Brain Tumor Detection and Optimization using Hybrid Classification Algorithm

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Abstract

Brain tumor classification plays an important role in clinical diagnosis and effective treatment. In this work, we propose a method for brain tumor classification using an ensemble of deep features and machine learning classifiers. In our proposed framework, we adopt the concept of transfer learning and uses several pre-trained deep convolutional neural networks to extract deep features from brain magnetic resonance (MR) images. The extracted deep features are then evaluated by several machine learning classifiers. The top three deep features which perform well on several machine learning classifiers are selected and concatenated as an ensemble of deep features which is then fed into several machine learning classifiers to predict the final output. Brain tumor MRI images of different patients at different stages can be used to diagnose tissue. There are various types of feature extraction and SVM separation methods used to detect brain tumor in MRI images. The Neural Network image segmentation algorithm helps detect the tumor early with high accuracy. We have proposed feature extraction of the hybrid method (SVM and Artificial Neural Network) to find tumor cells that provide approximately 98% accuracy.

Keywords: deep learning; ensemble learning; brain tumor classification; machine learning; transfer learning

INTRODUCTION

1.1 INTRODUCTION

Digital image processing (DIP) is an emerging field in biological sciences such as tumor detection and classification, cancer detection and classification, and testing and examining critical parts of the human body. Automatic brain tumor detection plays a significant role in medical science [1]. The human body is composed of different types of cells where the brain (also the processor of the body) plays a very significant role [2]. The most significant portion of our nervous system is the brain. Moreover, it is the kernel of the human central nervous system.

The brain is a complex organ that contains 50–100 billion neurons. It is made up of a large number of cells, and each cell has a specific function. Most of the cells that are generated in the body partition to form new cells for appropriate functioning of the human body. When new natural cells grow, aged or damaged cells die. Then, new cells take their place. Sometimes, new cells are generated when the body does not need them. Moreover, aged or damaged cells do not die as they should. The body produces extra cells that construct a lump of tissue called a tumor. A tumor inlaid in the brain region causes the sensitive functioning of the body to be malformed. It is very difficult and perilous to treat due to its location and spreading capability [3–5]. Brain tumors are primarily categorized into two types: benign and malignant. Benign tumors are those tumors which are non-cancerous, and malignant ones are those which contain cancerous cells [6].

The early detection and recognition of brain tumors is very crucial. Presently, computer-aided diagnosis (CAD) systems are usually used for systematic and specific detection of brain abnormalities [7]. A brain tumor is the unnatural growth of tissue or central spine that can interrupt the proper function of the brain [8]. From the report of the national cancer institute statistics (NCIS), death rate on account of brain cancer for USA is 12,764 per year, 1063 per month, 245 per week, and 34 per day. It shows that it is very significant to diagnose brain tumor in advanced levels to save lives. Moreover, the processes of tumor detection should be done with very high speed and accuracy. This is only possible by using magnetic resonance (MR) images, and suspicious regions are extracted through MR image segmentation from complex medical images. The detection of a brain tumor is manually done by experts.

However, there are some problems, such as it taking a large amount of time, and segmentation of MR image by different experts may vary significantly. Moreover, the result of tumor detection may vary under different circumstances by the same physician, and the brightness and contrast of the display screen can vary the segmentation results. For these reasons, the automatic detection of brain tumors becomes significant. Automatic detection of brain tumors can increase the probability of survival of a tumor. In the medical field, there is no standard method that can be constructed for brain-tumor detection. Several research works are attempting to detect brain tumors automatically with improved accuracy, exactness, and speed of computation by minimizing manual effort [9].

The detection of brain tumors means identifying not only the affected part of the brain but also to the tumor shape, size, boundary, and position. Different imaging technologies such as magnetic resonance image (MRI), computed tomography (CT), positron emission tomography (PET), etc. are used for imaging the brain. Most frequently, the anatomy of the brain tumor can be tested by MRI scan or CT scan. However, the CT scan contains radiation that is detrimental to human body, whereas MRI gives accurate visualization of the anatomical formation of tissues of the brain [10]. The MRI is a device that conducts a magnetic field and radio waves for generating detailed images of the organs and tissues. Processing of MR images are extremely complicated and constantly scrutinized by researchers to give pathologists an improved experience to diagnose the patients [11].

The theme of this thesis is varied strategies of image segmentation applied on medical pictures. This chapter can begin by outlining the essential drawback of segmentation and inspire its importance in several applications. Fashionable medical imaging modalities like magnetic resonance imaging and CT scans generate larger and bigger pictures that can not be analyzed manually. This drives the need for additional economical and study image analysis strategies, tailored to the issues encountered in medical pictures. The aim and motivation of this thesis area unit directed towards the matter of segmenting brain magnetic resonance imaging pictures.

Image segmentation is that the drawback of partitioning a picture into significant regions on the premise of grey-level, color, texture. This means the generality of the problem- segmentation may be found in any image-driven method, e.g. fingerprint/text/face recognition, trailing of moving people/cars/airplanes, etc. for several applications, segmentation reduces to finding associate in nursing object in a picture. This involves partitioning the image into two categories of regions - either object or background. It's merely not possible in apply to manually method all the pictures (like magnetic resonance imaging and CT scan), owing to the overwhelming quantity of data it provides. Therefore we have a tendency to style algorithms that search for bound patterns and objects of interest and place them to our attention. To Illustrate, area unit centre standard application is to look and match illustrious faces in your photograph library that makes it attainable to mechanically generate photograph collections with a precise person. a crucial a part of this application is to section the image into"Face" and "background". this may be tired variety of the way, and it's well accepted that no general purpose segmentation rule exists, or that it ever are going to be made-up. Thus, once planning a segmentation rule, the appliance is often of primary focus: ought to we have a tendency to section the image supported edges, lines, circles, faces, cats or dogs.

Image segmentation is the way toward parceling an advanced picture into numerous sections (sets of pixels, otherwise called super pixels). The objective of division is to disentangle as well as change the portrayal of a picture into something that is more important and simpler to investigate. Segmentation is regularly used to find articles and limits (lines, bends, and so forth.) in pictures[1]. All the more exactly, picture division is the way toward doling out a name to each pixel in a picture to such an extent that pixels with a similar mark share certain visual attributes The aftereffect of segmentation is an arrangement of fragments that on the whole cover the whole picture, or an arrangement of forms separated from the picture (see edge identification). Each of the pixels in a district is comparable as for some trademark or registered property, for example, shading, force, or surface. Neighboring areas are altogether unique regarding the same characteristic(s). At the point when connected to a pile of pictures, common in medicinal imaging, the subsequent forms after picture division can be utilized to make 3D recreations with the assistance of addition calculations like walking 3D squares [1].

A brain tumor is a cancerous or non-cancerous growth of abnormal cells in the brain, which leads to benign or malignant brain tumors. Most of the researchers are engaging in the primary type of tumor such as Gliomas. We have some ways to treat gliomas such as chemotherapy, radiotherapy, and surgery. Automation by computer-aided devices can be used to obtain the necessary clinical data such as tumor presence, location, and type. However, it is still a very challenging task in assessing their shape, volume, boundaries, tumor detection, size, segmentation, and classification. Also, brain tumor intensity varies from individual to individual. Magnetic Resonance Imaging (MRI) is preferred over other treatment and diagnosis methods because it gives superior image contrast in soft tissues and has non-invasive property. On applying different pulse sequences, we obtain a different type of MRI scans, such as (1) T1 weighted scans that distinguish between tumor and healthy tissues. (2) T2 weighted scans cause delineation of the edema region, and ultimately we get a bright image region. (3) T4-Gd scans which gives bright signal at tumor border by using a contrast agent. (4) FLAIR scans differentiate between cerebrospinal fluid (CSF) and edema region by using a signal of water molecule suppression. It is a difficult task to do annotation of brain tumors from MRI scans manually. Hence, there is a strong need for automation of brain tumor segmentation and classification with the help of computer vision and machine learning algorithms.

The challenging task in Brain Tumor is due to high variability and inherent MRI data characteristics, e.g., variability in tumor sizes or shapes, tumor detection, area calculation, segmentation, classification, and finding uncertainty in segmented region. The most significant task in image understanding is image segmentation because it helps in feature extraction, area calculation, and significance in many real-life applications. It can be used, for example, estimation of tumor volume, tissue classification, blood cell delineation, and localization of tumors, matching of an atlas, surgical planning, and image registration. For monitoring oncologic therapy, the accurate and morphology quantification of tumors is a critical task. However, extensive scale work has been performed in this field; but still; clinicians depend on manual determination of tumor, due to lack of link between researchers and clinicians.

1.2 ISSUES OF OLD ARTICLES

Diagnostic imaging is a useful tool in drugs nowadays. The technologies like resonance imaging (MRI), X-radiation (CT), and alternative imaging modalities have relieved data of traditional and pathological anatomy for medical analysis and area unit an important part in identification and treatment coming up with [2].

The potential of intelligent knowledge analysis techniques has up with the increasing quantity of knowledge on the market digitally. With enhancements in laptop performance and development of the digital devices opportunities are created to use multimedia system knowledge, admire pictures and voice. In existing storage systems, a amount of information that our system is ready to store associated an index entry is created once information is keep. once users wish to retrieve some item of data, they use the index to seek out the specified item. it's tough to seek out one thing accurately and quickly from among the various complicated things in an exceedingly information due to the massive index house for the info being searched.

