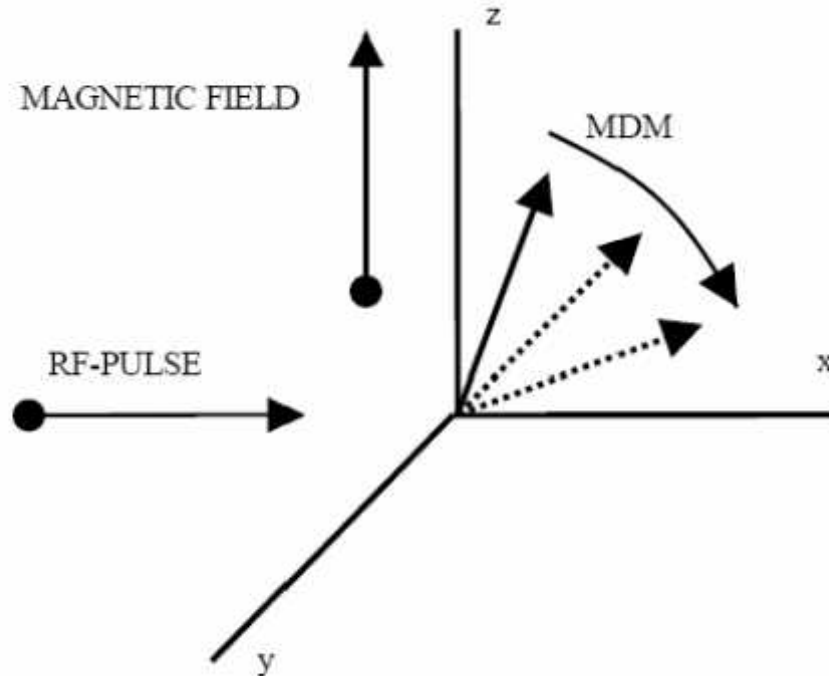


Fig. 3.3 Effect of Radiofrequency

3.3 Relaxation

Initially, main magnetic field is applied in z-direction. When RF pulse is applied, then MDM.s is moved to x-y plane. Now RF pulse is removed, then all MDM.s tip to its original state. So RF pulse transfers its energy to the system. After removing RF pulse, this energy is released during MDM.s is returning to its original lower state. This released energy is known as relaxation. During this period, it is signal that is measured during MRI.

The MDM of a H_2 nucleus have two components. One component is along the z-direction and the other component is along the x-y plane. When the RF-pulse is not applied, the amplitude of MDM.s component in the z-direction is maximum while the amplitude of MDM.s component in the x-y plane is zero. Now the RF-pulse is applied, then the amplitude of MDM.s component in the z-direction is zero while the amplitude of MDM.s component in the x-y plane is maximum.

For the period of relaxation, component in the z-axis will gradually increase while the in the x-y plane gradually decreases. So, the relaxation of the MDM.s of the H₂ nuclei has following components; first is a regrowth component along the z-axis and second is a decaying component in the x-y plane. The regrowth along the z-axis of the MDM.s is known as T₁ relaxation. The decay in the x-y plane of the MDM.s is known as T₂ relaxation .

3.4 Specialized application of MRI

(a) T₁-Weighted MRI

When the ratio of the amplitudes of MDM.s of different tissues in the z-axis is maximized, at that time if we measure the MRI signal then the signal is regarded as a T₁ weighted signal. A T₁ weighted signal can be obtained by changing certain scanner parameters. There are two main factors like TE and TR. TE is defined as the time duration between applying RF pulse to measurement of signal and TR is the time during two consecutive RF pulse. If TE and TR both are kept short, then the difference in T₁ for the various tissues is maximized and the obtained scan is regarded a T₁ weighted scan.

Another name of T₁ weighted scans are anatomical scans, because difference between grey and white matter is easily identified by using this scan. T₁ weighted scans can easily differentiate between fat and water by imaging water as dark colour and fat as brighter than water.

(b) T₂- Weighted MRI

Alternatively, when the MRI signal is measured at a point when the ratio of the amplitudes of the MDM.s of different tissues in the x-y plane is maximized, the signal is known as a T₂ weighted signal. A T₂ weighted signal can be obtained by changing certain scanner parameters. There are two main factors like TE and TR. TE is defined as the time duration between applying RF pulse to measurement of signal and TR is the time during two consecutive RF pulse. If TE and TR both are kept long, then the difference in T₂ for the various tissues is maximized and the obtained scan is regarded a T₂ weighted scan. Lesions appear very bright by help of this scan. So due to this reason, T₂ weighted scans are also regarded as pathological scans. T₂ weighted scans can easily differentiate between fat and water by imaging water as light colour and fat as darker than water.

(c) Spin Density Weighted MRI

Spin density is named as proton density also. Spin density weighted MRI attempt to contain no difference from either T_2 or T_1 decay. In this scan, signal value is changed only by changing the difference in the quantity of spins. It uses one of the spin echo or a gradient echo sequence depending upon application along with short TE and long TR.

(d) Diffusion MRI

Diffusion MRI is used to measure the diffusion of water molecules in biological tissues. Clinically, diffusion MRI is used to examine the disease like stroke, neurological disorders etc. and assist for good understanding the connection of white matter axons in the central nervous system. According to turbulence and Brownian motion, water molecules naturally move randomly in an isotropic medium. Reynolds number should be small for flows to be laminar. In biological tissues, above condition is valid due to low value of Reynolds number, so the diffusion may be anisotropic.

The recently developed technique known as diffusion tensor imaging (DTI) is used to measure diffusion in several directions and the partial anisotropy in every direction to be determined for all voxel.

Diffusion-weighted imaging (DWI) is another application of diffusion MRI. Following an ischemic stroke, DWI detects easily the small change which is occurred in the lesion. If we increase the obstacle to water diffusion, then signal value will be increase on a DWT scan. The enhancement in value happens within 5–10 minutes of the beginning of stroke symptoms and continues for up to 15 days.

(e) Magnetic Resonance Angiography

Magnetic resonance angiography (MRA) is used to take images of the arteries to detect disease like stenosis or aneurysms . MRA take the image of arteries of the leg, abdominal aorta, neck and the thoracic aorta. A various techniques can be used to generate the pictures, such as administration of a paramagnetic contrast agent (gadolinium) or using a technique known as "flow-related enhancement" where most of the signal on an image is due to blood that recently moved into that plane, see also FLASH MRI. By help of the method associated to phase accumulation, flow velocity map is produced effortlessly and correctly. Magnetic

resonance venography (MRV) is same as Magnetic resonance angiography in which image for vein is taken. In this method, the tissue is now excited inferiorly, while the signal is gathered in the plane immediately superior to the excitation plane—thus imaging the venous blood that recently moved from the excited plane.

(f) Magnetic Resonance Spectroscopy

Magnetic resonance spectroscopy (MRS) is technique which is applied for measuring the levels of various metabolites in body tissues. The MR signal produces a spectrum of resonances that corresponds to different molecular arrangements of the isotope being "excited". This mode is used to diagnose certain metabolic disorders, especially those affecting the brain, and to provide information on tumour metabolism.

Magnetic resonance spectroscopic imaging (MRSI) is a combination of spectroscopic and imaging methods to produce spatially localized spectra from within the sample or patient. The spatial resolution is much lower (limited by the available SNR), but the spectra in each voxel contains information about many metabolites. MRSI requires high SNR achievable only at higher field strengths (3 T and above) because the available signal is used to encode spatial and spectral information.

(g) Functional MRI

Functional MRI (fMRI) captures the signal changes in brain when neural activity is taken place. By this technique, whole brain is scanned at low resolution with a fast rate. If we increase or decrease the neural activity, it will change the MR signal through T_2^* changes; this process is called as the BOLD (blood-oxygen-level dependent) effect. By increasing the neural activity, requirement for O_2 is also increased. Then raising the amount of oxygenated haemoglobin in comparison to deoxygenated haemoglobin to overcompensate this extra requirement is done by vascular system. Deoxygenated haemoglobin attenuates the MR signal so oxygenated haemoglobin should be greater than deoxygenated haemoglobin. Nowadays fMRI is current research topic for research. In normal resting state, a high concentration of deoxyhamoglobin attenuates MR signal due to its paramagnetic nature.

3.5 Advantages

The MRI technique has various advantages compared to other imaging techniques. For example, it is fast and it does not use ionizing radiation. Due to the absorbed radiation is minimal, it can be used several times on the patients. Its isotropic resolution is around 1 mm^3 with 3T MRI scanners, which outperforms the 8 mm^3 of PET. It has a high versatility, because it can be used to study structural and functional brain features with different configurations. Its range of frequencies is small so it is not affected by the hardening beam effect of CT. The attenuation coefficient of the tissues is almost homogeneous.

3.6 Disadvantages

It is an expensive and complex technique. In order to optimize the image acquisition, there are many parameters that must be tuned up correctly. In addition, all the metal objects of the patients should be removed before the scanning starts, which is impossible for some kind of surgical implants. Besides, this technique is only suited to analyse soft tissues because the bones have not a significant contrast in the images.

3.7 Applications

MRI is an imaging technique used in medical science to view the internal structures of the body in detail & having incomparable role of importance in brain imaging. Magnetic resonance imaging (MRI) acts as vital role in field of human brain due to its incomparable property. MRI gives good distinguish between the various soft tissues of the body. So in this way MRI can be used to take the image of different body's parts like brain, muscles, the heart etc. First property of MRI techniques is that it is used in non-invasively form. Secondly it is chosen than other imaging methods because it does not involve any ionizing radiation.

MRI is used to detect diseased tissue from normal tissue. CT gives good spatial resolution but MRI gives similar resolution with far better contrast resolution.

CHAPTER 4

METHODOLOGY FOR MRI BRAIN IMAGE CLASSIFICATION USING POLYNOMIAL KPCA WITH NEURAL NETWORK

This Chapter introduces the various steps for the processing of MRI image. The MRI image analysis is performed under following sequence of operations:

1. Pre-processing of MRI image
2. Features Extraction Using Wavelet Transform
3. Features Reduction Using Kernel Principal Component Analysis
4. Classification using Artificial Neural Network

First of all, MRI image are converted into a format which is compatible with computer. With the help of MATLAB, the MR images are changed into matrices form. Then, pre-processing of image is done for improve the quality of MRI image. There are different methods to extract the features of MRI image but we use Wavelet Transform due to its versatility. Now feature which is extracted by wavelet transform have been reduced by kernel Principle Component Analysis. At last, neural network model is created using MATLAB programming. All programming are done in MATLAB software. We have taken training MRI images to train neural network. The test data is used to detect the normal brain image or abnormal. The proposed methodology is shown in Figure 4.1. The brain MRI images in this work are collected from Harvard Medical School.

4.1 Imaging data

The diagnosis methods have been implemented on a real human brain MRI dataset. The protocol includes high resolution axial of size 256×256 pixel images. Five sets of Training data is taken. Each set contains three Images .One set contains normal MRI Images & rest four sets contain abnormal brain MRI images. This dataset are collected from Harvard Medical School website [1].

Methodology

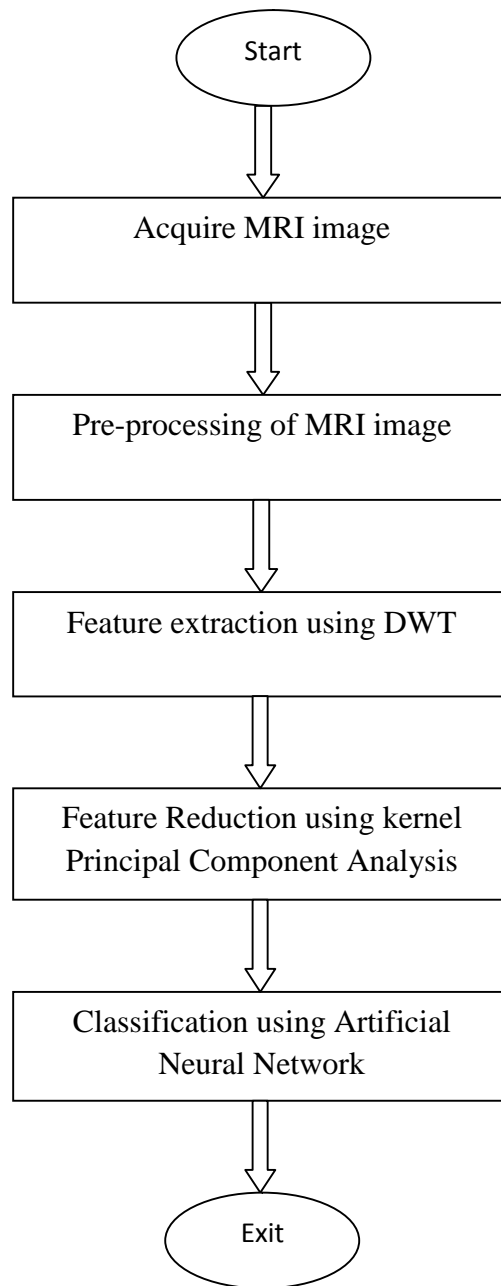


Fig. 4.1 Methodology

The detailed explanation of all above operations is presented here.

4.2 Pre-processing of MRI images

Due to data acquisition scanner problems, some MRI images are darker rather than others. For improving the quality of image, image enhancement techniques are employed. Intensity adjustment is one of the methods of image enhancement technique in which the intensity value of original image are mapped into a new range of intensity value. Here for improving the MRI image quality we are using gamma correction which is implemented in MATLAB using `imadjust` function.

4.3 Feature extraction using DWT

The transform of a signal is used to represent the signal. Information of signal does not change by applying transformation. By using Wavelet Transform, we can obtain time and frequency version of signal. Wavelet is waveform of effectively limited duration that has an average value of zero. In the Short Time Fourier Transform (STFT), both time and frequency are represented in limited precision. Precision is determined by size of window. For same signal, we cannot change window size. Once you choose a particular window size for time window, it will be same for all frequency. Due to all above reason, Wavelet transform is applied for analyzing non-stationary signals. The Wavelet has following properties like short time localized waves with zero integral value, possibility of time shifting, flexible etc. In Wavelet Transform, different frequencies are examined with different resolutions because it is based on multi-resolution technique. Wavelets are short time localized waves with zero average value. Its energy is concentrated in time or space. The waves are used in Fourier Transform and STFT for analyzing signals but in case of the Wavelet Transform, wavelets are used. The wavelet analysis produces a time scaling view of signal. In SIFT, window function is multiplied with input signal but in wavelet transform, wavelet function is multiplied with input signal for analyzing the signal, then transform is computed for each segment generated.

The analysis of a non-stationary signal using the FT or the STFT is not suitable for analyzing of a non-stationary signal ,although wavelet transform gives better result as compare to FT or SIFT. If in a signal trends, breakdown points, discontinuities and interruption etc are occurred, then this part is not analyzed by FT or SIFT. For this wavelet transform is used for analyzed this interruption parts of signal.

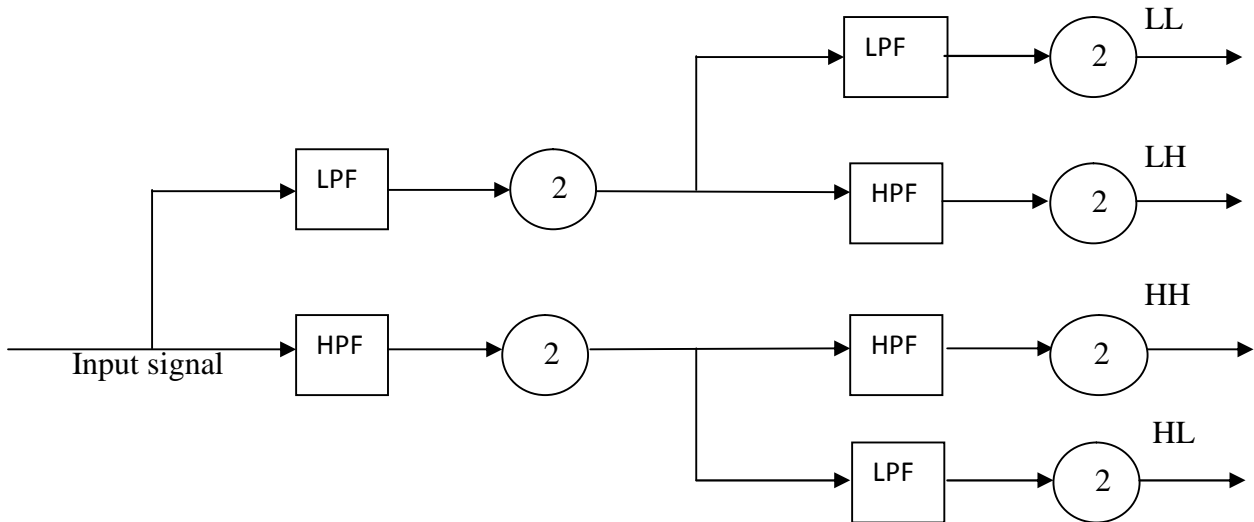


Fig. 4.2 Wavelet decomposition

$$\text{Detail component} = \text{det}_{j,k} = a(n) h_{\text{high } j}^*(n-2jk)$$

$$\text{Approximation component} = \text{app}_{j,k} = a(n) h_{\text{low } j}^*(n-2jk)$$

Where $a[n]$ is MRI image after pre-processing, $\text{det}_{j,k}$ represents the detail component of input signal $a[n]$ and $\text{app}_{j,k}$ represents the approximation component of input signal $a[n]$.