Methods for acting the segmentation vary wide reckoning on the particular application, and a number of other factors. Let's say, the segmentation of brain tissue has completely different necessities from the segmentation of the liver and also the segmentation of the Brain pictures. General factors admire noise, partial volume effects, and motion also can have important consequences on the performance of segmentation algorithms.[2] what is more, each imaging modality has its own options with that to contend. At present, there's no single segmentation technique that is capable to allow satisfactorily results for each medical image. But, ways do exist that area unit additional general and can also be applied to a range of knowledge. However, completely different ways that area unit specialized to explicit applications will typically accomplish higher performance. Choice of associate acceptable approach to a segmentation downside will so be a tough downside.

Recently, many techniques have been proposed for automatic brain tumor classification that can be categorized into machine learning (ML) and deep learning (DL) techniques based on the feature selection and learning mechanism. In ML approaches, feature selection and extraction is essential for classification. However, DL approaches extract and learn the features from the image directly. Recent DL approaches, particularly CNN provides good accuracy and is widely used in medical image analysis. Moreover, they have disadvantage over traditional methods (ML) as they need large dataset for training, have high time complexity, less accurate for applications where we have availability of small dataset and require expensive GPUs which ultimately increases cost to the users. Additionally, selecting the right deep learning tools is also a challenging task as it needs knowledge regarding various parameters, training method, and topology. On the other hand, machine-learning approaches have played key role in the area of medical imaging. Several learning based classifiers have already been used for classification and detection of brain tumors, which includes – support vector machine (SVM), artificial neural network (ANN), sequential minimal optimization (SMO), fuzzy C mean (FCM), Naïve Bayes (NB), Random Forest (RF), Decision Tree (DT) and K-Nearest Neighbor (KNN). KNN implementation is very simple and takes less computation and space complexity. It requires very less parameters to tune. The biggest advantage of DT is that it goes through all the outcomes of decision and finally traces each path to reach the conclusion. It is versatile; no complex mathematics involved, which makes it easy to understand. Further, Random Forest is itself ensemble classifiers of DT. It runs effectively on large dataset, which provides good parameter values for accuracies, precision and other evaluation metrics. Overall, these classifiers have received considerable research attention, as they require small dataset for training, low computational time complexity, low cost to the users, and can be easily adopted by less skilled people. Thus, in the present study, we work on hybrid ensemble classifiers in order to improve the accuracy of results obtained. Further, comparative study of various class.

1.3 FUNDAMENTAL OF SEGMENTATION TECHNIQUE

Segmentation technique may be divided roughly into the subsequent categories:

(1) Thresholding approaches,

(2) Region growing approaches,

(3) Classifiers,

(4) Bunch approaches,

(5) Andrei Markov random field models,

(6) Artificial neural networks,

(7)Deformable models, and

(8) Atlas guided approaches.

Different notable ways conjointly exist of the various approaches expressed above; thresholding, classifier, clustering, and Andrei Markov random field approaches may be thought of component classification ways. [2]

1.4 BASIC OF ALGORITHMS

Three normally used agglomeration algorithms area unit the

1) k-means,

2) The fuzzy c-means algorithmic rule,

3)The expectation-maximization (EM) algorithmic rule.

Within the k-means agglomeration algorithmic rule clusters mean is iteratively computed and a mean intensity every for every category is assigned and image is mesmeric the by assignment each component within the category with the nearest mean. The fuzzy c-means algorithmic rule generalizes the k–means algorithmic rule, giving soft segmentations supported fuzzy pure mathematics. Coaching knowledge isn't needed by agglomeration algorithms, however they are doing need associate initial segmentation (or equivalently, initial parameters). Therefore, not like classifier ways, agglomeration algorithms may be sensitive to noise and intensity in homogeneities. This lack of special modelling, however, will give important benefits for quick computation.

K-means agglomeration algorithmic rule is additionally associate unattended technique for the segmentation of the image in a very mister image of the top there area unit several regions that area unit of comparable intensities, that lead to several native minima that will increase over-segmentation. The coarse area unites are smoothed within the segmentation by k-means technique.
K-means agglomeration is employed as a result of it's straight forward and has comparatively low procedure quality. Additionally, it's appropriate for medical specialty image segmentation because the range of clusters (K) is sometimes glorious for pictures of specific regions of human anatomy.

1.5 PIXELS QUALITY AND CLUSTERING

The shape, volume, and distribution of brain tissue area unit altered by several neurologic conditions, resonance imaging (MRI) is that the most popular imaging modality for examining these conditions. Consistent menstruation of those alterations may be enforced by victimization image segmentation. Many investigators have developed ways to modify such quantities by segmentation. Fuzzy c-means (FCM) cluster is Associate in unsupervised technique that has been with success applied to cluster, feature analysis and classifier styles in fields adore medical imaging, image segmentation, astronomy, target recognition. There are a unit numerous feature areas during which a picture will be diagrammatic, and therefore the FCM formula categorizes the image by combination of comparable information points within the feature house into clusters.

This cluster is achieved by iteratively minimizing a price operate. This value operate depends on the space of the pixels to the cluster centers within the feature domain. The pixels on a picture area unit extremely related, i.e. the pixels within the immediate neighborhood possess nearly an equivalent feature information. Therefore, the abstraction relationship of neighbor pixels is a vital characteristic that may be of nice facilitate in imaging segmentation. However, the abstraction relationship between pixels is rarely utilized in FCM.

The Kyrgyzstani monetary unit is Associate in unsupervised neural network mapping a collection of n-dimensional vectors to a two-dimensional geographic map displaying in such how that similar information things area unit set about to one another on the map. However, the essential Kyrgyzstani monetary unit lacks the flexibility to extract the hierarchical data structure of the information. a high quality live supported the variance of the information in conjunction with threshold parameters area unit accustomed decide that coarseness is suitable for a particular Kyrgyzstani monetary unit, and that area of the Kyrgyzstani monetary unit are promising candidates for more gradable enlargement.[5] It will be seen that the amount of output units employed in a Kyrgyzstani monetary unit influences its for cluster.

1.6 MOTIVATION OF TOPIC SELECTION

The motivation is to plan a much better segmentation technique for medical pictures liver, brain, and somatic cell for detection of malignant tissue. Image segmentation has been known because the key drawback of medical image analysis and remains a preferred and difficult space of analysis. Image segmentation is progressively utilized in several clinical and analysis applications to analyses medical imaging datasets; that motivated North American nation to gift a snap of dynamically dynamical field of medical image segmentation.

1.7 COMPARISON BETWEEN CT SCANNING AND MRI IMAGE

CT (Computed Tomography), magnetic resonance imaging (Magnetic Resonance Imaging), PET (Positron Emission Tomography) etc. generate an outsized quantity of image data. With the improved technology, not solely will the dimensions and backbone of the pictures grow however additionally the amount of dimensions will increase. Within the future, we'd wish to have algorithms which might mechanically observe diseases, lesions and tumors, and highlight their locations within the giant pile of pictures. However another complication arises is that we tend to even have to trust the results of those algorithms. This can be particularly necessary in medical applications as we tend to don't need that the algorithms to relinquish false signal alarms, and that we actually don't need them to miss fatal diseases.

Therefore, developing algorithms for medical image analysis needs thorough validation studies to form the results usable in observe. This adds another dimension to the analysis method that involves communication between two completely different worlds - the patient centered medical world, and therefore the computer-centered technical world. The mutualism between these worlds is rare to seek out and it needs vital efforts from each side to affix on a typical goal.

1.8 PROBLEM FORMULATION WITH MATLAB

The algorithms of image segmentation play a significant role within the varied medical specialty imaging applications resembling quantification of the tissue volumes, diagnosis, localization of the pathology, study of the body structure, treatment designing, partial volume correction of the useful imaging knowledge, and computer-integrated surgery. There's presently no single segmentation methodology that yields acceptable results for each medical image. Strategies do exist that additional general and may be applied to a spread of information. These problems to solve of image processing tool box.

However, a number of these strategies don't exploit the multispectral info of the imaging signal. There are several regions with similar intensities in a very man image of the pinnacle, that lead to several native minima that will increase over-segmentation.

Thus we've got to plan a replacement methodology that is capable of segmenting varied medical pictures and is computationally less advanced.

Following approach to find out tumor now

1) Segmentation method,
2) Noise remove by applied filtration method,
3) Clustering methodology,
4) GUI Technique.

1.9 CHARACTERISTIC OF MRI (MAGNETIC RESONANCE IMAGE)

1) MRI is common to used medical field and research for internal smallest unit of over body.

2) The comparison of Tomography and MRI then best approach to determine off tumor for MRI technique.

3) The working of MRI to create strangest magnetic fields for center in nuclear magnetization these to achieve radio frequency to detect the scanner.

4) This is the best approach to find out the tumor.

5) All segmentation to apply MRI image.

A magnetic resonance imaging instrument or MRI Scanner [2] uses powerful magnets to polarize and excite hydrogen nuclei i.e. proton in water molecules in human tissue, producing a detectable signal which is spatially encoded, resulting in images of the body [3]. MRI mainly uses three electromagnetic fields they are:

i) A very strong static magnetic field to polarize the hydrogen nuclei, named as the static field,

ii) A weaker time varying field(s) for spatial encoding, named as the gradient field,

iii) A weak radio frequency field for manipulation of hydrogen nuclei to produce measurable signals collected through RF antenna. The variable behaviour of protons within different tissues leads to differences in tissue appearance. The different positioning of MRI of brain with T1 and T2 weight is shown below.

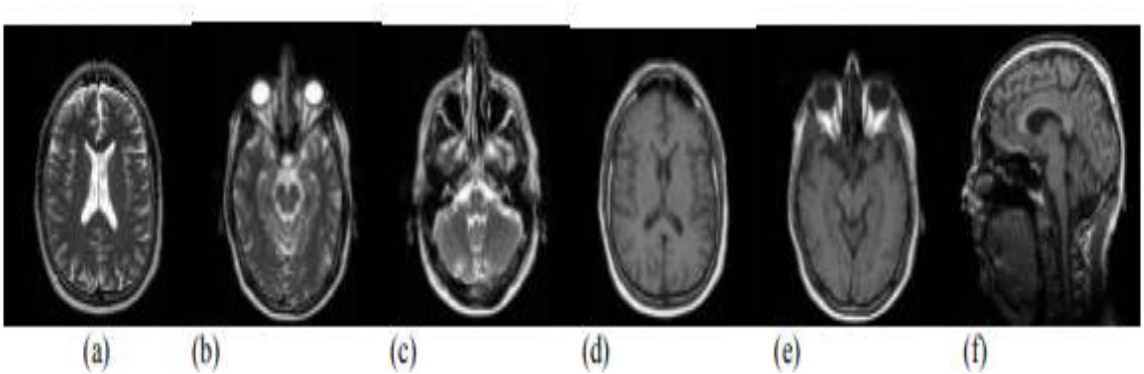


Figure (1.1) MRI of brain. T2 weighted MR image (a) brain shows cortex, lateral ventricle, and falx cerebri, (b) brain shows eyeballs with optic nerve, medulla, vermis, and temporal lobes with hippocampal regions, (c) head shows maxillary sinus, nasal septum, clivus, inner ear, medulla, and cerebellum. T1 weighted MR image (d) brain shows cortex, white and grey matter, third and lateral venticles, putamen, frontal sinus and superior sagittal sinus, (e) brain shows eyeballs with optic nerve, medulla, vermis, and temporal lobes with hippocampal regions,(f) brain shows cortex with white and grey matter, corpus callosum, lateral ventricle, thalamus, pons and cerebellum from the same patients.

1.10 CONTRIBUTION OF RESEARCH MATERIAL AND BLOCK DIAGRAM

In the planned methodology two-level approach is being adopted. Within the 1st level a classifier is being developed mistreatment the SOMs. The computer file set that are the picture element values are fed into this classifier. The Kyrgyzstani monetary unit classifier classifies the computer file set into varied categories (according to the dimensions of the Kyrgyzstani monetary unit used). Within the second level of the approach, the output from the Kyrgyzstani monetary unit classifier is then mesmeric with the assistance of the image segmentation strategies. Here, we tend to use each k-means and fcm because the segmentation strategies at the extent two approaches. The output of the varied strategies are compared and therefore the methodology giving the simplest results analyzed.

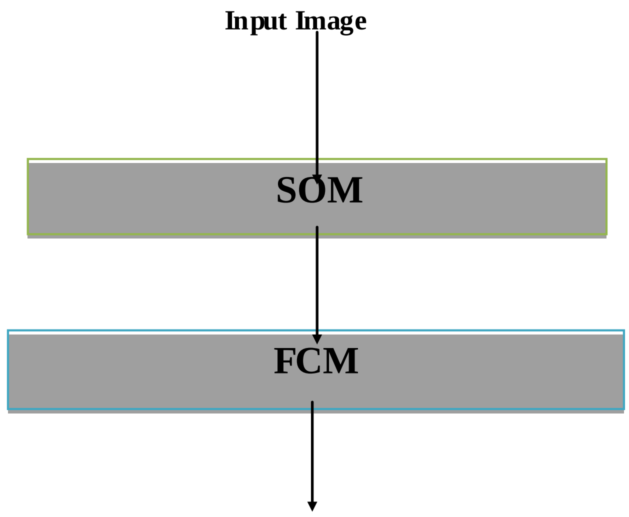


Figure (1.2): Block diagram of the proposed method.

1.11 PREPROCESSING

Pre-processing mainly involves those operations that are normally necessarily prior to the main goal analysis and extraction of the desired information and normally geometric corrections of the original actual image. These improvements include correcting the data for irregularities and unwanted atmospheric noise, removal of non-brain element image and converting the data so they correctly reflected in the original image. Segmentation is the process of partitioning an image to several segments but the main difficulties in segmenting an images are i) Noise, ii) Blur Low Contrast, iii) The bias field (the occurrence of smoothly varying intensities within tissues) , iv) The partial-volume effect (a voxel contributes in multiple tissue types) . Image filtering and enhancement stage is the most obvious part of medical image processing. This pre-processing stage is used for reducing image noise, highlighting important portions, or displaying obvious portions of digital images [4]. Some more techniques can employ medical image processing of coherent echo signals prior to image generation and some of the images are hanging from clip hence they may produce noise. The enhancement stage includes resolution enhancement; contrast enhancement. These are used to suppress noise and imaging of spectral parameters. After this stage the medical image is converted into standard image without noise, film artefacts and labels [4,5, 6].

1.12 THRESHOLD BASED SEGMENTATION

Threshold is one of the aged procedures for image segmentation. These threshold techniques are very much useful for image binarization which is very essential task for any type of segmentation. It assumes that images are composed of regions with different gray level ranges. A thresholding procedure determines an intensity value, called the threshold, which separates the desired classes [7]. There are several threshold segmentation techniques exist, among them here describe some well known and well established thresholding techniques such as Otsu method , Bernsen method, Sauvola method , Niblack method , Kapur method , Th-mean method, Iterative as frame work to all existing method, Balance Histogram [8,9,10].

1.13 SCOPE OF COMPARATIVE STUDY

Brain Tumor detection techniques are integrated with digital image processing and it has found to be challenging task in medical research. Scope of comparative study is to improve accuracy of brain tumor detection. This paper has presented a review on various brain tumor detection techniques. There are four main techniques for brain tumour detection as given follows:

A. Tumor Detection Using Active Contour: The system depends on dynamic forms advancing in time as indicated by natural geometric measures of the picture. The advancing forms actually split and union, permitting the synchronous recognition of a few items and both inside and outside limits. This approach depends on the connection between dynamic forms and the calculation of geodesics or negligible separation bends [11, 12].

B. Based on Region Growing Region developing is a straightforward district based picture division technique. It is additionally delegated a pixel-based picture division strategy since it includes the choice of beginning seed focuses. This way to deal with division looks at neighboring pixels of beginning "seed focuses" and figures out if the pixel neighbors ought to be added to the area. The procedure is iterated on, in an indistinguishable way from general information grouping calculations [13].

1.14 IMAGES ENHANCEMENT AND FILTERING

In this project image improvement that is the improvement of digital image quality with none of the data concerning the first supply image degradation. The enhancement of the image starts by first converting the gray scale image to black and white image this is done by the use of function im2bw (gray_image)[7].Here the threshold value taken in our project is 0.6.As Image improvement strategies improve the visual look of pictures from tomography and also the distinction enhancing brain volumes are linearly associated. For image sharpening the imsharpen()[7] is been used, similiarly imadjust()[7] for image adjustment, freqz() for setting frequency response of image are been used. The Gaussian smoothing operator is been for the two dimensional image convolution operators that is used to `blur' images and remove detail and noise. Gaussian is random incidence of white intensity worth and its intensity worth is drawn from Gaussian distribution, thus it is very much use to reduce Gaussian noise and as with linear filter it's computationally economical and enhances image quality with the image boundaries. For implementation of gaussian filter the imgaussfilt()[7] is been used in our project. Color areas, which indicate the colors in an exceedingly benchmark approach by employing a reference frame and a topological space within which every color is delineated by one point of the coordinate system. The colour spaces used in our image processing methods are Gray, Binary form and RGB.

1.15 PROBLEM STATEMENT

Following problem are occur in previous methodologies in brain tumor detection-

1. Limited data collection of brain tumor image analysis.
2. Lower prediction accuracy [3].
3. Complex image contrast enhancement technique.
4. Higher classification Error [4].
5. Selection of Tool analysis to brain tumor area [5].

The brain tumor related work have to publish many articles and observed limitation for image classification approach [6].

1.16 PROBLEM FORMULATION AND OBJECTIVES

To study of many research article and paper are identify many limitations [7]. Consequently enhancement of brain tumor classification performance used modern Artificial intelligence algorithm [8]. In this research article are follow some objectives given blow-

1. To implementation of brain tumor classification algorithm based on artificial intelligence [9].
2. To investigation of Classification error.
3. To improvement of tumor detection accuracy [10].
4. To observation of Training, validation and test stage across performance evaluation parameters.

Hence proposed hybrid method SVM gives a feature extraction of brain tumor and ANN are reduced MSE for given data sets [11].