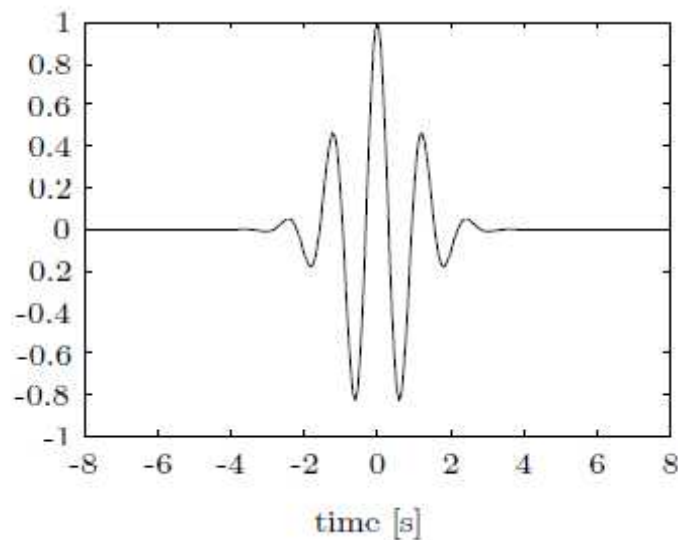


Fig. 4.3 Wavelet waveform

An analyzing function $\Psi(t)$ is classified as a wavelet if the following mathematical criteria are satisfied:

1. A wavelet must have finite energy

$$E = \int_{-\infty}^{\infty} |\Psi(t)|^2 dt < \infty$$

The energy E equals the integrated squared magnitude of the analyzing function $\Psi(t)$ and must be less than infinity.

2. If $\Psi(f)$ is the Fourier transform of the wavelet $\Psi(t)$, the following condition must hold

$$C = \int_0^{\infty} \frac{|\Psi(f)|^2}{f} df < \infty$$

This condition implies that the wavelet has no zero frequency component ($\Psi(0) = 0$), i.e. the mean of the wavelet $\Psi(t)$ must equal zero. This condition is known as the admissibility constant. The value of C depends on the chosen wavelet.

3. For complex wavelets the Fourier transform $\Psi(f)$ must be both real and vanish for negative frequencies.

4.3.1 Continuous Wavelet Transform

Fourier Transform is sum over all time of signal $x(t)$ multiplied by a complex exponential $e^{j2\pi ft}$ of different frequencies f . Continuous Wavelet Transform is sum over all time of signal, multiplied by scaled & shifted versions of wavelet function $\Psi_{u,s}(t)$:

$$\Psi_{u,s}(t) = \frac{1}{\sqrt{s}} \Psi\left(\frac{t-u}{s}\right)$$

Where u is the shift of $\Psi_{u,s}(t)$ along the signal time and s is scale (dilation of $\Psi_{u,s}(t)$ the inverse of frequency), $1/\sqrt{s}$ ensures energy normalization. The continuous wavelet transform is the coefficient of the basis $\Psi_{u,s}(t)$ [11]. It is

$$W_x(s, u) = \langle x, \Psi_{u,s} \rangle = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x(t) \Psi_{u,s}^*(\frac{t-u}{s}) dt$$

where $*$ denotes the complex conjugate pair and $\langle x, \Psi_{u,s} \rangle$ represents for the inner product.

Above equation is a mathematical expression for the Continuous Wavelet Transform (CWT) in which $x(t)$ is input signal which is multiplied by scaled & shifted version of wavelet function $\Psi_{u,s}(t)$. $\Psi(t)$ is the mother wavelet or the basis function. We can obtain different type of wavelet functions from mother wavelet by shifting and scaling. $\Psi(t)$ symbol is used for mother wavelet, the $\Psi_{u,s}(t)$ symbol is used if wavelet is complex. We can normalized the signal energy at

every scale by dividing the wavelet coefficients by factor $1/\sqrt{s}$. At every scale, energy is same in wavelet. Scale parameter s is used for contracting and dilating mother wavelet by altering the value of s . Wavelet's frequency and the window lengths are changed by varying the scale parameter s . Due to variation of frequency, frequency is not used for representing the wavelet analysis's result. The shifted version of wavelet can be applied to the signal by changing the value of the translation parameter u which gives the position of wavelet in time.

If we make the time-scale plane, then row is filled by taking constant value of s and varying value of u . The opposite process is taken place for column filling of time-scale plane. The elements of $W_x(s, u)$ are called as wavelet coefficients. Each wavelet coefficient is related to a scale (frequency) and a point in the time domain. Scaling is used either dilation or compression of a signal. The detail information of signal is achieved by using large scales (low frequencies) value that is used for dilation of the signal. Small scales (high frequencies) compress the signal and give the global information about the signal. Mathematically Wavelet Transform is the convolution of the signal and the mother wavelet.

4.3.2 Discrete Wavelet Transform

The Wavelet Series is obtained by the sampling of CWT. Its computation may consume significant amount of time and resources, depending on the resolution required. The Discrete Wavelet Transform (DWT) works on the principle of sub-band coding. By using DWT, fast computation of Wavelet Transform is achieved. The computation time and resources are reduced by using DWT. In 1983, pyramidal coding was developed which was same as sub-band coding. After that many improvement were done in pyramidal coding which has given another schemes known as multi-resolution analysis schemes.

In CWT, We can analyze the signal by multiplied the signal with shifted and scaled version of mother wavelet and in the case of DWT, digital filtering techniques are used for time-scale representation of signal. For this, digital signal is applied to filter which are having different cut off frequency at different scale.

4.3.3 Filter banks

A signal is separated into frequency bands with the help of a filter bank. A two channel filter bank is shown in Fig.4.4. Now applying a discrete time signal $a(n)$ into two filter $H_0(z)$ and $H_1(z)$ simultaneously of the analysis bank. These two filter divide the frequency content of the input signal in frequency bands of equal width. The filters $H_0(z)$ is a low pass filter and $H_1(z)$ is a high-pass filter. The output of $H_0(z)$ contains the low frequency band with half frequency content & the output of $H_1(z)$ contains the high frequency band with half frequency content but amount of sample does not changed. Now if the output of both filters is summed up, then the output signal will have the same frequency content as input signal but amount of samples will be doubled so to obtain original data down sampling by factor two is used. The synthesis filter bank [5] is used for reconstruction of the original signal. The synthesis filter bank consists of low pass filter and high pass filter and up sampler by 2. The output signal of analysis filter bank is worked as input signal to synthesis bank. This signal is firstly up sampled by 2 and then passed through $G_0(z)$ and $G_1(z)$. The outputs of the filters in the synthesis bank are added to obtain original signal i.e. input signal.

The output of both filters after down sampling by 2 is regarded as sub bands and the used filter bank technique is known as sub band coding.

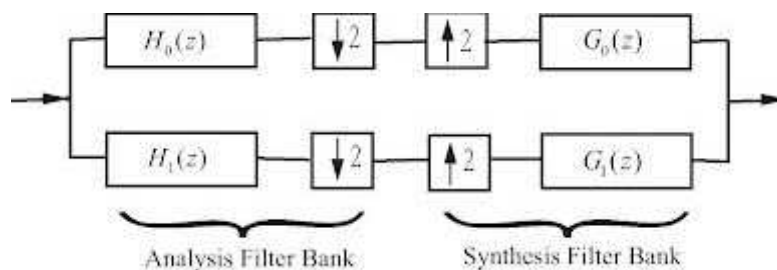


Fig. 4.4 A two channel filter bank

4.3.4 Conditions for Perfect Reconstruction

The filter bank should be biorthogonal for perfect reconstruction. There are some criteria for the designing of analysis and synthesis filters which should be satisfied to avoid aliasing, distortion and to guarantee a perfect reconstruction [5].

The input is applied to filters $H_0(z)$ (low pass filter) and $H_1(z)$ (high-pass filter) simultaneously that break input signal into low frequency bands and high frequency band respectively. The information would be lost in down sampling if filters were not ideal brick-wall filters. But it is very difficult to realize ideal filter. In addition to aliasing, there is another problem in the channel of filter like an amplitude and phase distortion. To avoid aliasing in the two channel filter bank, the filters of synthesis filter bank are designed as [5].

$$G_0(z) = H_1(-z)$$

$$G_1(z) = -H_0(-z)$$

To eliminate distortion, a product filter $P_0(z) = H_0(z) G_0(z)$ is defined. Distortion can be avoided if

$$P_0(z) - P_0(-z) = 2z^{-n}$$

Where n is the overall delay in the filter bank. Generally an n^{th} order filter produces a delay of n samples. The perfect reconstruction filter bank can be designed using following steps [5]:

1. Design a low-pass filter P_0 satisfying above equation.
2. Factor P_0 into $H_0(z) G_0(z)$ and use above two equation to calculate $H_1(z)$ and $G_1(z)$.

4.3.5 Multi-Resolution Analysis using DWT Filter Banks

In multiresolution analysis using DWT filter banks, resolution is changed in each step. We decimate (decompose) signal until we are able to reconstruct the signal. The CWT has a time-frequency resolution. In the discrete wavelet transform (DWT), filter bank are used for obtaining multiresolution.

The approximation of signal is obtained by applying the input signal to low pass and details of the signal is obtained by applying input signal to high pass filter. A three level filter bank is shown in a fig.4.5. Any levels of filter bank are constructed based on the desired resolution. Lowest half of the frequencies in $x(k)$ are represented by c_1 , down sampling doubles the frequency resolution. The numbers of samples in $c_1(k)$ are reduced to half of $x(k)$. In the second level, the outputs of $L(z)$ and $H(z)$ double the time resolution and decrease the frequency content, i.e. the width of the window is increased. After each level, the output of low pass filter is passed to another filter bank (high pass filter and low pass filter). For a particular set of filters $L(z)$ and $H(z)$ this structure is called the DWT, the filters are called wavelet filters.

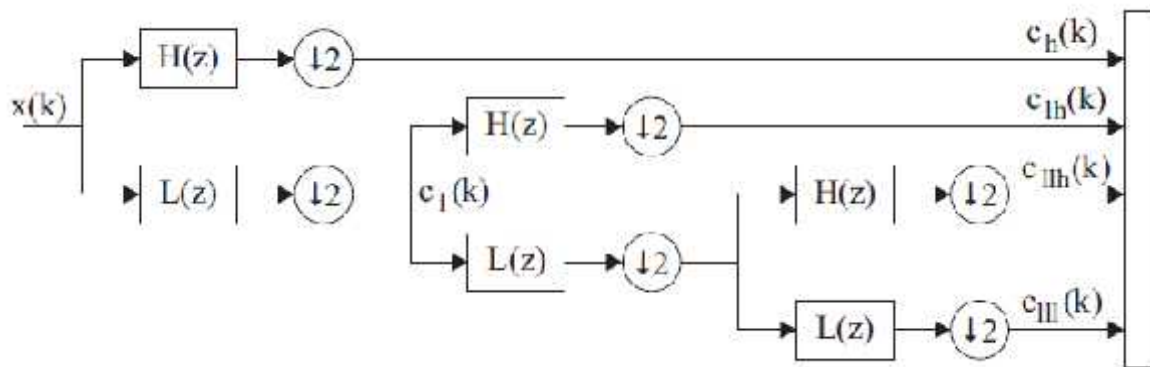


Fig. 4.5 Analysis filter bank

At each decomposition level, the input signal is divided into two frequency band after applying through LPF and HPF. The output of $L(z)$ contains the low frequency band with half frequency content & the output of $H(z)$ contains the high frequency band with half frequency content but amount of sample does not changed. Now if the output of both filters is summed up, then the output signal will have the same frequency content as input signal but amount of samples will be doubled so to obtain original sample down sampling by factor 2 is used. Decimation process produces half of data. When we use decimation, output coefficient should be reduced by 2. The output of LPF and HPF produces twice the data. If we have N input samples, it produces N approximation coefficient & N detail coefficient. To correct this, we down decimate the filter output by 2, by simply throwing away every second coefficient. It means we are neglecting alternate coefficient of signal portion. So this process is repeated until we will get desire level. The maximum number of levels depends on the length of the signal.

For example, if we have 200 sample & this sample are applied to wavelet function, and then decimate the signal. It reduces the signal by half, so 100 coefficients have left. So 50% compression is done. Then again apply wavelet & decimate it, the 50% compression or decimation of coefficient is done. So it is called multiresolution process because in each step, we are reducing the resolution of signal. We will stop the process until we are able to reconstruct the signal. Then the DWT of the original signal is obtained by concatenating all the coefficients $a[n]$ and $d[n]$, starting from the last level of decomposition.

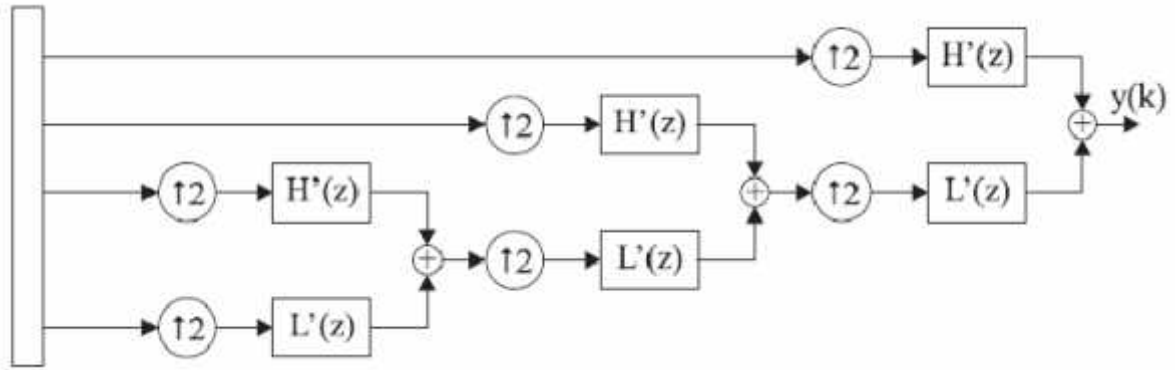


Fig. 4.6 Synthesis filter bank

Above fig. 4.6 represents that original signal is reconstructed by the wavelet coefficients. The reconstruction is the opposite process of decomposition. Unlike to analysis filter bank, at every level, the approximation and detail coefficients are up sampled by 2 and passing through the low pass and high pass synthesis filters and then added. This process is repeated until we will get the same number of levels as in the decomposition process to get the original signal. Mallat was the first to implement this scheme, using well known filter design called 'two channel sub band coder' yielding fast wavelet transform.

4.3.6 Features Extraction Using Discrete Wavelet transform in 2-D Image

In this project, features are extracted from MR images using discrete wavelets transform. The features are represented in form of (DWT) coefficients. The Wavelet coefficients are extracted from MR images by DWT. Wavelets are obtained by scaling and shifting the mother wavelets. Wavelets give localized frequency information of a signal that is useful for classification. The Wavelet has following properties like short time localized waves with zero integral value, possibility of time shifting, flexible etc. In Wavelet Transform, different frequencies are examined with different resolutions because it is based on multi-resolution technique.

The signal is decomposed in the time-frequency scale plane by wavelet transform. MRI image is applied through series of half band LPF and HPF. The output of HPF is detail coefficients and LPF are approximation coefficients. The image can be represented at different resolution levels by wavelet transform. At resolution j , it provides an approximation of the original image I_j and three detail of image D_2^V, D_2^H, D_2^D .

Fig.4.7 shows a decomposition of image at two levels. It has been shown that the wavelet coefficients have the information relating to the original image at different scales [6]. At the particular scale and translation, the degree of correlation or similarity between the image and the mother wavelet can be represented by wavelet coefficient.

A_2	D_2^V	
D_2^H	D_2^D	D_1^V
D_1^H		D_1^D

Fig.4.7 Two level decomposition

$$\text{Detail component} = \text{det}_{j,k} = a(n) h_{\text{high } j}^*(n-2jk)$$

$$\text{Approximation component} = \text{app}_{j,k} = a(n) h_{\text{low } j}^*(n-2jk)$$

Where $a[n]$ is MRI image after pre-processing, $\text{det}_{j,k}$ represents the detail component of input signal $a[n]$ and $\text{app}_{j,k}$ represents the approximation component of input signal $a[n]$.