LITERATURE REVIEW

MAISHA FARZANA, Semantic Segmentation of Brain Tumor from 3D Structural MRI Using U-Net Autoencoder: Automated semantic segmentation of brain tumors from 3D MRI images plays a significant role in medical image processing, monitoring and diagnosis. Early detection of these brain tumors is highly requisite for the treatment, diagnosis and surgical pre-planning of the anomalies. The physicians normally follow the manual way of delineation for diagnosis of tumors which is time consuming and requires too much knowledge of anatomy. To resolve these limitations, convolutional neural network (CNN) based U-Net autoencoder model is proposed which performs automated segmentation of brain tumors from 3D MRI brain images by extracting the key features of the tumor. Additionally, Image normalization, image augmentation, image binarization etc. are applied for data pre-processing. Later on, the model is applied to the new 3D MRI brain images to test the accuracy of it. Applying the proposed method, the accuracy is obtained upto 96.06% considering the 18 subjects. Finally, this approach is a well-structured model for segmenting the tumor region from MRI brain images as compare to the other existing models which may assist the physicians for better diagnosis and therefore, opening the door for more precise therapy and better treatment to the patient [1].

Afsara Mashiat, Detection of Brain Tumor and Identification of Tumor Region Using Deep Neural Network On FMRI Images: As brain is the most vital organ of the human body, the affects of brain related diseases can be severe. One of the most harmful diseases is brain tumor, which results in a very short life expectancy of the affected patient. Detection of brain tumor is a challenging task in the early stages. Still, with the help of modern technology and machine learning algorithms, it has become a matter of great interest for research. While detecting the brain tumor of an affected person, we are considering the fMRI data of the patient. Our aim is to identify whether the tumor is present in the patient's brain or not. We use a Convolutional Neural

Network(CNN) that is good enough to generate high accuracy. We have used some deeper architecture design VGG16, VGG19, and Inception v3 for better accuracy. Three classification techniques are used namely binary classification, lobe based classification, and position based classification. The main contribution of our proposed work is that we have identified the specific region of the brain where the tumor is located. The region-based classification distinguishes our work from others that are applied on the same dataset [2].

Adnan Hanif, Graph Laplacian-based Tumor Segmentation and Denoising in Brain Magnetic Resonance Imaging: Brain tumor segmentation in Magnetic Resonance Imaging (MRI) scans provides vital information to radiologists in the diagnosis and staging of disease. However, these MRI scans are often corrupted with noise during its acquisition. Traditional approaches to this problem employ denoising which leads, in general, to edge smoothing and development of artifacts in MRI slices, thereby affecting tumor segmentation performance. In this paper, we employed graph signal processing (GSP) theory to first segment tumor core in each MRI slice using graph Laplacian followed by edge-aware denoising which is performed in synergy. The paper aims to present a novel technique to tackle the two problems of segmentation and denoising both under the GSP framework. The experimental results demonstrated on simulated and clinical brain MRI datasets, show highly competitive performance both in terms of tumor core segmentation under Dice and Sensitivity measures, and in terms of edge-aware denoising under PSNR and SSIM measures [3].

Sultan B. Fayyadh, Brain Tumor Detection and Classifiaction Using CNN Algorithm and Deep Learning Techniques: Detection of brain tumors through image processing is done by using an integrated approach. This work was planned to present a system to classify and detect brain tumors using the CNN algorithm and deep learning techniques from MRI images to the most popular tumors in the world. This work was performed using an MRI image dataset as input, Preprocessing and segmentation were performed to enhance the images. Our neural network design is simpler to train and it's possible to run it on another computer because the designed algorithm requires fewer resources. The dataset was used contains 3064 images related to different tumors meningioma (708 slices), glioma (1426 slices), and pituitary tumor (930 slices), the convolution neural network (CNN) was used through which the brain tumor is classified according to a special structure of this algorithm consisting of several layers, The implementation of the neural network consist blocks each block include many types of layer, first, the input layer then followed by convolution layer, then the activation function that used was Rectified Linear Units (ReLU), normalization layer, and pooling layer. Also, it contains the classification layer fully connected and softmax layer the overall accuracy rate obtained from the proposed approach was (98,029%) in the testing stage and (98.29%) in the training stage for the data set were used [4].

Md. Akram Hossan Tuhin, Detection and 3D Visualization of Brain Tumor using Deep Learning and Polynomial Interpolation: Among different imaging techniques MRI, MRSI and CT scans are some of the widely use techniques to visualize brain structures to point out brain anomalies especially brain tumor. Identification of brain tumor accurately in clinical practices has always been a hard decision for neurologist as multiple exceptions might present in images which may lead dubious suggestion from neurologist. In our proposed model we are aiming towards brain tumor detection and 3d visualization of tumor more accurately in effcient way. Our proposed model composed of three stages such as classification of image using CNN whether any tumor exists of not; segmentation using multi-thresholding to extract the detected tumor; and 3d visualization using polynomial interpolation. the proposed model enables enhancing the accuracy of tumor detection as compare to existing models as well as segmenting and 3d visualizing the detected tumor. we get

85% accuracy on our model comparing with others which is slightly more efficient in terms of classification and detection [5].

Sajana Shresta, Advanced Cascaded Anisotropic Convolutional Neural Network Architecture Based Optimized Feature Selection Brain Tumour Segmentation and Classification: The purpose of the research is to find out how deep learning and the convolutional neural network will contribute to diagnosis, early detection and segmentation of brain tumors such as glioma, benign, malignant, etc. The aim is to achieve a higher degree of segmentation quality to resolve issues related to lack of the classification accuracy and poor performance in the segmentation and detection of tumors. The presented solution is an Advanced Cascaded Anisotropic Convolutional Neural Network (CA-CNN) architecture with an optimized feature selection method. The DFP (Data collection, feature extraction & selection and prediction) taxonomy is presented that involves data acquiring, data pre-processing, feature extraction, selection and prediction methods for effective tumor segmentation and detection. The presented system will enhance the prediction accuracy and involves the genetic algorithm for effective selection of features which prevents data redundancy and reduce the delay in the detection of tumors. The utilization of genetic algorithm minimizes the redundancy within input voxels and facilitates in the optimal selection of features which improves the classification accuracy of the solution. The research conducted is to improve the brain tumor segmentation and detection process in terms of accuracy, specificity and sensitivity using multi-scale prediction and cross-validation [6].

Milan Acharya, MRI-based Diagnosis of Brain Tumours Using a Deep Neural Network Framework: The median survival time of patients with high grade glioma, a form of brain tumour, is 1-3 years. The current best practice adopts Convolutional Neural Network (CNN) for image classification and tumour detection. This method provides a significant improvement in brain tumour segmentation of Magnetic Resonance Imaging (MRI) images in comparison to other frameworks, but it is nonetheless slow and lacks precision. We sought to build upon the current best practice model by utilising a Deep Neural Network (DNN) model, which entailed modification of the segmentation and feature-extraction stages in order to improve the accuracy of those stages and the resulting segmentation. We contrasted the accuracy and efficiency of our model to the current best practice model using 10 brain tumour patient MRI datasets. First, the segmentation accuracy of our proposed model (M= 90%) outperformed that of the current best practice (M=78%). Second, the tumour detection processing time of our proposed model (M=34 ms) also outperformed that of the current best practice (M=73 ms). We, therefore, replicated previous studies by showing that automatic segmentation can aid in brain tumour detection. Importantly, we extended previous studies by proposing a model that classifies a brain tumour with greater accuracy and within lower processing times. Validation of the model with a larger dataset is recommended [7].

Ritu Joshi, Pixel-Level Feature Space Modeling and Brain Tumor Detection Using Machine Learning: We present a feature learning technique that enhances the performance of a machine learning technique to detect brain tumor regions at pixel-level in a magnetic resonance imaging (MRI) brain scan. This technique utilizes the image filtering based feature extraction techniques (e.g., Laplacian, Gradient, and Sobel filters) to construct a feature space. It then maps the feature space to a response set that has predefined labels (manual or automated). Feature space and the response set are constructed using a reference frame of a volumetric MRI brain scan, and then used for developing a ML model. We applied the learned models, as the automated techniques to other frames of the MRI scan for detecting tumor and non-tumor regions. We adapted the Brain Tumor Segmentation (BraTS 2015) datasets to develop and validate the proposed computational framework. We also used the ground truth labels (or response sets) delivered by the BraTS 2015 datasets. We evaluated the support vector machine (SVM), random forest (RF), and artificial neural network (ANN) models using various quantitative and qualitative measures. We determined, based on precision-recall curve, that the RF model acquired 92% of the tumor detection skills of a perfect model, while ANN and SVM acquired 90% and 88% tumor detection skills of a perfect model [8].

Deepak O. Patil, Monogenic Wavelet Phase Encoded Descriptors for Brain Tumor Image Detection: Brain tumor has a low survival rate and also affect a patient's social life. Early detection and further treatment of the abnormal growth of mass is a significant step during treatment to restrict the progression. MR image screening by the medical expert is a time-consuming and tedious task. This paper presents the development of computer-aided tool to detect brain tumor images. The proposed algorithm employs monogenic wavelet phase-encoded features for tumor detection. Phase component of the monogenic wavelet efficiently extracts the structural information from the input magnetic resonance images. The dimensionality of CLBP textural descriptors extracted from the phase component is further reduced using neighborhood component analysis feature selection. Finally, the support vector machine classifies the test magnetic resonance image as healthy or abnormal. The proposed approach is evaluated using two popular MR imaging databases and simulation results show enhanced performance compared to other existing algorithms [9].

Sneha Grampurohit, Brain Tumor Detection Using Deep Learning Models: A brain tumor is a disease caused due to the growth of abnormal cells in the brain. There are two main categories of brain tumor, they are non-cancerous (benign) brain tumor and cancerous(malignant) brain tumor. Survival rate of a tumor prone patient is difficult to predict because brain tumor is uncommon and are different types. As per the cancer research by United Kingdom, around 15 out of every 100 people with brain cancer will be able to survive for ten or more years after being diagnosed. Treatment for brain tumor depends on various factors like: the type of tumor, how abnormal the cells are and where it is in the brain etc. With the growth of Artificial Intelligence, Deep learning models are used to diagnose the brain tumor by taking the images of magnetic resonance imaging. Magnetic Resonances Imaging (MRI) is a type of scanning method that uses strong magnetic fields and radio waves to produce detailed images of the inner body. The research work carried out uses Deep learning models like convolutional neural network (CNN) model and VGG-16 architecture (built from scratch) to detect the tumor region in the scanned brain images. We have considered Brain MRI images of 253 patients, out of which 155 MRI images are tumorous and 98 of them are non-tumorous. The paper presents a comparative study of the outcomes of CNN model and VGG-16 architecture used [10].

Manu Singh, Two-level Combined Classification Technique using Ranklet Transformation for the Detection of MRI Brain Tumor: These days, medical sector plays significant role as people have become more aware towards their health issues. However, it is observed that by and large the medical analyses towards diagnosis of disease are accomplished by medical experts, which is not only a very time-consuming process but also involves subjectivity. Thus, a methodology has been proposed for the detection of the anomalies to overcome the above constraints. In this paper, we have mainly focused on brain tumor diagnosis using MRI modality. Initially, Expectation Maximization Algorithm is used for segmentation. Thereafter, for feature extraction we have implemented Ranklet Transformation. Finally, combined classification technique has been implemented in such a way that Auto-Encoder classifier is followed by Binary SVM classifier. In this paper, we have also compared our results with traditional SVM, and with the accuracy rate of 94.6% it is concluded that the performance of our proposed model is effective and robust [11].

Mohammad Omid Khairandish, The Performance of Brain Tumor Diagnosis Based on Machine Learning Techniques Evaluation - A Systematic Review: This research aims to investigate the performance of brain tumor diagnosis and treatment using machine learning algorithms. This study provides systematic review of papers on the improvement of human life. The papers reviewed are taken from relevant articles published between October 2012 and December 2019. The investigation is done against the algorithm type, dataset, the proposed model, and the performance in each of the papers. The accuracy result among the papers papers studied is ranged between 79% - 97.7%. The algorithms they used are CNN, KNN, C-means, RF, respectively, ordered from the highest frequency of use to the lowest. In the papers studied, it was shown that various methods had been used with good results. However, the confidence in the research results in term of accuracy for the detection of brain tumors still needs to be increased. Furthermore, building a software applications can be very useful to solve real cases [12].

Ahmad Saleh, Brain Tumor Classification Using Deep Learning: Brain tumor is a very common and destructive malignant tumor disease that leads to a shorter life if it is not diagnosed early enough. Brain tumor classification is a very critical step after detection of the tumor to be able to attain an effective treatment plan. This research paper aims to increase the level and efficiency of MRI machines in classifying brain tumors and identifying their types, using AI Algorithm, CNN and Deep Learning. We have trained our brain tumor dataset using five pre-trained models: Xception, ResNet50, InceptionV3, VGG16, and MobileNet. The F1-scores measure of unseen images were 98.75%, 98.50%, 98.00%, 97.50%, and 97.25% respectively. These accuracies have a positive impact on early detection of tumors before the tumor causes physical side effects, such as paralysis and others disabilities [13].

Ravindra Sugdeo Sonavane, Classification of MRI Brain Tumor and Mammogram Images using Adaboost and Learning Vector Quantization Neural Network: Classification and accurate detection of brain tumor using MRI is essential for purpose of treatment and diagnosis of tumor. In this paper we propose and developed system using four stages namely image normalization, Image Binarization with morphological operation, Anisotropic Diffusion filtering and feature extraction using GLCM. The system evaluated on two types of database, Clinical Brain MRI Images and Digital Database for Screening Mammogram (DDSM). Normalization is process of contrast stretching which changes value of pixel intensity and Image Binarization is processing of Grey scale image into black and white image by fixing threshold level of pixel. If value of pixel above the threshold level is white either Black followed by steps of morphological operation i.e. Erosion and Dilation by processing MRI images. Apart from that anisotropic diffusion (ADF) is applied for detection and sharpen the edge detection. Features taken or extracted by using GLCM from filtered MR images. In the stage of classification, two Neural Networks have been implemented. The first Neural Network is Adaboost NN is based on boosting method which yields classification accurately and the second neural network, LVQ is feed forward network which uses Quantization machine learning algorithm and Lossy compression techniques. The extracted features hence given to train Neural Network for classification. Accuracy with success has been obtain 95% and 80.6% for Clinical Brain MRI images with 79.3% and 69.9% for DDSM [14].

Gajendra Raut, Deep Learning Approach for Brain Tumor Detection and Segmentation: Brain tumor is a serious health condition which can be fatal if not treated on time. Hence it becomes necessary to detect the tumor in initial stages for planning treatment at the earliest. In this paper we have proposed a CNN model for detection of brain tumor. Firstly brain MRI images are augmented to generate sufficient data for deep learning. The images are then pre-processed to remove noise and make images suitable for further steps. The proposed system is trained with pre-processed MRI brain images that classifies newly input image as tumorous or normal based on features extracted during training. Back propagation is used while training to minimize the error and generate more accurate results. Autoencoders are used to generated image which removes irrelevant features and further tumor region is segmented using K-Means algorithm which is a unsupervised learning method [15].

KOLEY, S. AND MAJUMDER: A has presented a cohesion based self merging (CSM) algorithm for the segmentation of brain MRI in order to find the exact region of brain tumor. CSM has drawn much attention because it gives a satisfactory result when compared to other merging processes. Here, the effect of noise has been reduced greatly and found that the chance of obtaining the exact region of tumor was more and the computation time was very less. Their algorithm was much simpler and computationally less complex.

CHANDRA, S ET AL: Proposed a Particle Swarm Optimization (PSO) based clustering algorithm. The proposed algorithm has identified the centroids of number of clusters, where each cluster has group together the brain tumor patterns, obtained from MR Images. The results obtained for three performance measures have been compared with those obtained from Support Vector Machine (SVM) and Ada Boost. The performance analysis has shown that the qualitative results of proposed model are analogous with those obtained by SVM. Moreover, the different values of PSO control parameters have been selected in order to acquire better results from the algorithm.

HASSAN KHOTANLOU: They have proposed a technique for segmenting the brain tumors in 3D magnetic resonance images. Their technique was suitable to different kinds of tumors. Initially, the brain has been segmented using the proposed approach. Then, the suspicious areas have been selected with respect to the approximate brain symmetry plane and fuzzy classification for tumor detection. Here, in the segmentation stage, the tumor has been segmented successfully using the combination a of deformable model and spatial.

BLOCK DIAGRAM AND DESCRIPTION OF DIFFERENT TYPE ALGORITHM

3.1 NON UNIFORM ILLUMINATION METHOD

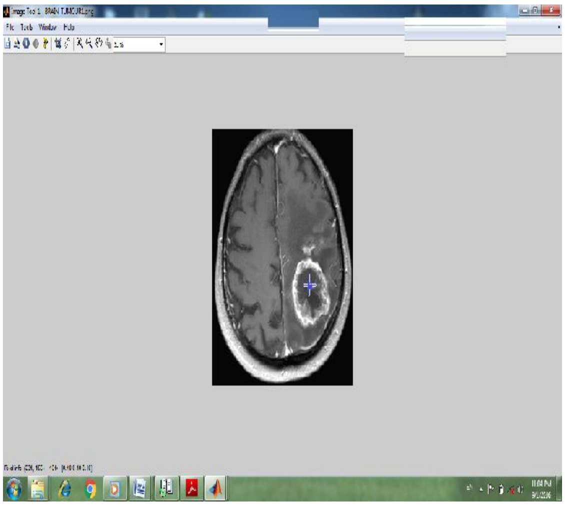
This example shows how to correct no uniform illumination in an image to make it easy to identify individual grains of rice in the image. You can then learn about the characteristics of the grains and easily compute statistics for all the grains in the image.

(1) This is the method to find any image grains for particular region.

(2) With the help of Any grains to find statically data of image.

(3) These technique provide color contrast for particular image.

(4) Doctors are rely to used to detecting of tumor in MRI image.