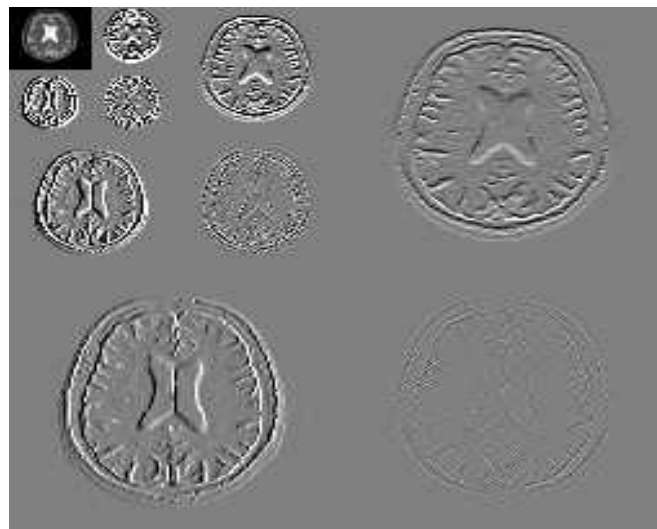


Fig. 4.8 DWT of MRI Image

The $h(n)$ and $g(n)$ are the high-pass and low-pass filters, respectively. We can analyze any function at various resolutions. In fig. 4.9 two levels DWT is applied to MR image. After applying transformation 4 sub-band (LL, LH, HH, and HL) images are obtained at each scale.

Only Sub-band image LL goes to next level for DWT calculation. In this project, feature is extracted using Haar wavelet function.

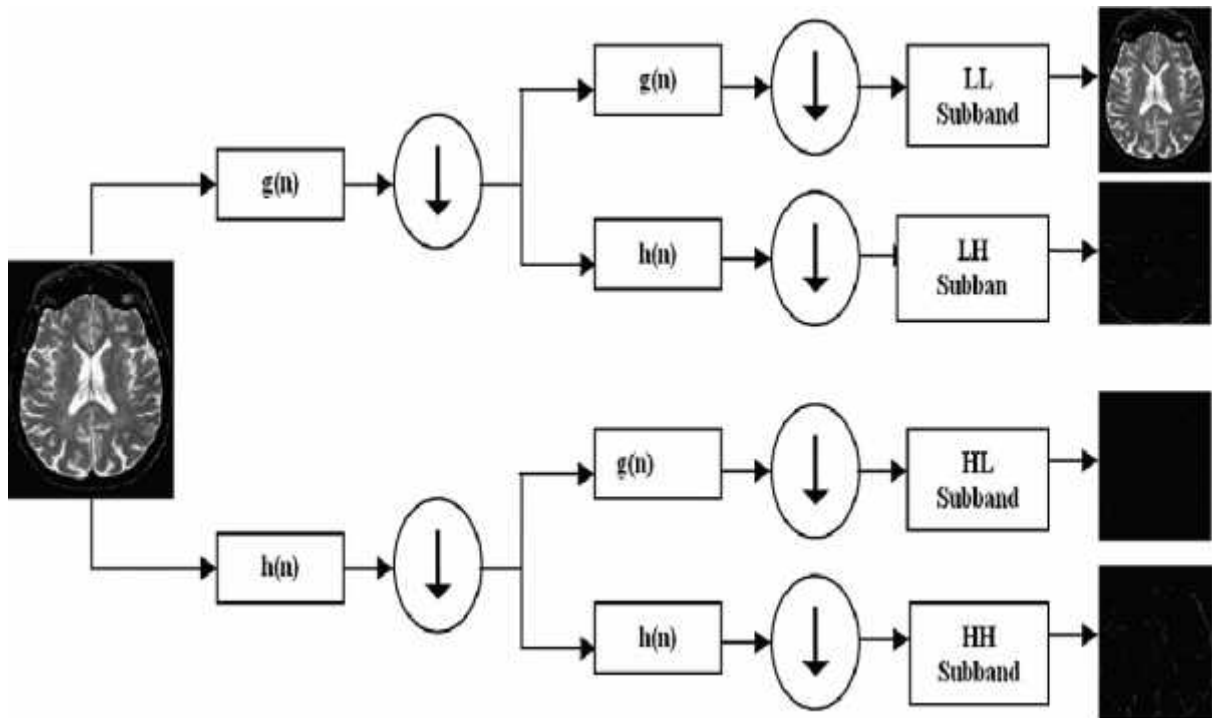
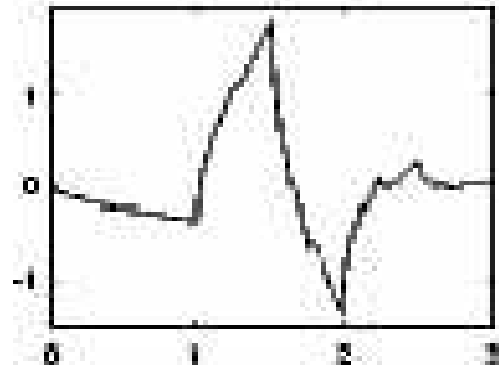
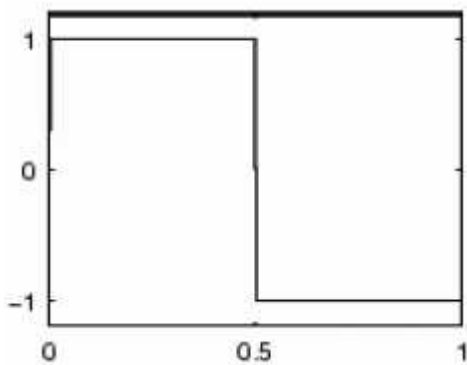


Fig. 4.9 Wavelet decomposition of MRI Image

4.3.7 Wavelet Families

For Wavelet Transformation, there are various basis functions. All wavelet functions are generated by shifting and scaling of mother wavelet. In this project, Haar wavelet is used for extracting the features of MRI in form of wavelet coefficient. Depending upon application, the appropriate mother wavelet should be chosen in order to use the Wavelet Transform effectively. Fig. 4.10 shows the wavelet families.



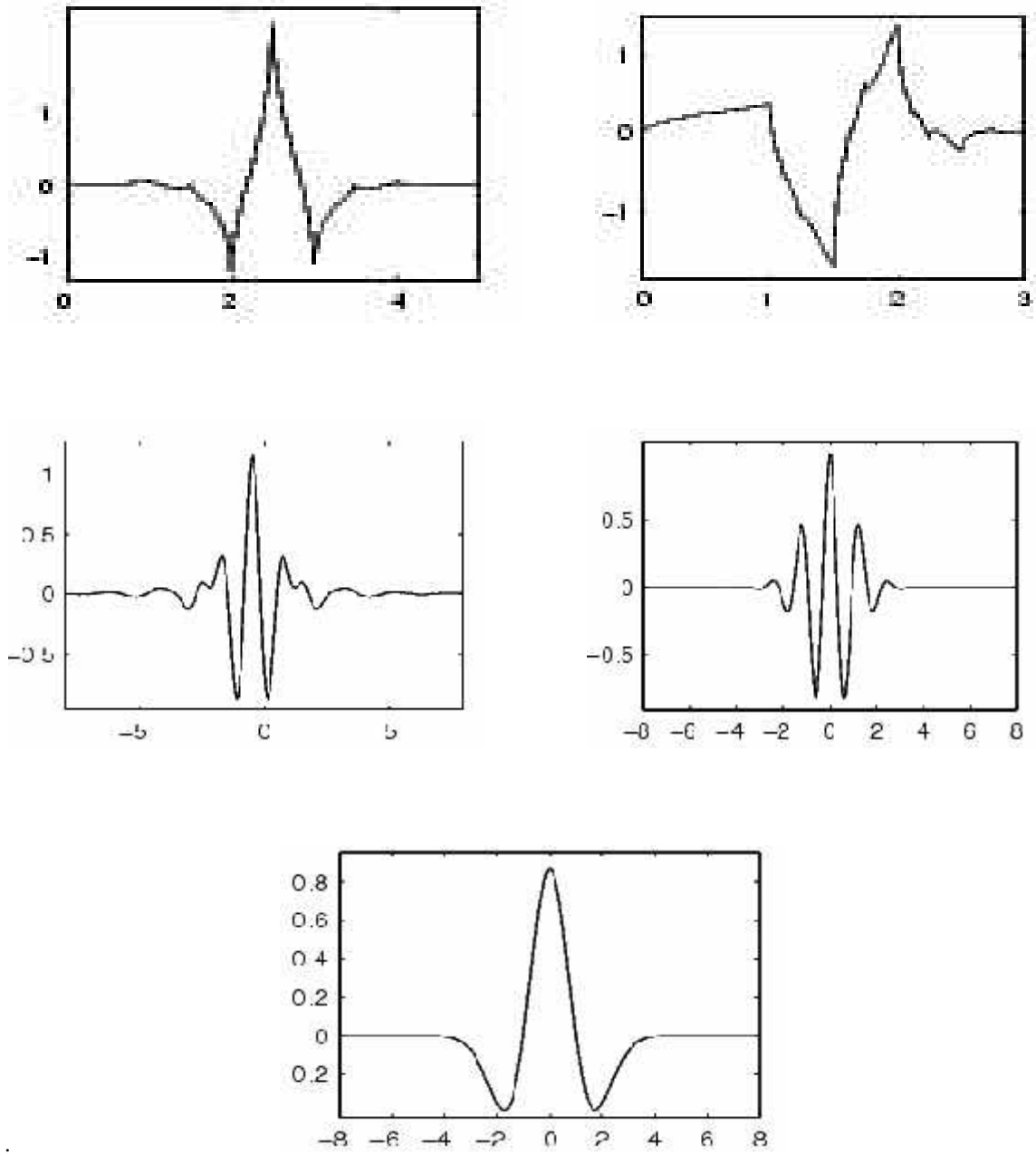


Fig. 4.10 Wavelet families (a) Haar (b) Daubechies4 (c) Coiflet1 (d) Symlet2 (e) Meyer (f) Morlet (g) Mexican Hat

4.4 Feature Extraction using kernel Principal Component Analysis (KPCA)

In PCA, for feature reduction covariance matrix is constructed. But in KPCA, it is difficult to construct covariance matrix in feature space due to nonlinear projection. Due to this reason, kernel trick is used and develop the kernel matrix $Ke(x, x') = \langle \phi(x), \phi(x') \rangle$ without explicitly doing the mapping [8] [13].

KPCA uses the same theory as the statistical method Principal Component Analysis (PCA), namely that it seeks to project the set of data onto a low-dimensional subspace that captures the highest possible amount of variance in the data. However, while PCA performs a linear separation of the data in the original space (referred to as R_d), KPCA embeds the data into a high dimensional space, called the feature space (referred to as F), by a mapping function and performs a linear separation in that space instead. In this way also nonlinear separations of data are made possible [22] [26]. Kernel PCA performs nonlinear projection. Thus, while kernel PCA looks for linear features in feature space, these features correspond to nonlinear features in the original lower dimensional space R_d , as shown in Fig. 4.11

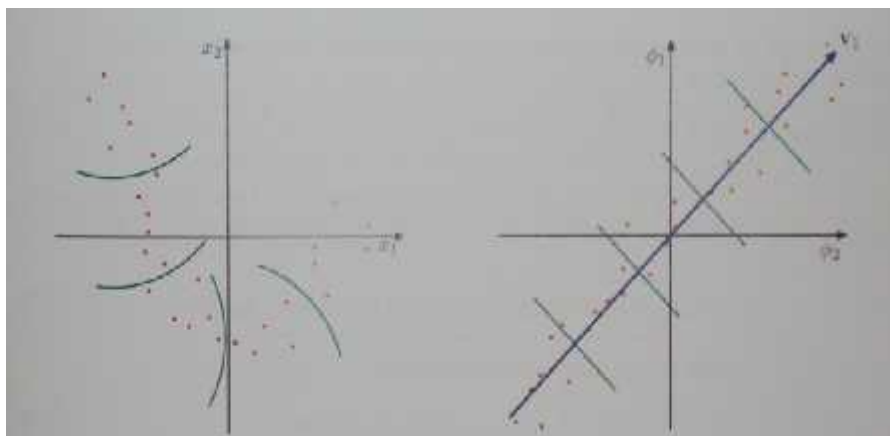


Fig.4.11 Nonlinear projection

The data in the feature space is projected onto a low-dimensional subspace, spanned by the eigenvectors that capture most of the variance. One important fact is that it is not necessary to know the mapping ϕ or the feature space F explicitly in order to perform kernel PCA. Instead computations are performed on the inner product of pairs of points which are stored in a kernel matrix. The procedure of working with the data in feature space without knowing the mapping ϕ is known as "the kernel trick" and is a central part of the kernel PCA method. The

advantage of kernel PCA over standard (linear) PCA is illustrated in Fig.4.12. Kernel PCA embeds the points into a high dimensional space and then projects them onto a subspace spanned by eigenvectors, resulting in the plot to the right. The two classes of points in the plot to the right can be linearly separated from each other.

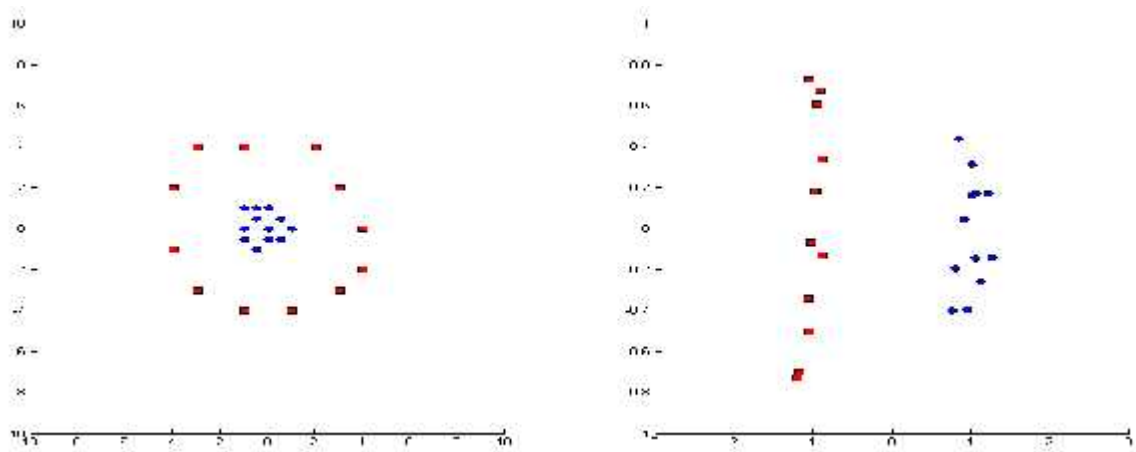


Fig.4.12 (a) Before applying KPCA (b) After applying KPCA

4.4.1 Mathematical formulation

Let we have n data points which is represented by

$$X = \{x_1, x_2, x_3, \dots, x_n\}$$

where $x_i \in \mathbb{R}^d$, $i=1$ to n . Let us assume that in the original space the data in X is centred, so that

$$\sum_{i=1}^n x_i = 0$$

If data is not centred, we use below formula to centre the data [18].

$$\widetilde{x}_k = x_k - \frac{1}{n} \sum_{i=1}^n x_i$$

Where \widetilde{x}_k is the k^{th} data point in the new, centred set.

Kernel PCA performs nonlinear projection. Given input $(x_1 \dots x_n)$, KPCA calculates the principal components in the feature space $(x_1) \dots (x_n)$.

$$: \mathbb{R}^d \rightarrow F$$

where F is defined as the feature space. Thus, (x_i) the image of the data vector $x_i \in \mathbb{R}^d$.

Let the kernel matrix K_e be a symmetric and positive semi definite $n \times n$ matrix, with its elements defined by the inner product of all pairs of points (x_j) and (x_k) in feature space so that

$$K_{e_{ij}} = (x_j \cdot x_k) \quad j, k = 1, \dots, n$$

According to Mercer's Theorem, K_{ij} is represented by kernel function $k_e(x_i, x_j)$.

$$K_{e_{ij}} = k_e(x_j; x_k) \quad j, k = 1, \dots, n$$

This way the features space F and the mapping are defined by the kernel function that is used. This is known as "the kernel trick".

The power of kernel methods is that we do not have to compute $\phi(x)$, explicitly. We can directly construct the kernel matrix from the training data set. Two commonly used kernels are the polynomial kernel and Gaussian kernel.

1) Polynomial kernel

$$K_e(x_j, x_k) = (x_j^T x_k)^p$$

where p represent order of polynomial.

or

$$K_e(x_j, x_k) = (x_j^T x_k + d)^p$$

Where d is constant value greater than zero.

2) Gaussian kernel

$$K_e(x_j, x_k) = \exp(-\|x_j - x_k\|^2 / 2\sigma^2)$$

or

$$K_e(x_j, x_k) = \exp(-\|x_i - x_j\|^2)$$

Kernel PCA uses the $N \times N$ kernel matrix.