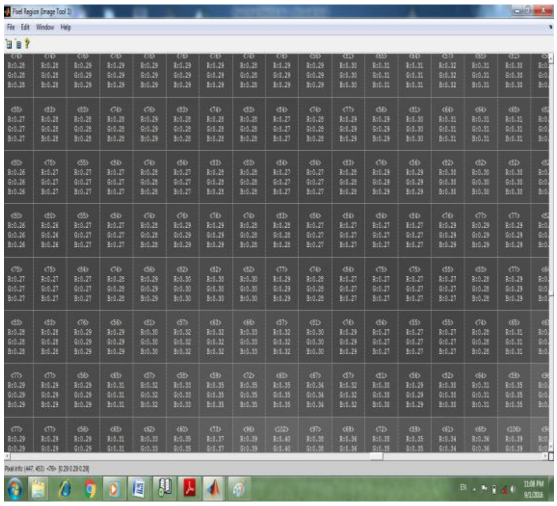


Figure (3.1) (a) Pixels of image.

Figure (3.1) (b) MRI image of Brain.

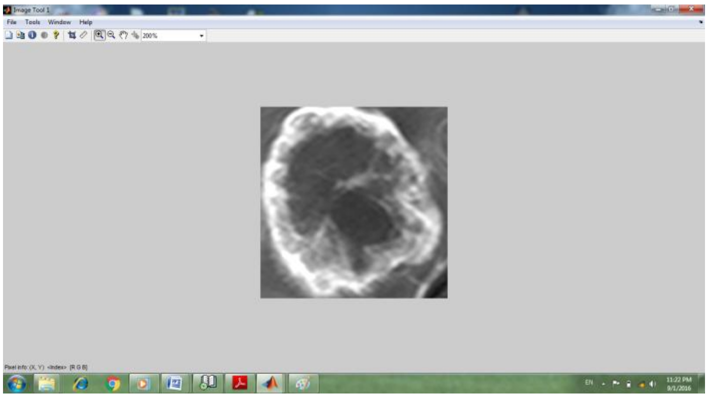


Figure (3.1) (c) Tumor position.

3.2 COLOR-BASED SEGMENTATION USING K-MEANS CLUSTERING METHOD

This example shows how to segment colors in an automated fashion using the L*a*b* color space and K-means clustering.

(1) In this method to create suitable gape of higher and lower intensity of any tumor cell and sub cell.

(2) These are removed the white Gaussian noise of any image.

(3) These methods are also called by the opening by reconstruction and closing by reconstruction.

(4) Statically to remove the noise.

Figure (3.2) (a) Experimental colored image.

3.3 MARKER-CONTROLLED WATERSHED SEGMENTATION METHOD

This example shows how to use watershed segmentation to separate touching objects in an image. The watershed transform is often applied to this problem.

Properties of water Segmentation method

1) These are based on the principle of morphology
2) And high capture region.
3) Intensity the intensity of any object.
4) Using the gray color contrast tumor and back ground of image.
5) Watershed method is a suitable approach to find out the tumor.
6) These are tracking the light and dark pixel to converting for high and low intensity for a lightness these are remove noise and highly efficient method.

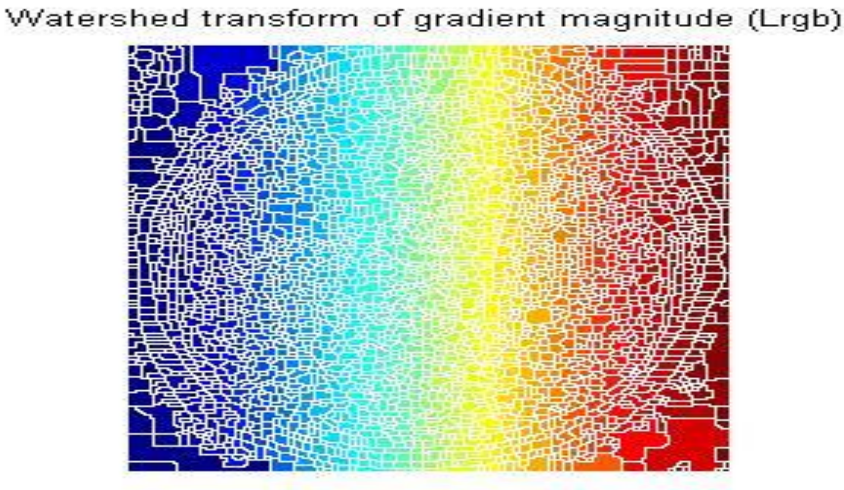


Figure (3.3) (a): Watershed Segmentation.

3.4 TEXTURE SEGMENTATION USING TEXTURE FILTERS USING

This example shows how to use texture segmentation to identify regions based on their texture. Your goal is to segment two kinds of fabric in an image using texture filters. Properties of Texture Segmentation method

(1) Accuracy to increasing by using high pass filter method.

(2) Edge detection are also below pass filter applied to detecting of brain tumor.

(3) This method increasing the boundaries intensity of any object.

(4) Sharpening to improve images.

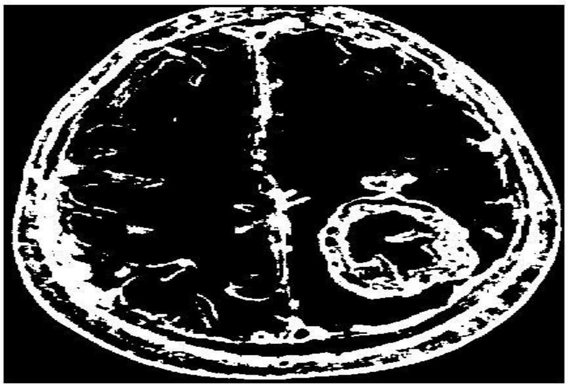


Figure (3.4) (a) Texture Segmentation.

3.5 DETECTING A CELL USING IMAGE SEGMENTATION METHOD

This example shows how to detect a cell using edge detection and basic morphology. An object can be easily detected in an image if the object has sufficient contrast from the background. In this example, the cells are prostate cancer cells. Properties cell Using image Segmentation of method Noise reduction

(1) Matlab code are predefined that is serve averaging filter.
(2) Averaging filter to improve the sharpness of any image.
(3) And Gaussian filter intensity increasing and pixels quality.
(4) These are reduction of blurring.
(5) Time response is very fast.

Figure (3.5) (a): Detecting a cell.

3.6 DISTINGUISH BETWEEN SEGMENTATION TECHNIQUES

[1] In terms of image accuracy:

Later the images would go through a Modified Histogram Clustering - Color Threshold technique to identify the position of the tumor. According to various MRI scan images, the threshold values of the image's HSV for the tumor happens to be common and lies between these values:

HSV	High (%)	Low (%)
Hue	23	10
Saturation	70	07
Value	100	70

We used 50 neuro images to optimize our system and 100 out-of-sample neuro images to test our system. The proposed tumor detection and localization system was found to be able to accurately detect and localize brain tumor in magnetic resonance imaging. The proposed system achieved an error rate of 8% in identifying and localizing tumors.

[2] In terms of noise reduction of images:

The proposed brain tumor detection and localization framework comprises five steps: image acquisition, pre-processing, edge detection, modified histogram clustering and morphological operations. After morphological operations, tumors appear as pure white color on pure black backgrounds. We used 50 neuro images to optimize our system and 100 out-of-sample neuro images to test our system.

[3] In terms of efficiency:

The proposed tumor detection and localization system was found to be able to accurately detect and localize brain tumor in magnetic resonance imaging. This system achieved an error rate of 8%. The preliminary results demonstrate how a simple machine learning classifier with a set of simple image-based features can result in high classification accuracy. The preliminary results also demonstrate the efficacy and efficiency of our five-step brain tumor detection and localization approach and motivate us to extend this framework to detect and localize a variety of other types of tumors in other types of medical imagery.

[4] In terms of cost of instrument:

We propose an automatic brain tumor detection and localization framework that can detect and localize brain tumor in magnetic resonance imaging. The proposed brain tumor detection and localization framework comprises five steps: image acquisition, pre-processing, edge Detection, modified histogram clustering and morphological operations. After morphological operations, tumors appear as pure white color on pure black backgrounds. We used 50 neuro images to optimize our system and 100 out-of-sample neuro images to test our system. The proposed tumor detection and localization system was found to be able to accurately detect and localize brain tumor in magnetic resonance imaging. The preliminary results demonstrate how a simple machine learning classifier with a set of simple image-based features can result in high classification accuracy.