We are now ready to kernelize the procedure by replacing x_i with $\phi(x_i)$.

$$K_{e_{ij}} = (\phi(x_j) \cdot \phi(x_k))$$

For a noncentred set, this centering can be achieved by the inner product computation.

$$(\tilde{K}_e)_{ij} = (\phi(x_j) - \bar{\phi}) \cdot (\phi(x_k) - \bar{\phi})$$

Where \tilde{K} is the centered kernel matrix and $\bar{\phi}$ is the centre point in the feature space, given by

$$\bar{\Psi} = \frac{1}{n} \sum_{i=1}^n \Psi(x_i)$$

The eigenvectors of $\widehat{K_e}$ can be obtained by solving the given equation

$$\widehat{K_e} V = \lambda V$$

where the columns of V represent the normalized eigenvectors and λ is a matrix in which the diagonal consist of the corresponding eigenvalues and all other elements in λ are zero. The eigenvectors in V are assumed to be ordered according to the size of their corresponding eigenvalues, in descending order. Also the eigenvalues in λ are sorted in descending order [18].

Using a similar calculation, you can find that this can be expressed easily in terms of K_{eij} .

$$K_{e1} = K_e - \frac{1}{N} K_e - K_e \frac{1}{N} + \frac{1}{N} K_e \frac{1}{N}$$

Where $\frac{1}{N}$ is $N \times N$ matrix with all element equal to $1/N$.

4.5 Artificial Neural Network

Neural networks are defined as “A network of weighted, additive values with nonlinear transfer functions. Human brain is a densely interconnected network of approximately 10^{11} neurons, each connected to, on average, 10^4 others. Neuron activity is excited or inhibited through connections to other neurons. Artificial neural network (ANN) is a machine learning approach that models human brain and consists of a number of artificial neurons. An artificial neural network consists of a number of interconnected neuron which is similar to biological neurons in the brain. Artificial neural network (ANN) is a machine learning approach that models human brain and consists of a number of artificial neurons”.

Neural networks are developed for solving prediction or classification problems. Neural networks are modeled based on the principle of the biological neuron system. An electrochemical stimulus is given to a neuron from multiple sources. A neuron generates electrical impulses in response to electrochemical stimuli. These generated electrical pulses are propagated to other neurons. Human nervous system contains like 1010 to 1020 neurons. Each neuron store several bits of “information”. “The total weight of an average brain is 1.5 kg, so an average neuron weights something less than 1.5×10^{-9} g”.

Neurons receive input from sensory or other types of cells and send outputs to other neurons. About 10% of neurons are used as input and output and remaining 90% are interconnected with other neurons which store information or perform various transformations on the signals being propagated through the networks. A neuron possesses nucleus, a cell body, numerous dendrite links providing input connections from other neurons through synapses, and an axon trunk that carries an action potential output to other neurons through terminal links and synapses. A single neuron is connected to hundreds or even tens of thousands of other neurons. The two types of synapses are used for that are excitatory and inhibitory. An internal electric potential are generated by neural activity. The input activity which is given by other cells via the synapses decreases or increases this generated potential. When the cumulative inputs raise the potential above a threshold value, the neuron “fires” by propagating a sequence of action potential spikes down the axon to either excite or inhibit other neurons. The pulses cause a chemical neurotransmitter substance to be released at the terminating synapses which, in turn, can excite or inhibit other neurons. The rate of pulse propagation ranges from about 5 to 125 ms⁻¹, and the time required for a stimulus to “traverse” a synapse

is about 10ms during which the neuron cannot fire again. The activity of a neuron is measured by the firing frequency of the potential analogue spikes which it generates. Fig.4.13 below shows a simplified biological neuron.

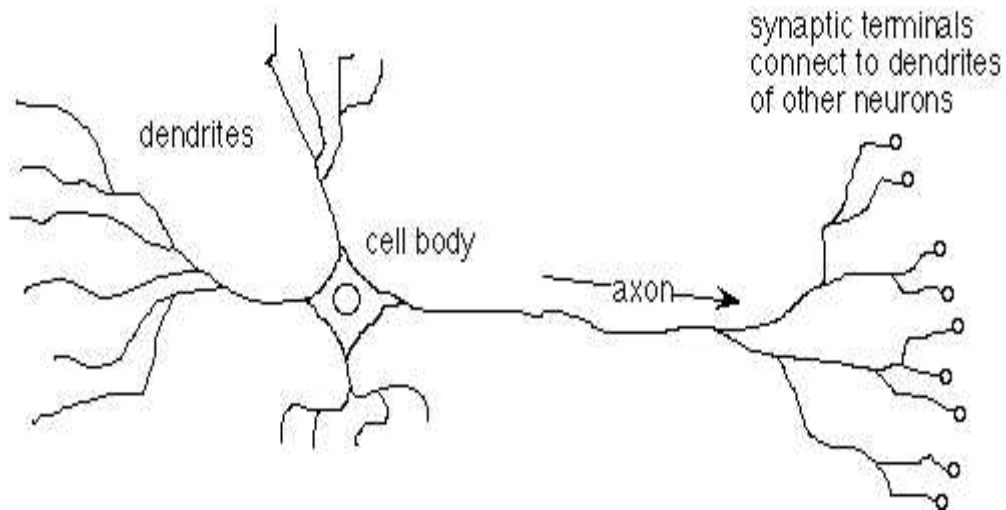


Fig. 4.13 Biological neuron

The above Biological neuron [27] can be modeled as an artificial neuron which is shown below fig. 4.14.

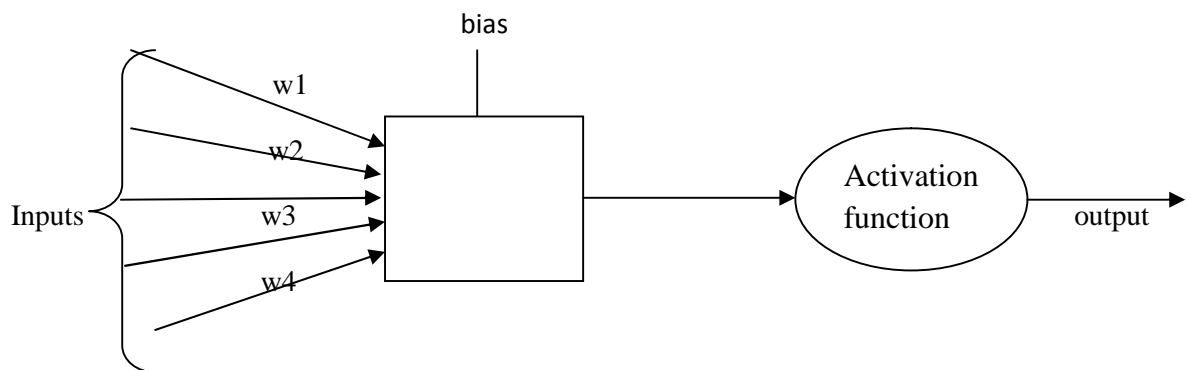


Fig. 4.14 Single neuron model as a processing device

1. The synapses works as weight element in neuron. Specifically, a signal is applied at the input of synapse. The input signal is multiplied by the synaptic weight w_k . The weight w_k is positive or negative depending upon type of synapse.

2. A summer output is the weighted sum of input signal.

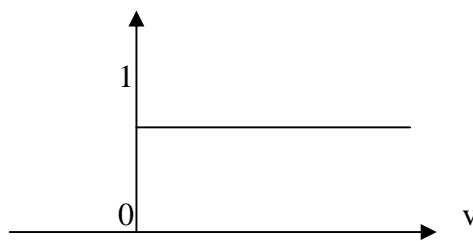
3. The output of summer is applied to an activation function which is used to limit the amplitude of the output of a neuron. The commonly used normalized amplitude range are [0, 1] or [-1, 1]. A bias is used for altering the input of the activation function.

4.5.1 Activation Function

Typically, $\phi(\cdot)$ is a non-linear function called as activation function. There are normally used classes for activation function like the binary and bipolar threshold functions, the piece-wise linear function (“hard-limited” linear function), and the so-called sigmoid function. Different kinds of activation function are given below.

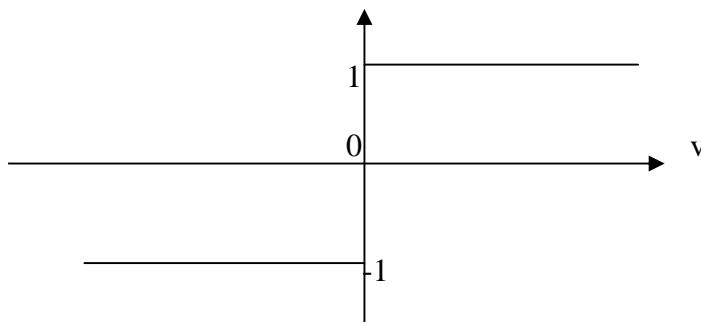
a. Binary threshold activation function

$$\phi(v) = \begin{cases} 0, & v < 0 \\ 1, & v \geq 0 \end{cases}$$



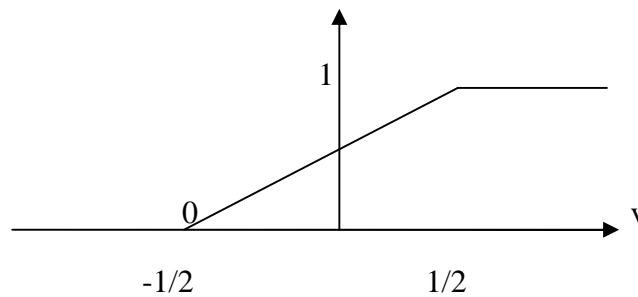
b. Bipolar threshold activation function

$$\phi(v) = \begin{cases} -1, & v < 0 \\ 1, & v \geq 0 \end{cases}$$



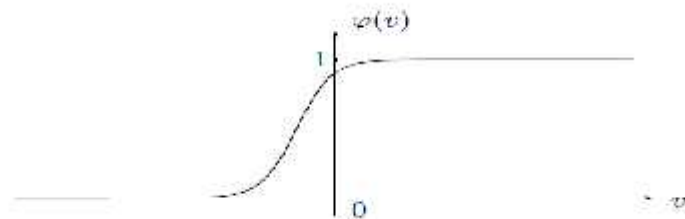
c. Piecewise-linear activation function

$$\phi(v) = \begin{cases} 1 & v \geq \frac{1}{2} \\ v + \frac{1}{2} & -\frac{1}{2} < v < \frac{1}{2} \\ 0 & v \leq -\frac{1}{2} \end{cases}$$



d. Sigmoid (logistic) activation function:

A sigmoid function is any differentiable function $\phi(\cdot)$, say, such that $\phi(v) \rightarrow 0$ as $v \rightarrow -\infty$, $\phi(v) \rightarrow 1$ as $v \rightarrow \infty$ and $\phi'(v) > 0$.



A specific example of a sigmoid function is given by

$$\phi(v) = \frac{1}{1 + \exp(-av)}$$

From above equation, it is clear that if value of a is large, slope will be more. If $a = 0$, this sigmoid function equal to the binary threshold function but this case is not valid when $v = 0$, for this $\phi(0) = 1/2$, for all a . This is called as the threshold limit of ϕ .

In mathematical terms, we may describe a neuron k can be written by giving equations

$$v_k = \sum_{j=1}^p W_{kj} X_j$$

$$y_k = \phi(v_k)$$

4.5.2 Neural Network Architecture

A neural network is formed by putting the input unit, hidden unit and output unit at the vertices. Flow of signal is represented by arcs. Input is applied to input unit which is used for transmitting the signal to other unit. Output units only receive the signal from other units. Then units are labelled with integer. The unit j is connected to unit k if $j < k$. If the network follow the condition $j < k$, then this is called a feed-forward network. This is illustrated in the Fig. 4.15.

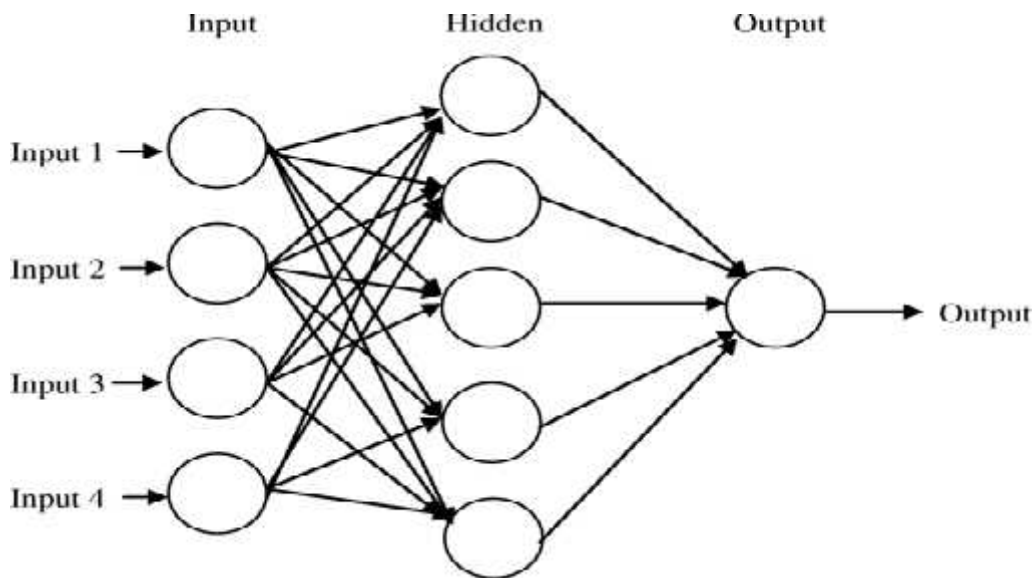


Fig. 4.15 Feed forward neural network with one output

4.5.3 Feed Forward Networks

Two fundamental kinds of networks are occurred in neural networks i.e. using feedback and without using feedback. In networks with feedback, the output values are applied back to input for tracking the input value. If the output is calculated for each input value, then this is called the network without feedback. If the information is flow in forward direction, then it is called as feed forward networks. There are different types of feed forward network. Back Propagation network come into the category of feed forward network. Radial Basis function is another type of network which include in this category. Figure 4.16 shows a Feed forward network [21].

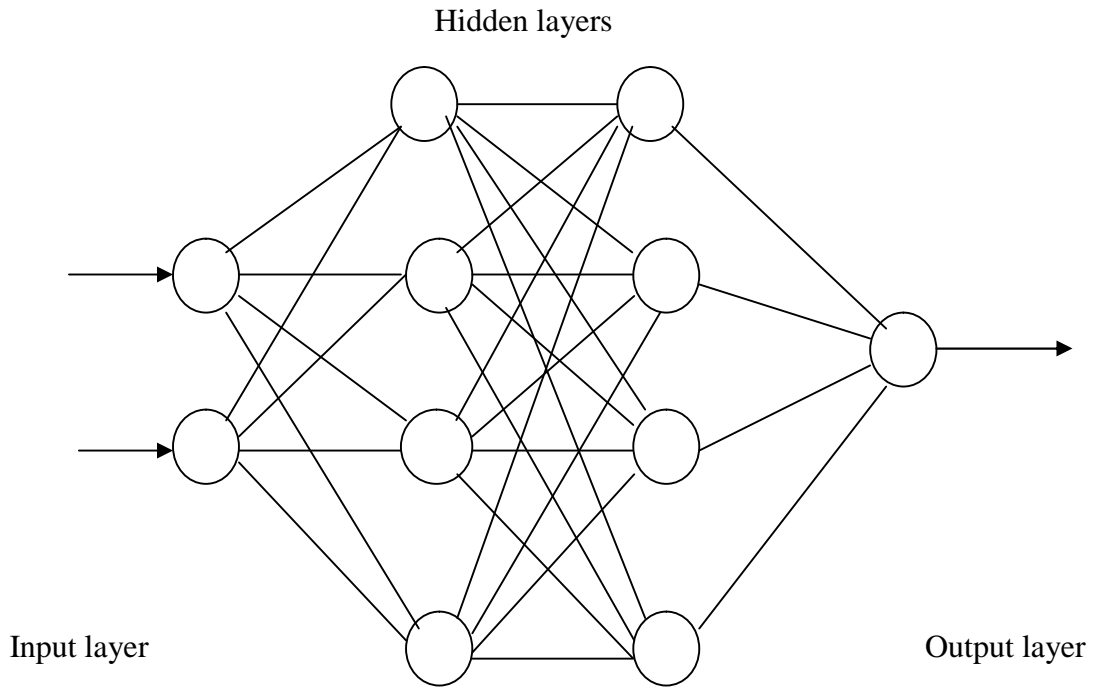


Fig.4.16 Feed forward neural network architecture

4.5.4 The Multilayer Perceptron Neural Network Model

The figure 4.17 shows a perceptron network with three layers. This network consists of input layer, one hidden layer and an output layer. Each layer contains three neuron. For each predictor variable in input layer, there is one neuron. In the perceptron neural network which is given in figure, the output of neuron that is u_j are connected to the input(s) of other neurons that is h_j with some weighted value .