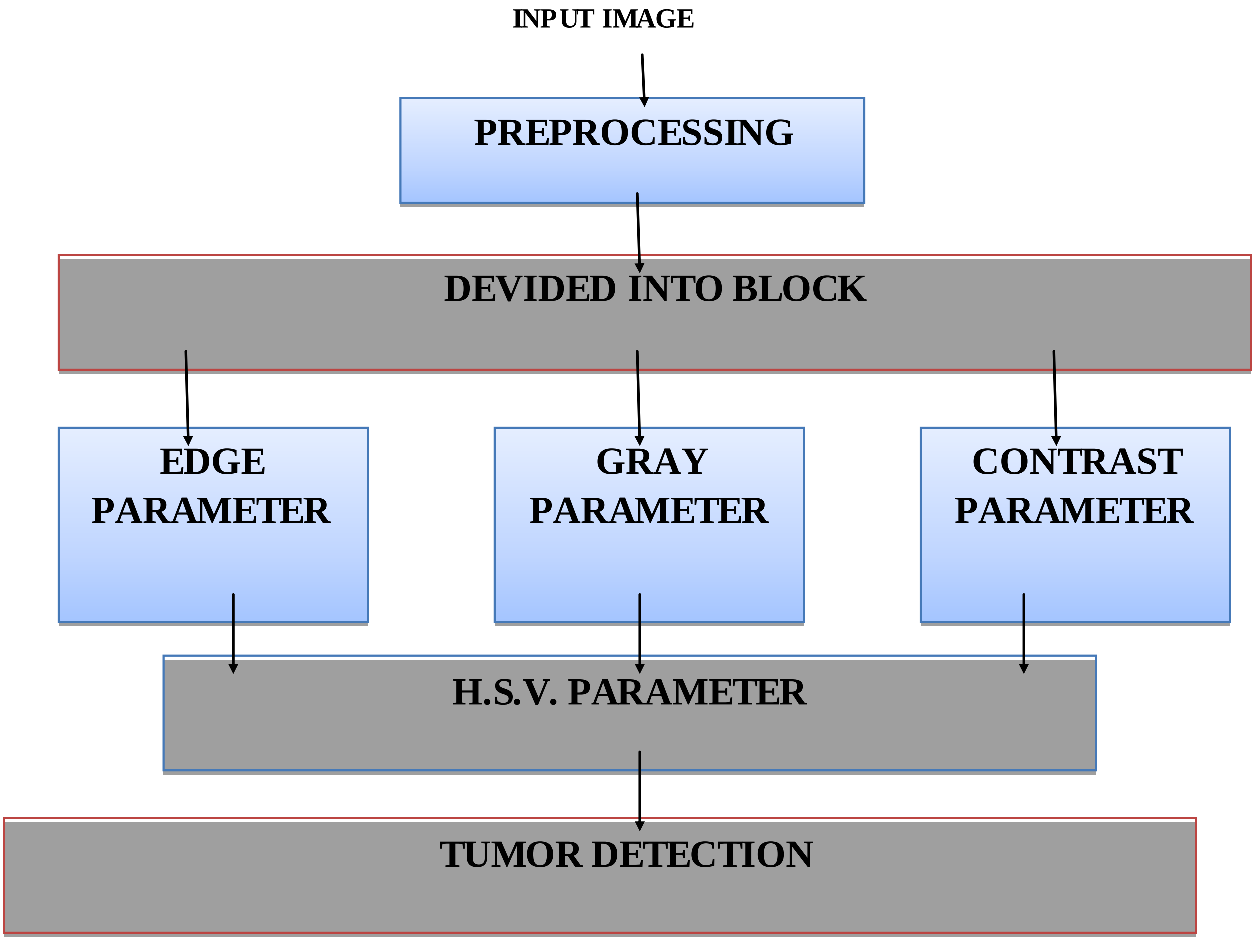


Figure (3.6): Comparison between CT Scanning And MRI Image

3.7 ADVANTAGES OF SOM OVER FCM AND K-MEANS

We have used self-organizing map (SOM) and a method of image processing to create a clustering mechanism that efficiently classifies image objects having an unknown probability distribution without requiring the determination of complicated parameters. This clustering mechanism is fast and highly reliable. The clustering method using the SOM promises to be a valuable tool for classifying large numbers of objects as it reduces the large data set by mapping it to a low dimensional map. It speeds up cluster processing

PROPOSED METHODOLOGY

4.1 PROPOSED METHODOLOGY

In this section are gives a description of proposed method purpose and each method steps. Now major novelty of proposed algorithm gives a hybridization of SVM and ANN. Both method are best approach of data training and improvement of classification accuracy [12].

A. Image Data Collection

We have applied technology to unlicensed databases that is, BraTS. BraTS data accessed with student registration details [13]. A large TA database of MR scan containing containing lumps and edema regions described by hand have been made available for this purpose.

They also provide computer-generated imagery of brain tumors commonly referred to as artificial images. These artificial images also have corresponding images of real world. In this database, all brain images of high glioma or low glioma type [14]. They contain three different folders: challenging data, viewer or ground reality and training data.

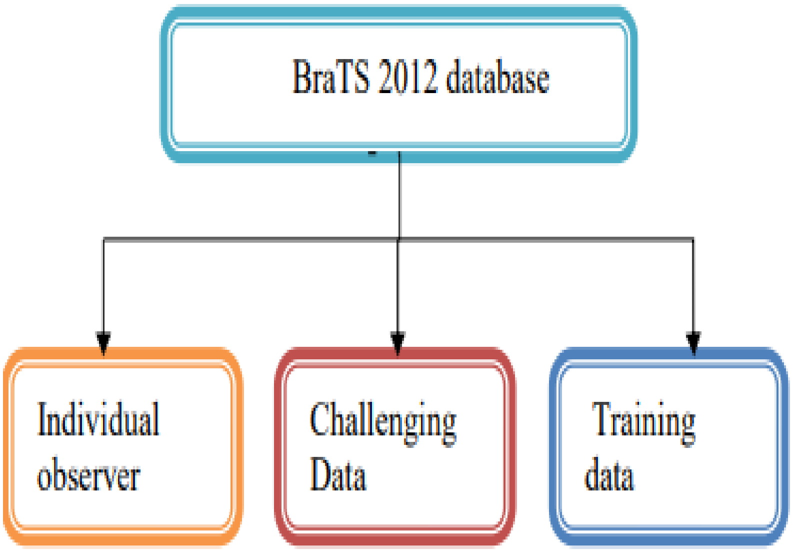


Figure (4.1) Contents of brats database.

B. Image Acquisition/resizing:

In this steps data set image resize at 256x256 ideal image matrix form. This step not to change any pixel quality but change all dimensions of image X and Y axis. For ideal situation any image RGB is main color and Hue, saturation and view is image quality control parameters. These color are generate a matrix for 256x256 dimensions [15].

$$\begin{bmatrix} \boldsymbol{Rt} \\ \boldsymbol{Gt} \\ \boldsymbol{Bt} \end{bmatrix} = [\textbf{Pixcel parameters values}] \begin{bmatrix} \boldsymbol{ht} \\ \boldsymbol{vt} \\ \boldsymbol{st} \end{bmatrix}$$

Magnetic resonance imaging (MRI) segmentation is a complex issue. This paper proposes a new method for estimating the right number of segments and automatic segmentation of human normal and abnormal MR brain images. The purpose of automatic diagnosis of the segments is to find the number of divided image areas of an image according to its entropy and with correctly diagnose of the segment of an image also increased the precision of segmentation.

C. K-MEANS

K-Means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their intrinsic distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them. The algorithm which follows for the k-means clustering is given below. The cluster centers are obtained by minimizing the objective function.

Mathematical representation:

Where there are k clusters S_i , i= 1,2,….,k and μ_i is the centroid or mean point of all the points $x_i \in S_i$

$$\Sigma\Sigma\ (XYZ)^2 \ldots\ldots\ldots\ldots(1)$$

1. Initialize the centroids with k random values.
2. Repeat the following steps until the cluster labels of the image do not change anymore.
3. For each data point, we calculate the Euclidean distance from the data point to the mean of each cluster.

$$c^{(i)} = \arg\min ||x^{(i)}-\mu_j||^2 \ldots\ldots\ldots\ldots(2)$$

If the data point is not closest to its own cluster, it will have to be shifted into the closest cluster. If the data point is already closest to its own cluster, we will not shift it

4. Compute the new centroid for each of the clusters.

$$\mu_i = \sum\{c_{(i)} = j\}x^{(i)} / \sum\{c_{(i)} = j\} \ldots\ldots\ldots\ldots(3)$$

Where k is a parameter of the algorithm (the number of clusters to be found), i iterates over the all the intensities, j iterates over all the cancroids and μ_i are the centroid intensities.

K-MEANS SEGMENTATION

K-Means is the one of the unsupervised learning algorithm for clusters. Clustering the image is grouping the pixels according to the some characteristics. In this paper input image is converted into Standard format 512 X 512, then find the total no. of pixels using Length = Row X Column. Then covert 2D image into 1D and create no. of clusters depend on user. The k-means algorithm initially it has to define the number of clusters k. Then k-cluster center are chosen randomly. The distance between the each pixel to each cluster centers are calculated. The distance may be of simple Euclidean function. Single pixel is compared to all cluster centers using the distance formula. The pixel is moved to particular cluster which has shortest distance among all. Then the centroid is re-estimated. Again each pixel is compared to all centroids. The process continuous until the center converges.

ALGORITHM

1. Give the no of cluster value as k.
2. Randomly choose the k cluster centers.
3. Calculate mean or center of the cluster.
4. Calculate the distance b/w each pixel to each cluster center.
5. If the distance is near to the center then move to that cluster.
6. Otherwise move to next cluster.
7. Re-estimate the center.

8. Repeat the process until the center doesn't move.

DISADVANTAGES OF FCM AND K-MEANS

These methods use the minimum distance clustering algorithm as a clustering system. In these methods, input data is treated as multi-dimensional vectors, the degree of similarity between input data is expressed as a distance (e.g., the Euclidean distance), and the classification of the input data is done using these distances.

1) FCM is higherally complex and higher noise.
2) K-mean clustering approach lower complexity and higher efficient statistical data to provide.
3) These are very iterative method.
4) K -mean approach easily implemented.
5) K value input to algorithm these are dependent for user selecting.
6) Work only numerical data on any image.
7) Gives hierarchal clustering.