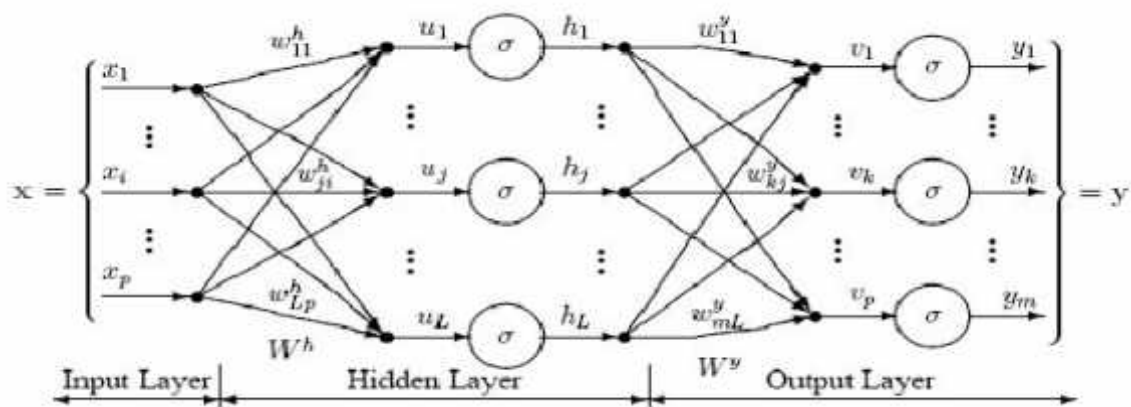


Fig. 4.17 Perceptron Network

4.5.5 Learning an Artificial Neural Network

There are two types of learning an artificial neural network namely supervised and unsupervised learning. We can change the weights of neuron by learning so that error will be minimum. As a stop criterion for the learning process, generally a total error E is used that is usually chosen to be the sum of the single error values. A new value of error is estimated after each iteration. This process will continue until we will get zero value of error or when network is unable to calculate error value.

In supervised learning, input and desire output data both are available to network. In this method, present output is compared to target or desire output. Then error will be generated if there is difference between present output and desire output. Then this error is propagated to network so that error will be minimized by modifying the value of weights. The data which contain both input and output data are known as training set. The neural network is trained with the help of training data set. The training data set should be large enough so that it contains all necessary information for network to train. The training set contain not only large data set but also contain large variety of data set, so that network will give best results for all types of input set i.e. test data set. Following process take place in supervised learning.

- 1) The pair of input-output is selected, then input data is applied to network for training purpose.
- 2) The input is propagated in forward direction through different layer i.e. input layer, hidden layer and reached to output layer.
- 3) The output of network is calculated and compared to desire output. If there is a difference, error e is calculated and added to the total error E .
- 4) If error value is not equal to zero, then weight are changed so that error value tends to zero.

The most commonly learning rule for this type is gradient descent rule. The algorithm stops when it reaches a local minimum. Sometime this rule is failed when minimum error is not reached.

In unsupervised learning algorithm, there are only input patterns. The self organizing map is example of this learning algorithm. In this learning method, network tries to map similar

input patterns to output that are similar to each other. The network is trained here without target. So in this, weights are modified by minimizing cost function. At the end of the learning phase, the weights would have been adapted in such a manner such that similar patterns are clustered into a particular node.

4.5.6 Perceptron learning rule

The perceptron learning rule is technique which is used for determining the weights of neural network. The perceptron is the simplest type of neural network. The perceptron classifies the classes which are linear separable. McCulloch and Walter Pitts proposed one type of neural model which give output 1 when weighted sum of inputs signal is greater than some threshold value, otherwise output will be zero. The neuron in perceptron model is same as neuron in McCulloch and Walter Pitts. This model contains a single neuron, adjustable weights and bias .In 1950, Rosenblatt introduced the perceptron network and introduced the perceptron learning rule for training perceptron network. He also proved that if the patterns belonged to linearly separable classes, then perceptron learning rule will converge and give accurate weights of network. In perceptron model, a single neuron performs only two classes classification.

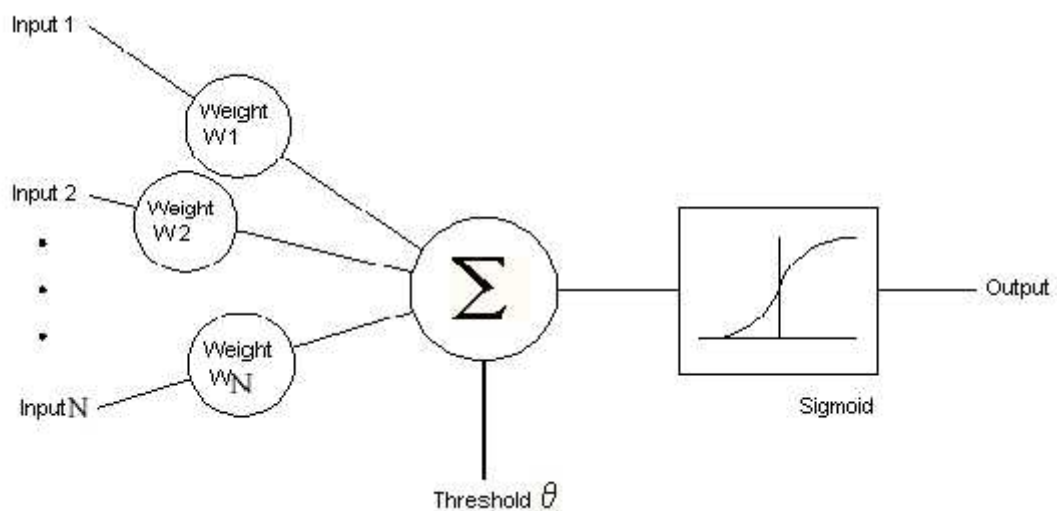


Fig. 4.18 Single layer perceptron network

The training technique which is employed to train Perceptron neural network is known as perceptron-learning rule. Perceptrons are used for pattern classification. Let us assume we contain set of training samples having an input vector p and a desired output $t(k)$. The desire

output $t(k)$ is either 1 or -1 for classification. The perceptron-learning rule is simple rule which is given below.

1. Firstly initialize the weights of network randomly for connection.
2. Secondly from the set of training samples chose an input vector p .
3. Now check for network output y_k . If it is equal to $t(k)$, stop the process otherwise change weights of network according to:

$$w_i = \alpha (t_k - y_k) p_i ; \quad (\alpha = \text{learning rate})$$

$$w_i (\text{new}) = w_i (\text{old}) + \alpha (t_k - y_k) p_i ; \quad w_i (\text{new}) \text{ is updated value of}$$

weight

4. Go back to step 2.

4.5.7 Back propagation Learning

The Perceptron learning rule is used for single layer neuron but for more than layer neuron network this training algorithm is not suitable because the output of hidden layer is not available for calculating the output and updating the weight. So for Multilayer perceptrons, the Perceptron learning algorithm is not used. For this, error back propagation learning is employed in which training is done in a supervised manner. Back propagation learning rule is based on the error-correction learning rule. In this learning rule, firstly input signal (vector) are applied into input layer and this signal is propagated in forward direction layer by layer through hidden layer to output layer. Then output vector is generated for applied input vector which is known as actual response of the neural network. This is called forward pass. In forward pass, weights of neuron are fixed. Now actual output are compared with desire output or target output. If the difference between actual output and desire output is not equal to zero, then error signal will be generated. This error signal is propagated in backward direction. So this is called as "error back propagation". Now according to perceptrons error correction rule, weights are updated for minimizing the error signal. In backward pass, weights of neurons are modified so that actual response tends to desire output.

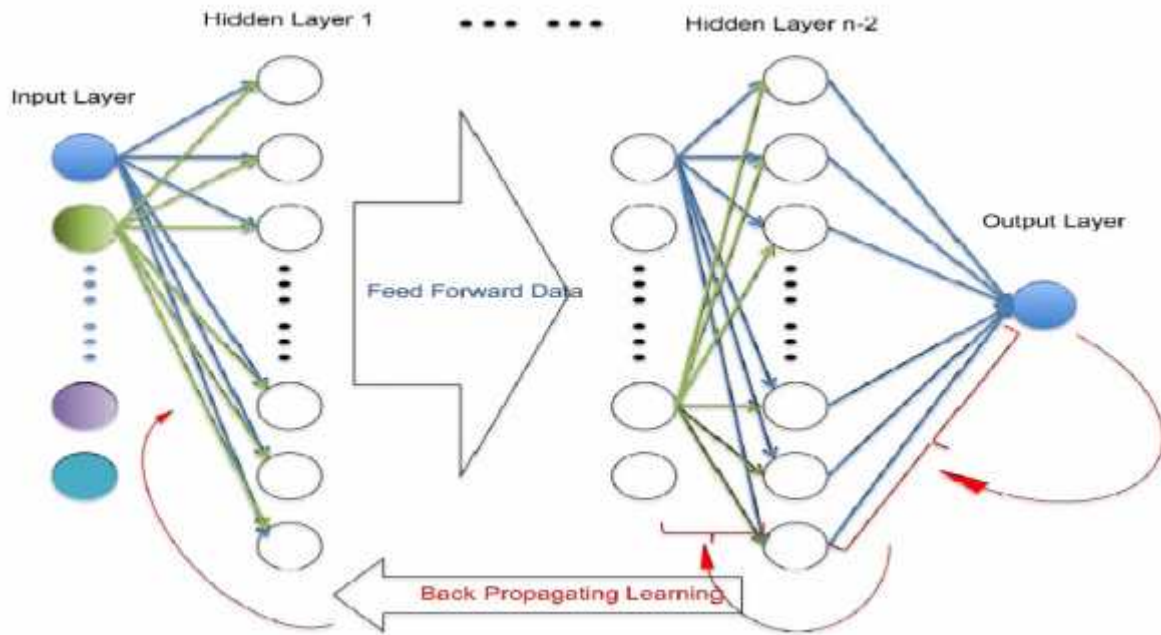


Fig. 4.19 A Feed-forward network with back propagation learning

The feed-forward network with back-propagation neural network is shown in above figure 4.19. It is fully connected. It means each neuron in a present layer is connected to its all neurons in the previous layer. Input data propagate the direction from left to right side (Feed Forward Data arrow) and learning process goes on left-to-right direction to adjust nodes weights to improve next trial (Back Propagating Learning arrow).

4.5.8 Multi-class pattern classification using neural networks

In this project, we are using multiclass pattern in which we have taken five classes. Back propagation Learning is applied here for classifying the classes of MRI. Multi-class pattern recognition is more difficult than two classes problems. There are many system are developed for classify binary classes.

Some example of neural network systems

There are two types of neural network architectures for multi class pattern classification. In first architecture has single neural network system with M outputs and second architecture consists of a system of multiple neural networks (see Fig. 4.20 (b) and (c)).

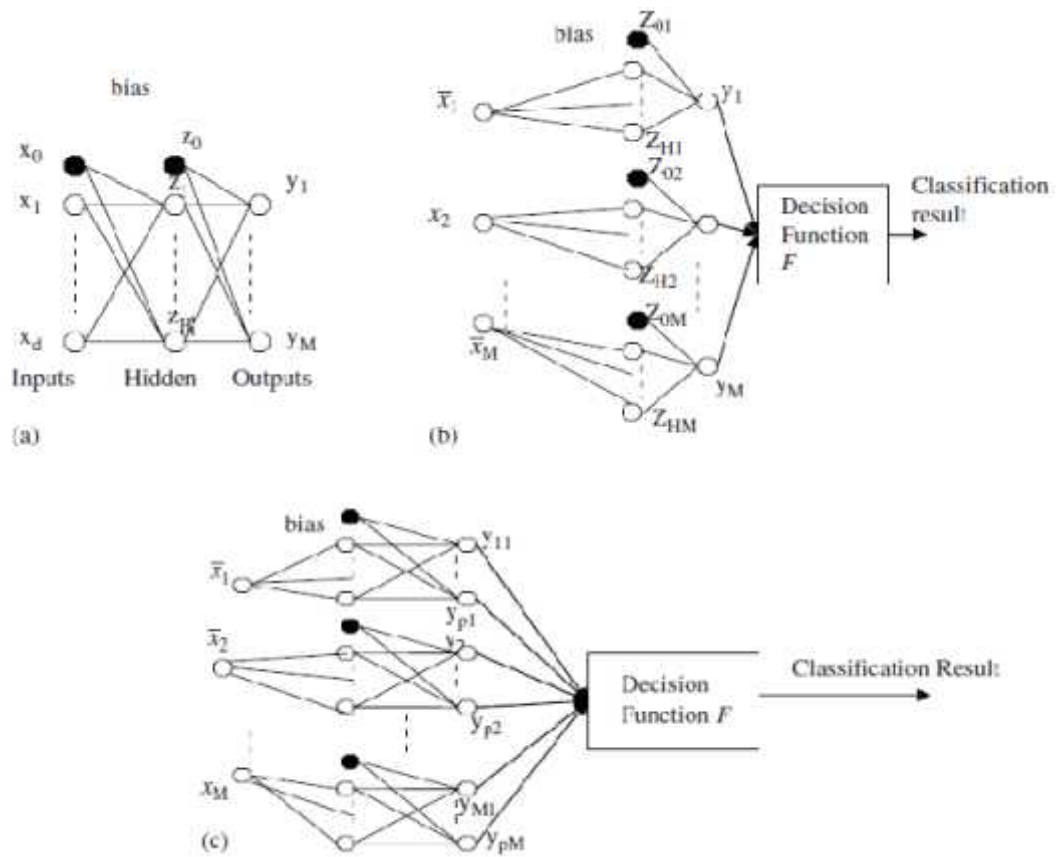


Fig. 4.20 Different neural network architectures for implementing N-class pattern classification.

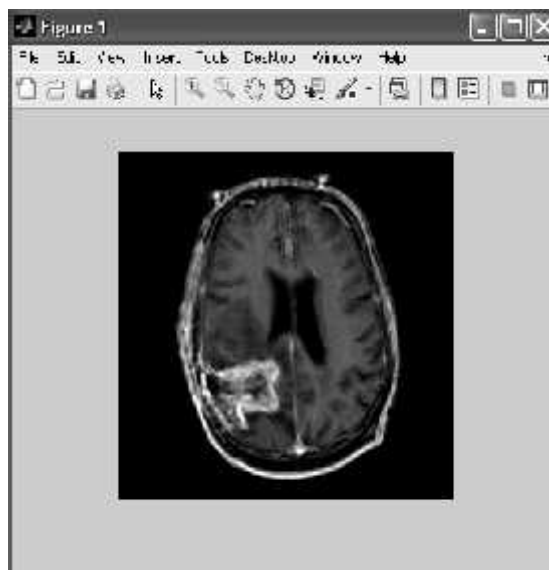
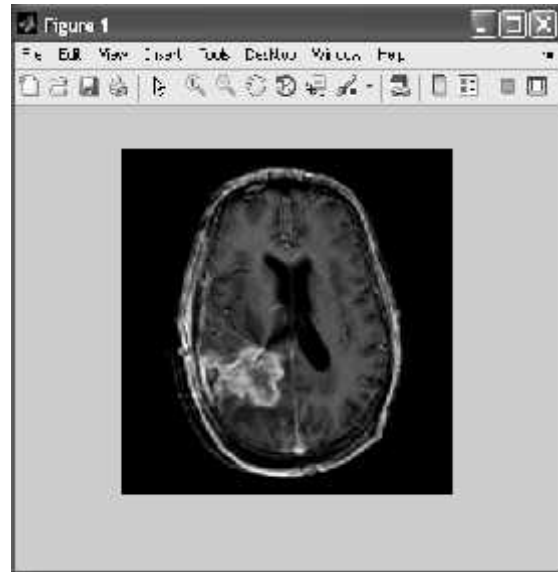
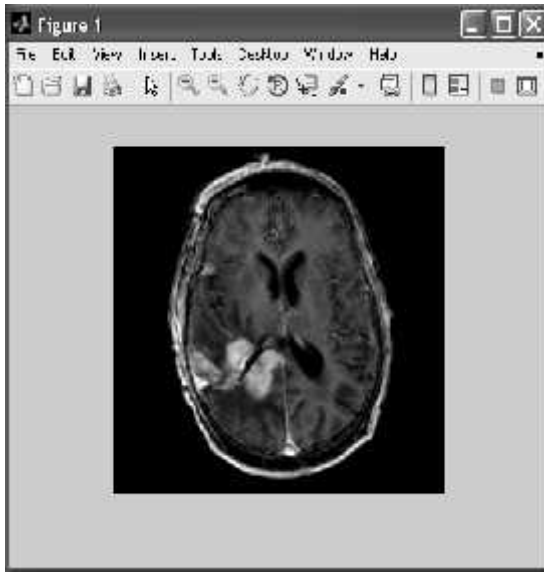
CHAPTER 5

SIMULATION RESULTS

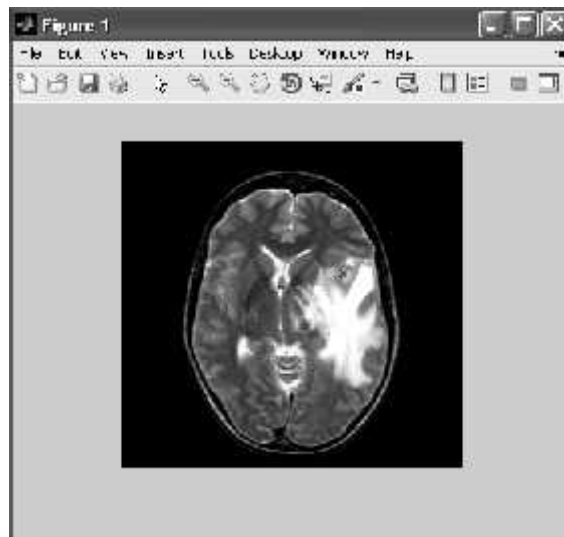
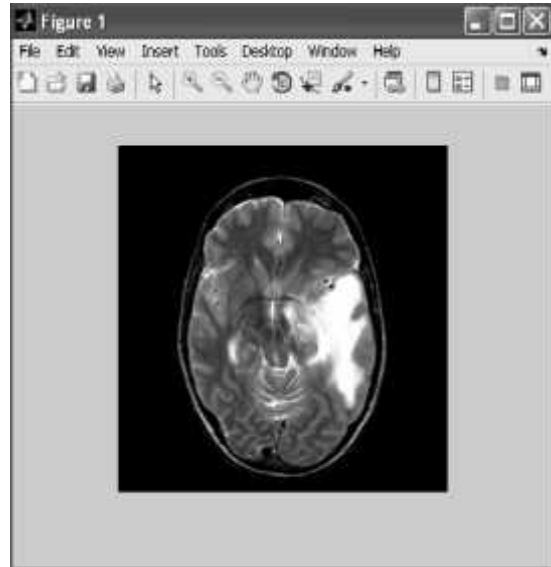
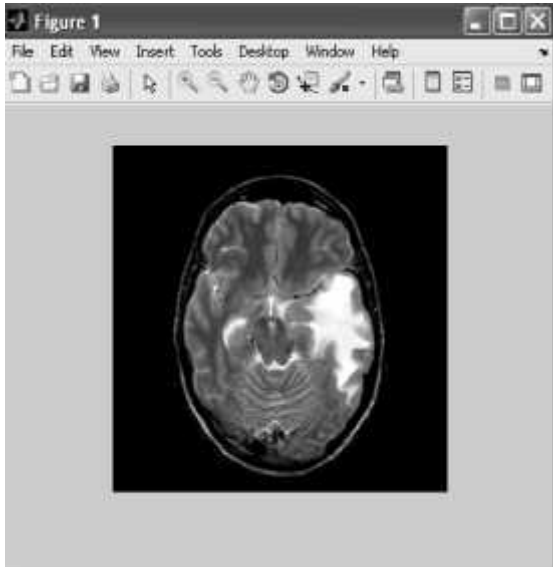
Following sets of MRI data are taken for training & testing purpose.

TRAINING DATA

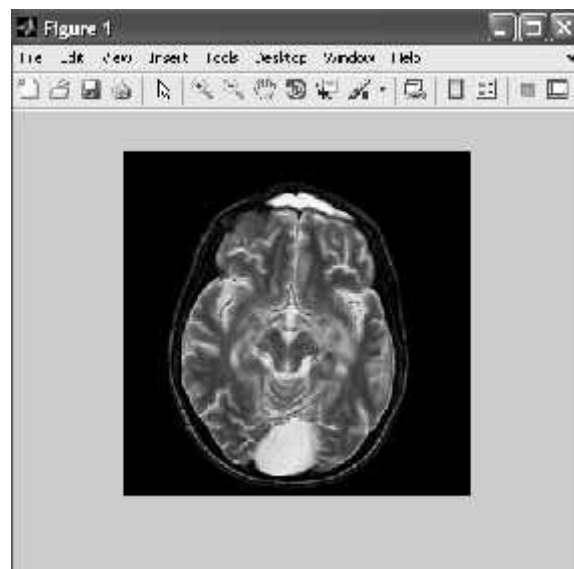
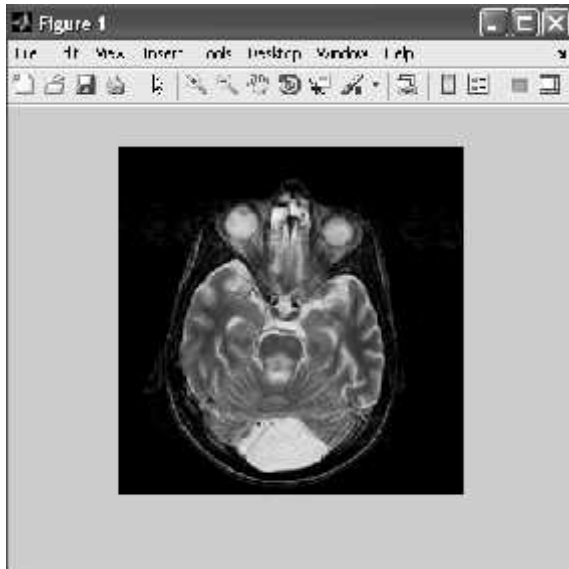
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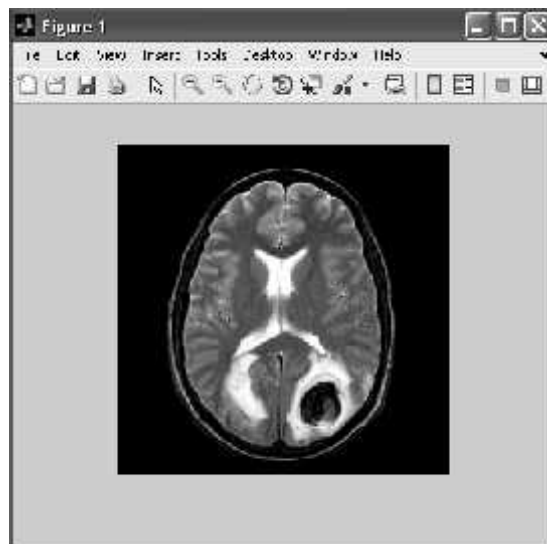
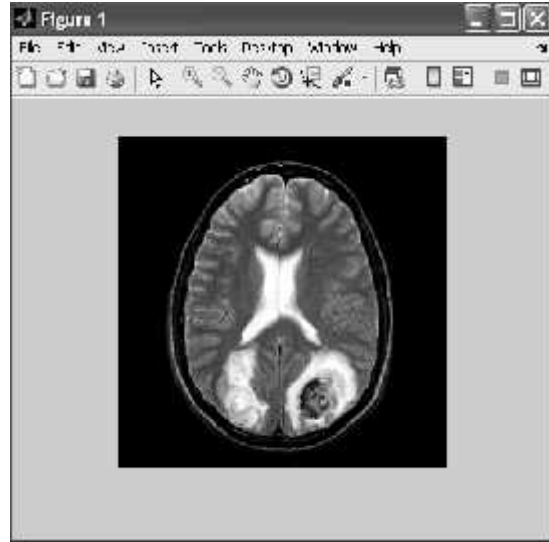
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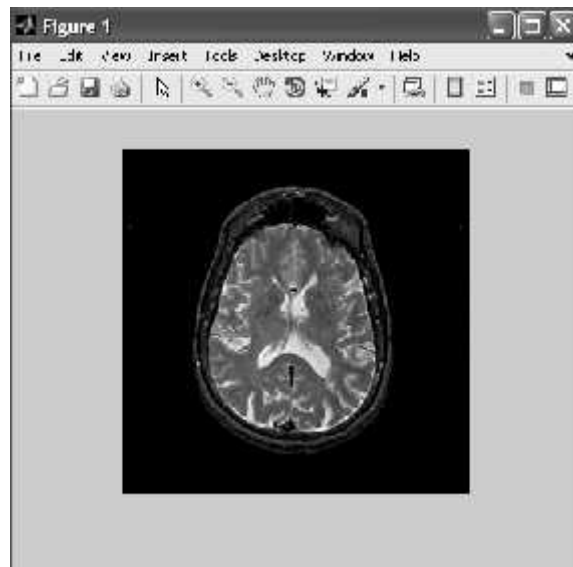
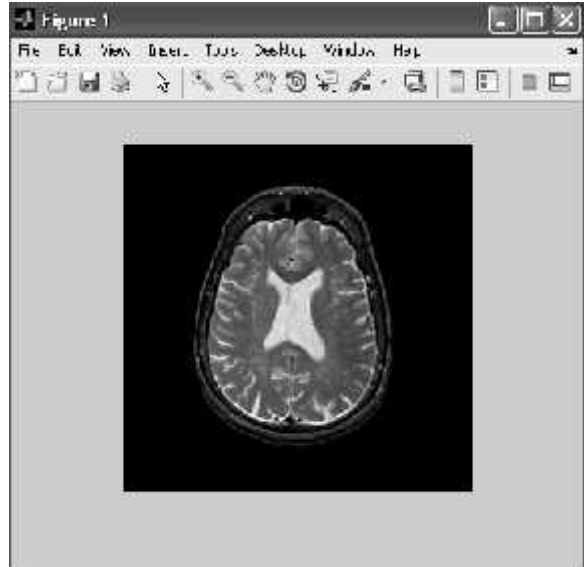
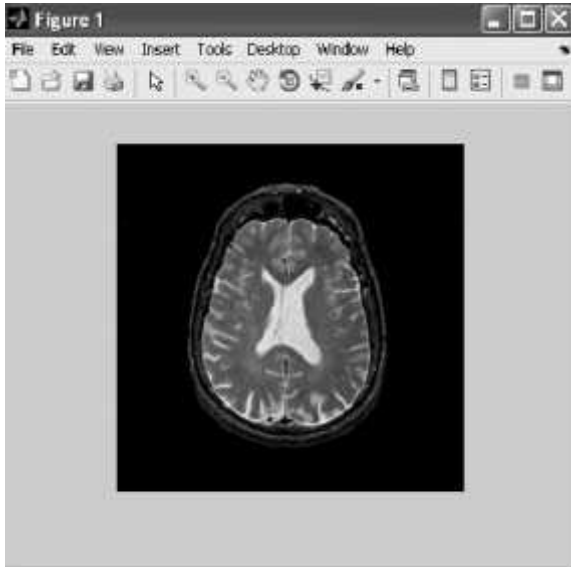
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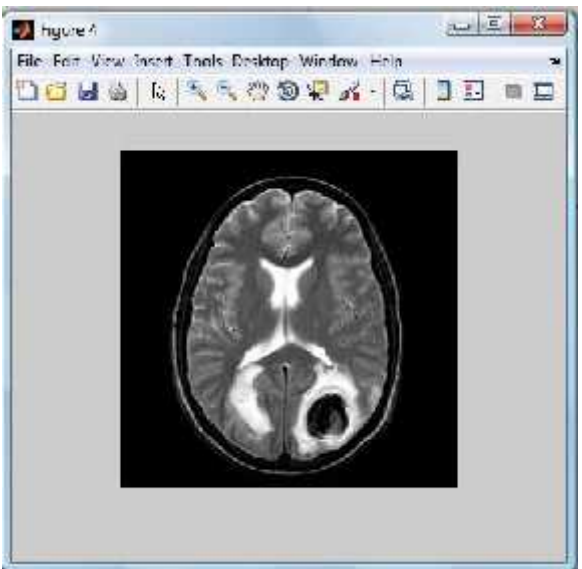
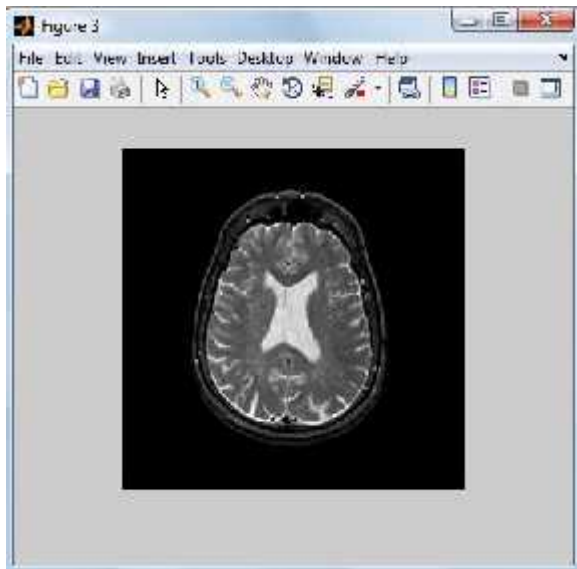
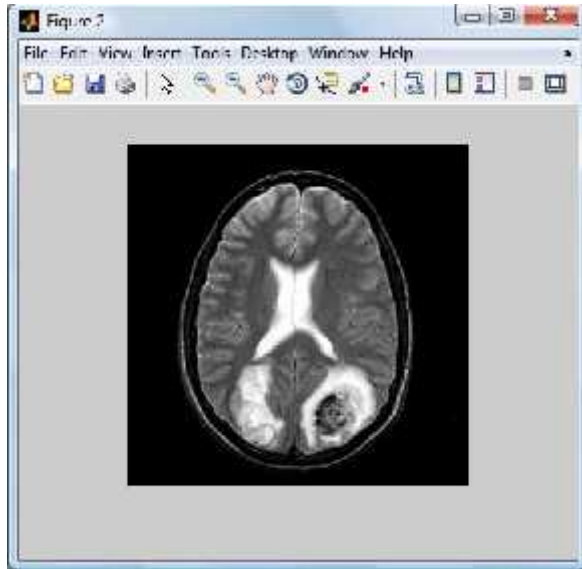
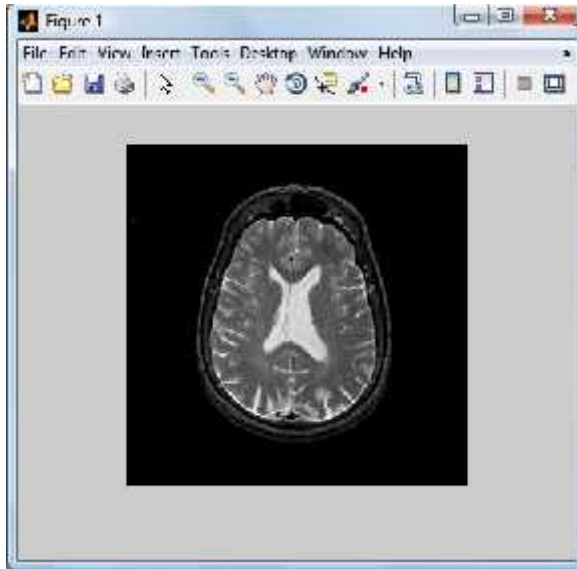
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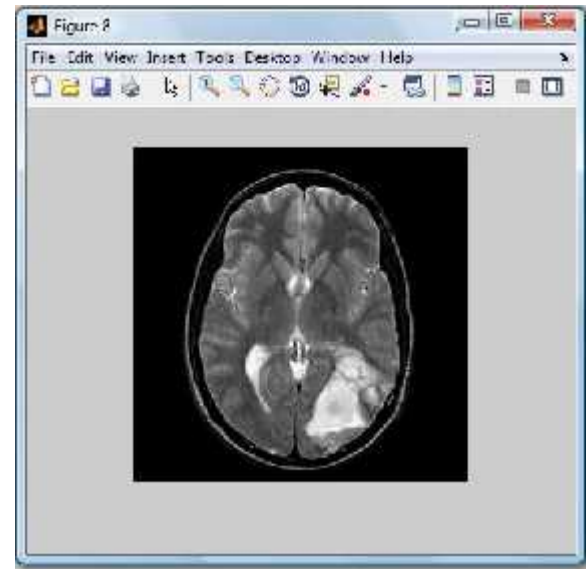
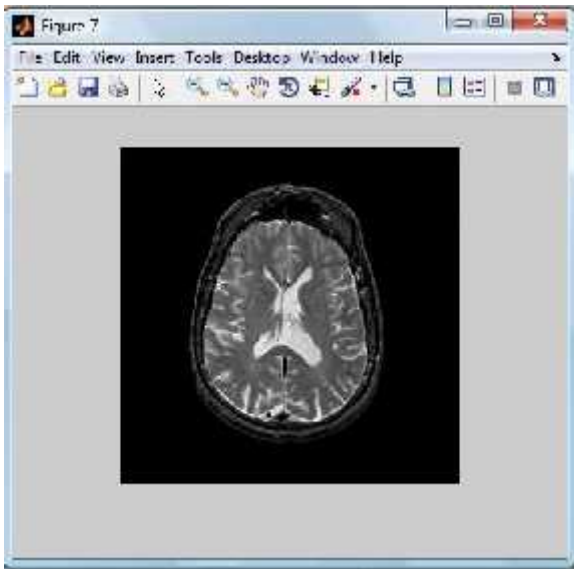
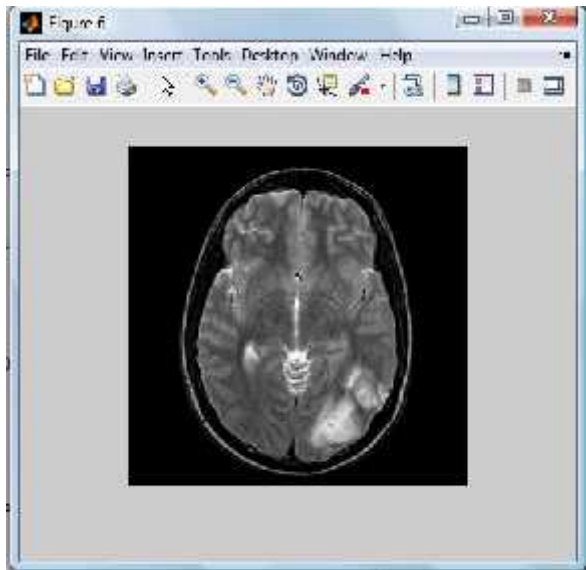
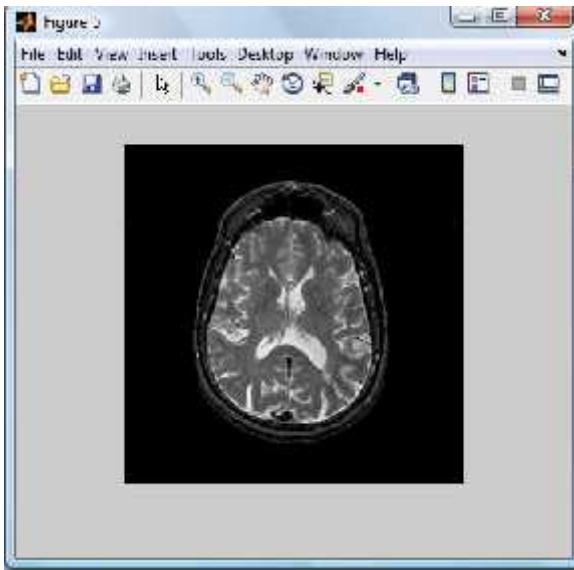


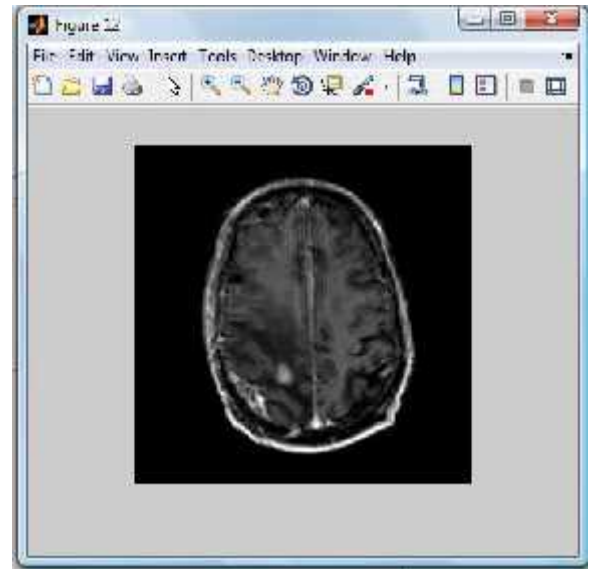
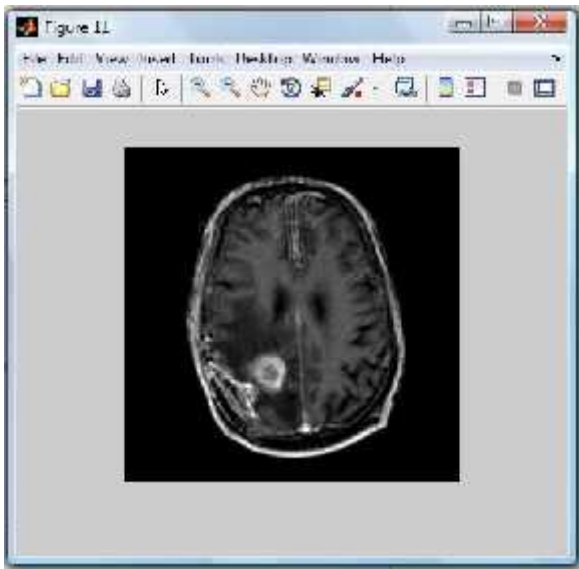
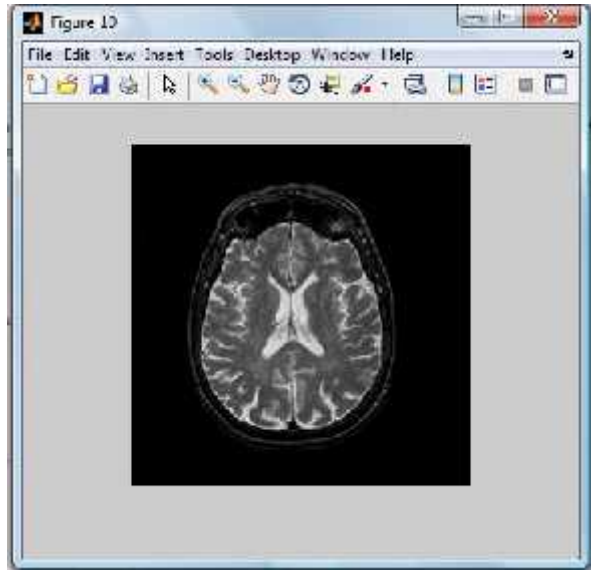
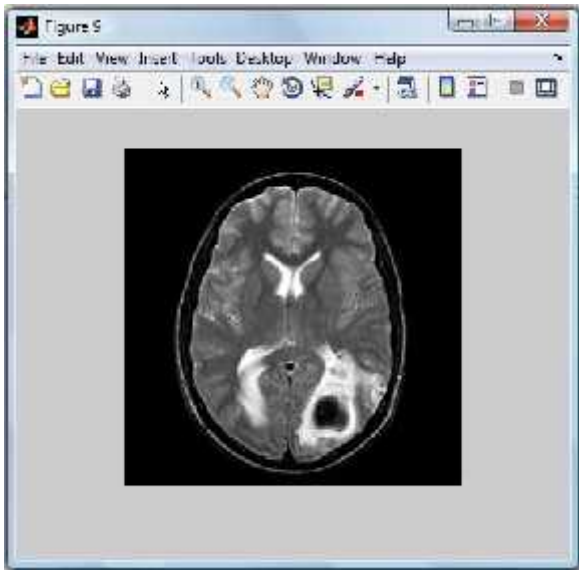
CLASS 5:

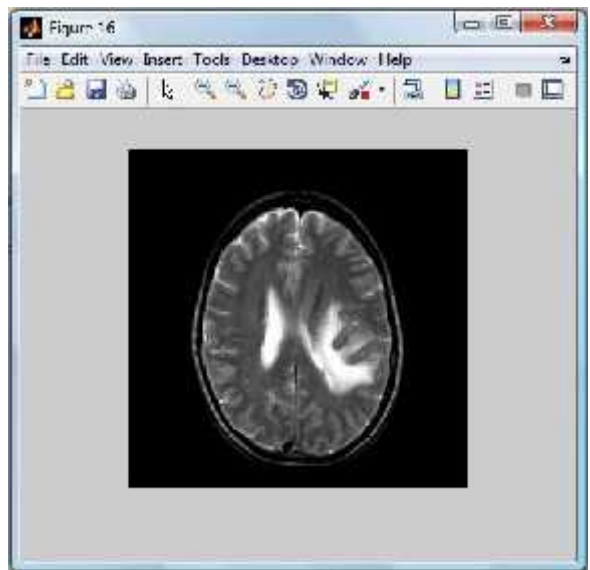
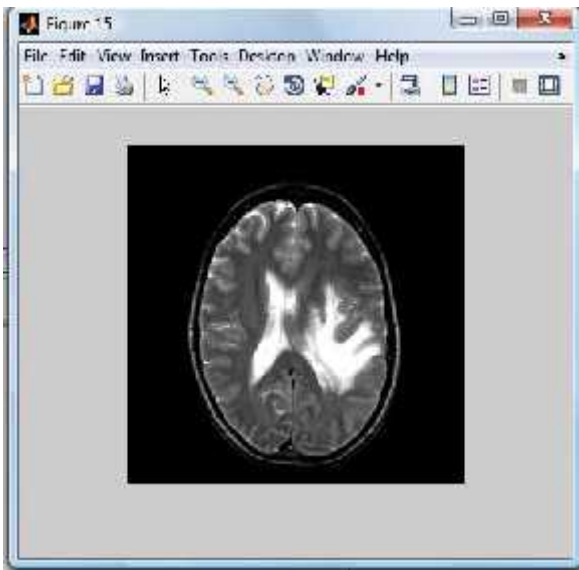
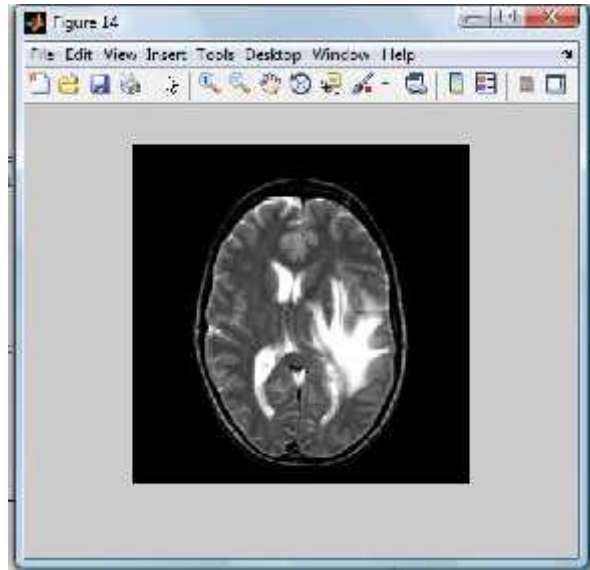
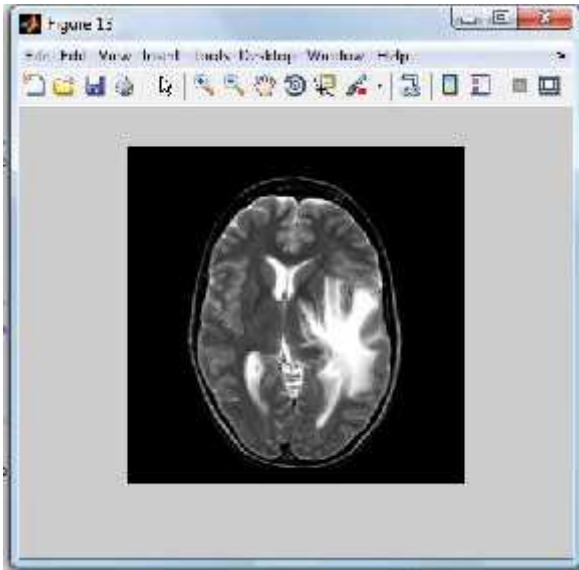


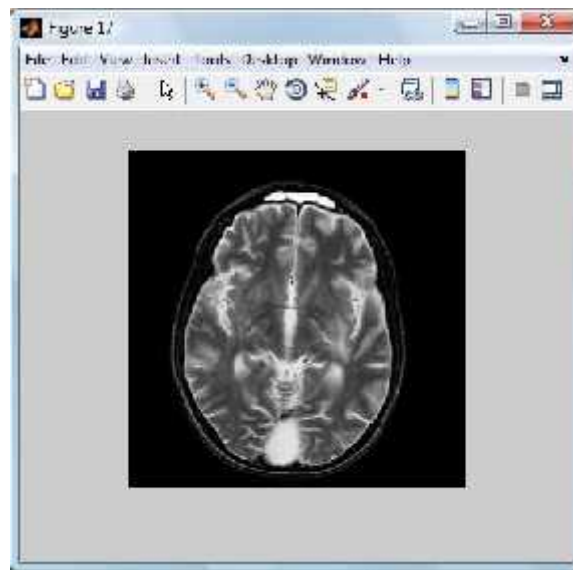
TEST DATA







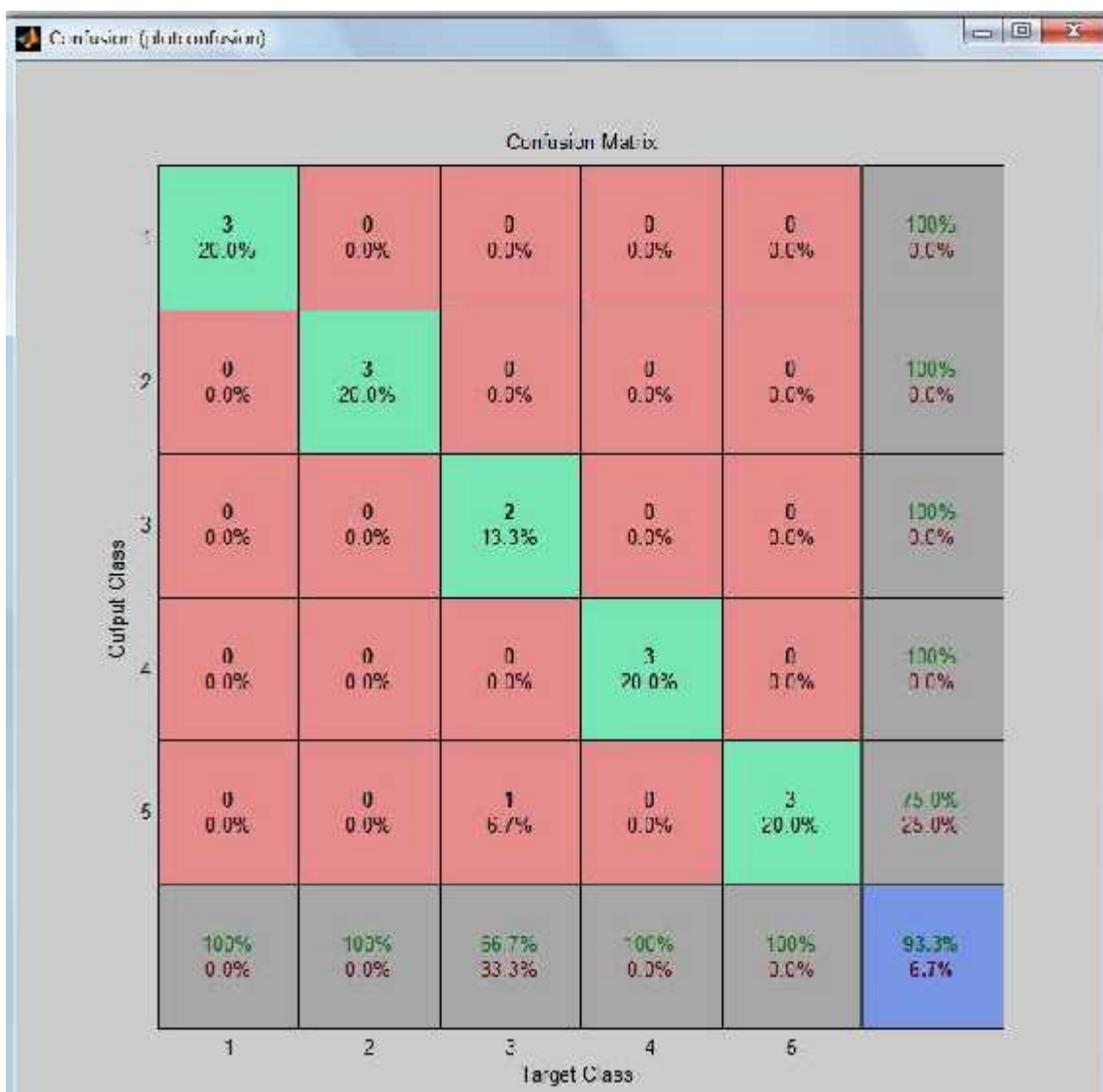




Five sets of Training data is taken. Each set contains three Images .One set contains normal MRI Images & rest four sets contain abnormal brain MRI images. Testing is done on 17 MRI images. The classification is done using artificial neural network & is implemented on MATLAB. For feature reduction, KPCA is used. There are various type of KPCA. In this project polynomial Kernel Principal Component Analysis is used which give good classification accuracy. The results are obtained in the form of confusion matrix where power of kernel is varied as shown below.

$$K(x_j, x_k) = (x_j^T x_k)^p$$

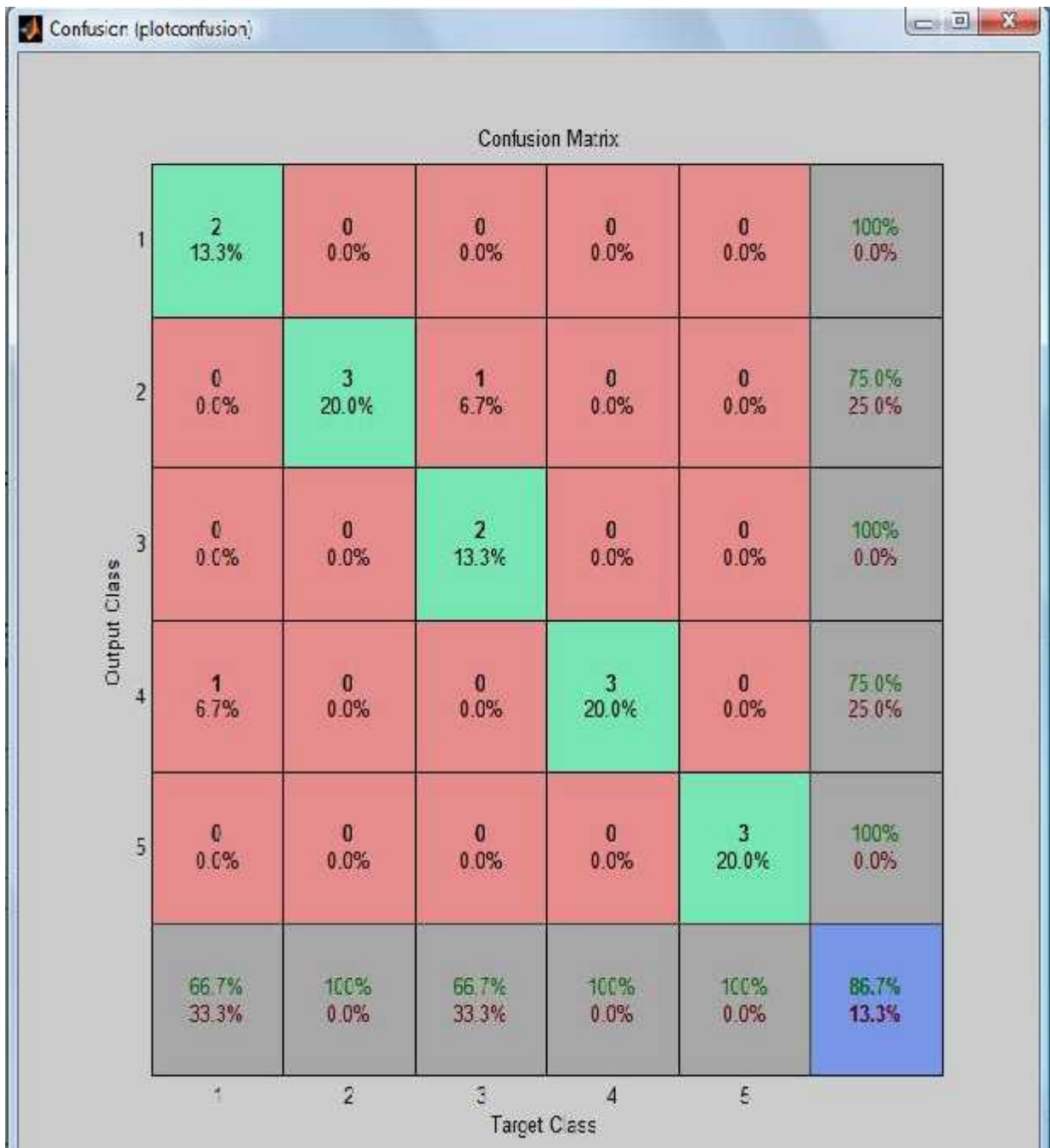
Where p is polynomial power



Kernel's power p=2

$$K_e(x_j, x_k) = (x_j^T x_k)^p$$

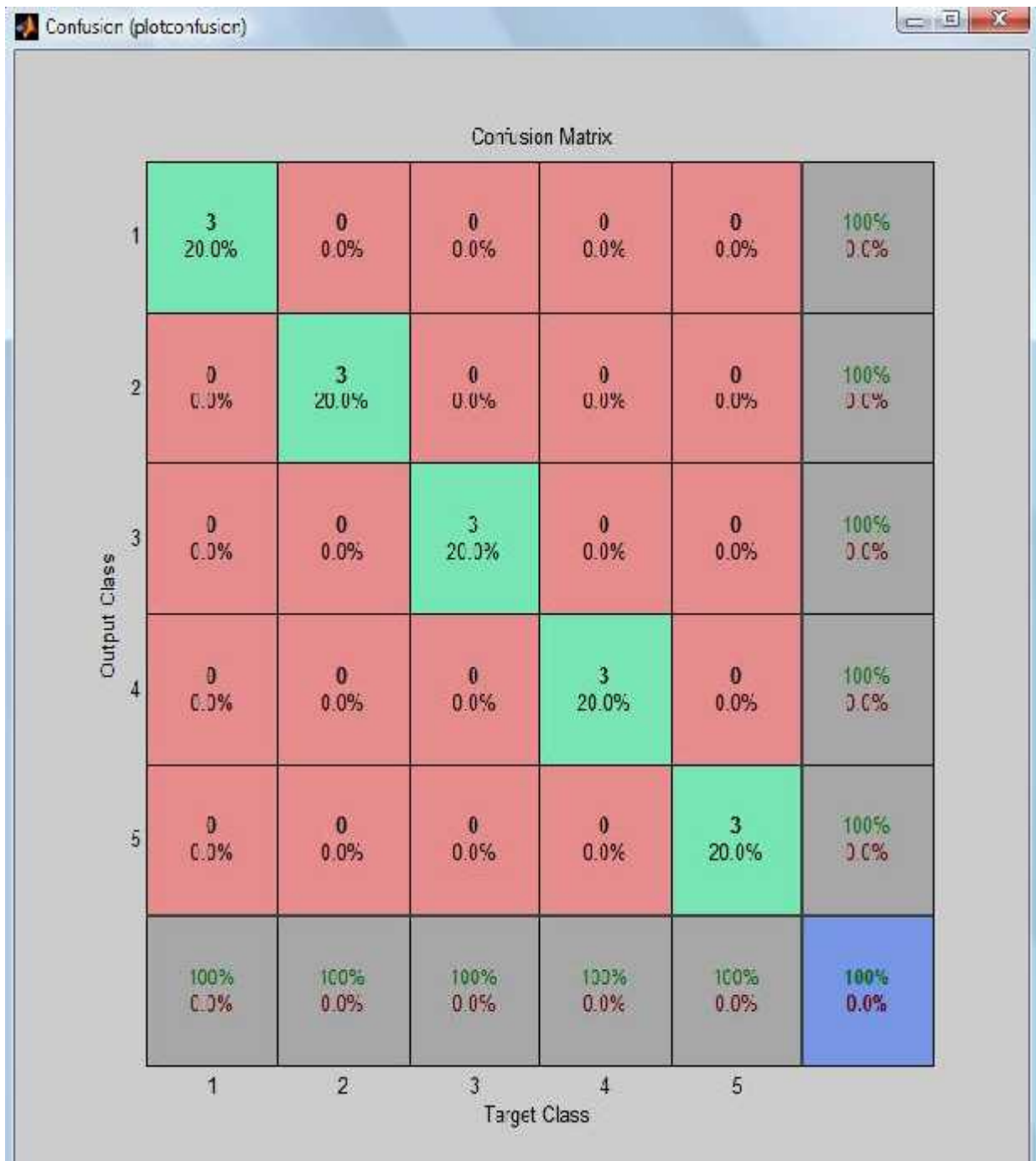
Where p is polynomial power



Kernel's power p=3

$$K(x_j, x_k) = (x_j^T x_k)^p$$

Where p is polynomial power



Kernel's power p=4

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

This work proposed the development of an automated brain MRI diagnostic system, which can classify whether the MR image belongs to a normal brain or pathological brain. For this purpose, five classes of training data have been taken. This work consists of following stages namely pre-processing, feature extraction, feature reduction and classification. In first stage, MR image is obtained & converted it into data form & then pre-processing is done for improving the quality of images. For this gamma correction is used to increase the contrast in MRI image. In second stage, we apply discrete wavelet transform (DWT) using Haar wavelet for obtaining the feature related to MRI images. Then Polynomial Kernel Principal component analysis is applied to get dominant features vectors & thus reducing the number of features vectors. Finally, for classification artificial neural network is used. Here, firstly neural network is trained using training data. Once, the neural network is trained classification is done on test data. We can obtain various classification rate by using different power of applied kernel. Confusion matrix obtained by classification give 93.7% accuracy with $p=2$, 86.7% accuracy with $p=3$, 100% accuracy with $p=4$. From above result, we can conclude that KPCA with kernel's power=4 gives best classification result.

6.2 Future Scope

Here, in this project, discrete wavelet transform (DWT) is used as feature extraction technique. According to latest research on brain MRI analysis, DWT gives best features vectors. There are various others transforms techniques available for extracting image features due to this DWT can be replaced by other method for obtaining the best result. So in future, we can modify our current work by adopting different feature extraction method so that higher classification rates can be obtained.

There are many possible directions for future work, which include the following:

- 1) In this project the number of medical image is less. For future work the number of brain medical images should be increased and using the real ones. By increasing the number of image, more training data set can be performed.

- 2) Perform the segmentation process to detect disease and also its size. The classification would be better performed after the segmentation method and the segmentation results will be used in classification.

- 3) Design a combining multiple classifiers that use different features such as texture features, Shape feature and size features, etc in order to get an accurate classification of the normal and abnormal brain image. A combined feature is more meaningful than the one feature representation alone and can significantly improve the performance.

REFERENCE

1. Harvard Medical School, Web, data available at <http://med.harvard.edu/AANLIB/>
2. Ethem Alpaydm, "Introduction to Machine Learning" Second Edition, The MIT Press Cambridge, Massachusetts London, England
3. I. Daubechies, "Ten lectures on wavelets", vol. 61 of CBMS-NSF Regional Conference Series in Applied Mathematics. Philadelphia, PA: Society for Industrial and Applied Mathematics (SIAM), 1992.
4. Horowitz, A. L. (1995), "MRI physics for radiologists", (3rd ed.) New York: Springer- Verlag
5. G. Strang and T. Nguyen, "Wavelets and Filter Banks", Wellesley-Cambridge Press, second edition, 1997. ISBN 0-9614088-7-1.
6. Stephane Mallat, "A WAVELET TOUR OF SIGNAL PROCESSING" Second Edition, Ecole Polytechnique, Paris Courant Institute, New York University, 1999, Elsevier (USA)
7. Buxton, R. B. (2002), "Introduction to functional magnetic resonance imaging: Principles and techniques", Cambridge: Cambridge University Press
8. E. Kokiopoulou and Y. Saad." PCA and kernel PCA using polynomial filtering: a case study on face recognition" November 16, 2004
9. Gerard Blanchet ,Maurice Charbit, "Digital Signal and Image Processing using MATLAB", TK5102.9.B545 2006 ,621.382'2--dc22
10. R. C. Gonzalez and R. E. Woods, "Digital Image Processing," 2nd edition, New Jersey, Prentice Hall, 2008.
11. Madhubanti Maitra , Amitava Chatterjee and Fumitoshi Matsuno, "A Novel Scheme for Feature Extraction and Classification of Magnetic Resonance Brain Images Based on Slantlet Transform and Support Vector Machine" , SICE Annual Conference 2008 ,August 20-22, 2008, The University Electro-Communications, Japan
12. N.Hema Rajini, R.Bhavani , "Classification of MRI Brain Images using k- Nearest Neighbor and Artificial Neural Network", IEEE-International Conference on Recent Trends in Information Technology, ICRTIT 2011, MIT, Anna University, Chennai. June 3-5, 2011
13. Xunheng Wang, Yun Jiao, Zuhong Lu, "Discriminative Analysis of Resting-state Brain Functional Connectivity patterns of Attention-Deficit Hyperactivity

Disorder using Kernel Principal Component Analysis”, 2011 Eighth International Conference on Fuzzy Systems and Knowledge Discovery (FSKD), 978-1-61284-181-6/11/\$26.00 ©2011 IEEE

14. Mohd Fauzi Othman and Mohd Ariffanan Mohd Basri, “Probabilistic Neural Network for Brain Tumor Classification”, 2011 Second International Conference on Intelligent Systems, Modelling and Simulation, 978-0-7695-4336-9/11, © 2011 IEEE.
15. M. Shasidhar, V.Sudheer Raja and Vijay Kumar, “MRI Brain Image Segmentation Using Modified Fuzzy C-Means Clustering Algorithm”,978-0-7695-4437-3/11 \$26.00 © 2011 IEEE
16. Noramalina Abdullah, Lee Wee Chuen, Umi Kalthum Ngah, Khairul Azman Ahmad, “Improvement of MRI Brain Classification using Principal Component Analysis”, 2011 IEEE International Conference on Control System, Computing and Engineering
17. Vinod Kumar, Jainy Sachdeva, Indra Gupta, Niranjan Khandelwal, Chirag Kamal Ahuja, “Classification of brain tumors using PCA-ANN”, 978-1-4673-0126-8/11/2011 IEEE
18. Daniel Olsson, Master's Thesis Report Applications and Implementation of Kernel Principal Component Analysis to Specific Data Sets, January 28, 2011
19. V.P.Gladis Pushpa Rathi and Dr.S.Palani, “A Novel Approach For Feature Extraction And Selection On MRI Images For Brain Tumor Classification” pp. 225–234, 2012
20. Amer Al-Badarnah, Hassan Najadat, “A Classifier to Detect Tumor Disease in MRI Brain Images”, 2012 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining
21. S.N.Deepa & B.Aruna Devi, “Artificial Neural Networks design for Classification of Brain Tumour” 2012 International Conference on Computer Communication and Informatics (ICCCI -2012), Jan. 10 – 12, 2012, Coimbatore, INDIA
22. Quan Wang, “Kernel Principal Component Analysis and its Applications in Face Recognition and Active Shape Models”arXiv:1207.3538v1 [cs.CV] 15 Jul 2012
23. Shahla Najafi, Mehdi Chehel Amirani, and Zahra Sedghi, “A New Approach to MRI Brain Images Classification”, pp 2012 IEEE

24. Mubashir Ahmad, Mahmood ul-Hassan, Imran Shafi, Abdelrahman Osman, "Classification of Tumors in Human Brain MRI using Wavelet and Support Vector Machine", IOSR Journal of Computer Engineering (IOSRJCE) ISSN: 2278-0661, ISBN: 2278-8727 Volume 8, Issue 2 (Nov. - Dec. 2012), PP 25-31, www.iosrjournals.org
25. Lavneet Singh and Girija Chetty, "Detecting The Brain Abnormalities From MRI Structural Images Using Machine Learning And Pattern Recognition Tools", IJREISS Volume 2, Issue 11 (November 2012) ISSN: 2250-0588
26. Devvi Sarwinda, Aniat M. Arymurthy, "Feature Selection Using Kernel PCA for Alzheimer's Disease Detection with 3D MR Images of Brain", ICACSYS 2013 ISBN: 978-979-1421-19-5
27. Walaa Hussein Ibrahim, Ahmed Abdel Rhman Ahmed Osman and Yusra Ibrahim Mohamed, "MRI Brain Image Classification Using Neural Networks", 2013 International Conference On Computing, Electrical And Electronics Engineering (Iccee), 978-1-4673-6232-0/13/\$31.00 ©2013 IEEE
28. D. SRIDHAR, MURALI KRISHNA, "Brain Tumor Classification Using Discrete Cosine Transform and Probabilistic Neural Network", 2013 International Conference on Signal Processing, Image Processing and Pattern Recognition [ICSIPR], 978-1-4673-4862-1/13/\$31.00 ©2013 IEEE
29. V. Amsaveni, N. Albert Singh, "Detection of Brain Tumor using Neural Network" 4th ICCCNT – 2013 July 4-6, 2013, Tiruchengode, India
30. Ms. Suchita Goswami and Mr. Lalit kumar P Bhaiya, "Brain Tumour Detection using Unsupervised Learning based Neural Network", 2013 International Conference on Communication Systems and Network Technologies
31. Hari Babu Nandpuru, Dr. S. S. Salankar and Prof. V. R. Bora, "MRI Brain Cancer Classification Using Support Vector Machine", 2014 IEEE Students' Conference on Electrical, Electronics and Computer Science