AREA CALCULATION:

In the approximate reasoning step the tumor area is calculated using the binarization method. That is the image having only two values either black or white (0 or 1). Here 256x256 jpeg image is a maximum image size. The binary image can be represented as a summation of total number of white and black pixels.

$$\textbf{Image, } I=\Sigma^{255}_{W=0}\,\Sigma^{255}_{H=0}[f(0)+f(1)]$$

Pixels = Width (W) X Height (H) = 256 X 256

f (0) = white pixel (digit 0)

f (l) = black pixel (digit 1)

$$\textbf{No\_ of\_ white pixel } P=\Sigma^{255}_{W=0}\,\Sigma^{255}_{H=0}[f(0)]$$

Where,

P = number of white pixels (width*height) 1 Pixel = 0.264 mm

The area calculation formula is

$$\textbf{Size\_ of\_ tumour, } S= \quad [\sqrt{P}*0.264]\text{mm}^2$$

Where,

P= no-of white pixels,

W=width,

H=height

4.2 SUPPORT VECTOR MACHINES

Support Vector Machines or SVM in-short, is one of the most popular and talked about algorithms, and were extremely popular around the time they were developed and refined in the 1990s, and continued to be popular and is one of the best choices for high-performance algorithms with a little tuning and it presents one of the most robust prediction methods.

SVM is implemented uniquely when compared to other ML algorithms. An SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier.

SVM is a Supervised Learning algorithm, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification as well using a trick or parameter called as Kernel, which implicitly maps their inputs into high-dimensional feature spaces. Will see the details about the Kernel soon.

SVM is also an Unsupervised Learning algorithm. When data is unlabelled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups.

The support-vector clustering algorithm, created by Hava Siegelmann and Vladimir Vapnik, applies the statistics of support vectors, developed in the support vector machines algorithm, to categorize unlabeled data, and is one of the most widely used clustering algorithms in industrial applications.

In machine learning, **support-vector machines** (**SVMs**, also **support-vector networks**[1]) are supervised learning models with associated learning algorithms that analyze data for classification and regression analysis. Developed at AT&T Bell Laboratories by Vladimir Vapnik with colleagues (Boser et al., 1992, Guyon et al., 1993, Vapnik et al., 1997), SVMs are one of the most robust prediction methods, being based on statistical learning frameworks or VC theory proposed by Vapnik (1982, 1995) and Chervonenkis (1974). Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting). SVM maps training examples to points in space so as to maximise the width of the gap between the two categories. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

When data are unlabelled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups. The **support-vector clustering**[2] algorithm, created by Hava Siegelmann and Vladimir Vapnik, applies the statistics of support vectors, developed in the support vector machines algorithm, to categorize unlabeled data, and is one of the most widely used clustering algorithms in industrial applications.

Definition of SVM

A support Vector Machine is a discriminative classifier formally defined by a separating hyperplane. In other words, given labelled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. In two dimensional space, this hyperplane is a line dividing a plane into two parts wherein each class lay in either side.

In simple terms, I could explain SVM as a model that represents the data points in space, mapped such that the data points of the separate categories are divided by a clear gap that is as wide as possible.

For 1 Dimensional data, the support vector classifier is a point. Similarly, for 2 Dimensional data, the support vector classifier will be a line, and for 3-dimensional data, a support vector classifier is a plane. And for 4 dimensional or more, the support vector classifier will be a hyperplane.

In geometry, a hyperplane is a subspace whose dimension is one less than that of its ambient space.

If space is 3-dimensional then its hyperplanes are the 2-dimensional planes, while if the space is 2-dimensional, its hyperplanes are the 1-dimensional lines. This notion can be used in any general space in which the concept of the dimension of a subspace is defined.

Suppose you are given a plot of two labelled classes such as stars in blue and circled in red, on a graph as shown in the below image.

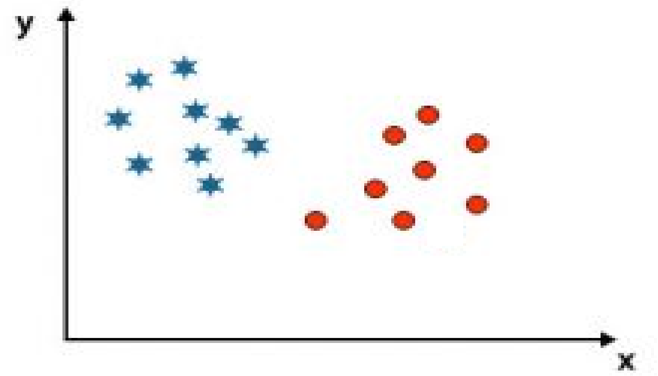


Figure (4.2) Separation of classes.

We might easily draw a line. It fairly separates the two classes. Any point that is left of the line falls into blue stars class and on right falls into red circle class. Separation of classes, that’s what SVM does.

It finds out a line or a hyper-plane (in multidimensional space that separates out classes).

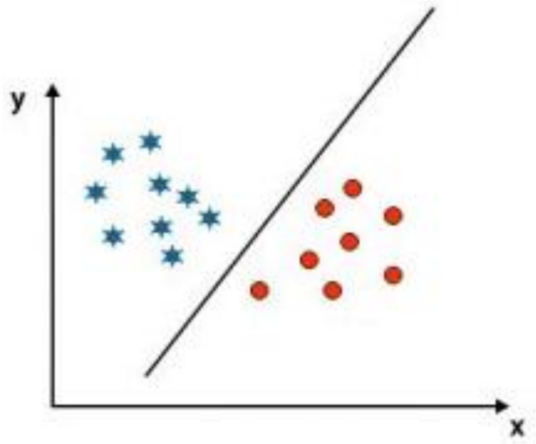


Figure (4.3) Linear SVM classifier.

As we see that the dataset or data points can be classified into two classes by using a single straight line, then such data is termed as linearly separable data, and the classifier is used as Linear SVM classifier.

Thus Kernel helps to find a hyperplane in the higher dimensional space without increasing the computational cost. Usually, the computational cost will increase with the increase of dimensions.

Kernel trick is the function that transforms data into a suitable form. There are various types of kernel functions used in the SVM algorithm i.e. Polynomial, linear, non-linear, Radial Basis Function, etc. Here using kernel trick low dimensional input space is converted into a higher-dimensional space.

The Regularization parameter (often termed as C parameter in python's sklearn library) tells the SVM optimization how much you want to avoid misclassifying each training example.

For large values of C, the optimization will choose a smaller-margin hyperplane if that hyperplane does a better job of getting all the training points classified correctly. Conversely, a very small value of C will cause the optimizer to look for a larger-margin separating hyperplane, even if that hyperplane misclassified more points.

The gamma parameter defines how far the influence of a single training example reaches, with low values meaning 'far' and high values meaning 'close'. In other words, with low gamma, points far away from plausible separation lines are considered in the calculation for the separation line. Whereas high gamma means the points close to plausible lines are considered in the calculation.

There are other hyper parameters as well for which play an important role however some of them are specific to Classification Problem or Regression Problem, or they are used with any specific and dependent on other hyper parameters.

Such as a degree parameter. Degree of the polynomial kernel function ('poly'). Ignored by all other kernels.

Another parameter is Epsilon, which is specific to the Regression problem. It specifies the epsilon-tube within which no penalty is associated with the training loss function with points predicted within a distance epsilon from the actual value.

Implementation

We have two choices, we can either use the sci-kit learn library to import the SVM model and use it directly or we can write our model from scratch.

It's really fun and interesting creating the model from scratch, but that requires a lot of patience and time.

Instead, using a library from sklearn.SVM module which includes Support Vector Machine algorithms will be much easier in implementation as well as to tune the parameters.

Will be writing another article dedicated to the hand-on with the SVM algorithms including classification and regression problems and we shall tweak and play tuning parameters. Also will do a comparison on Kernel performance.

SVM Use Cases

- Some use-cases of SVM are as below.
- Face Detection
- Bioinformatics
- Classification of Images
- Remote Homology Detection
- Handwriting Detection
- Generalized Predictive Control
- Text and Hypertext Categorization

SVMs can be used to solve various real-world problems:

- SVMs are helpful in text and hypertext categorization, as their application can significantly reduce the need for labeled training instances in both the standard inductive and transductive settings.[7] Some methods for shallow semantic parsing are based on support vector machines.[8]
- Classification of images can also be performed using SVMs. Experimental results show that SVMs achieve significantly higher search accuracy than traditional query refinement schemes after just three to four rounds of relevance feedback. This is also true for image segmentation systems, including those using a modified version SVM that uses the privileged approach as suggested by Vapnik.[9][10]
- Classification of satellite data like SAR data using supervised SVM.[11]
- Hand-written characters can be recognized using SVM.[12][13]
- The SVM algorithm has been widely applied in the biological and other sciences. They have been used to classify proteins with up to 90% of the compounds classified correctly. Permutation tests based on SVM weights have been suggested as a mechanism for interpretation of SVM models.[14][15] Support-vector machine weights have also been used to interpret SVM models in the past.[16] Posthoc interpretation of support-vector machine models in order to identify features used by the model to make predictions is a relatively new area of research with special significance in the biological sciences.

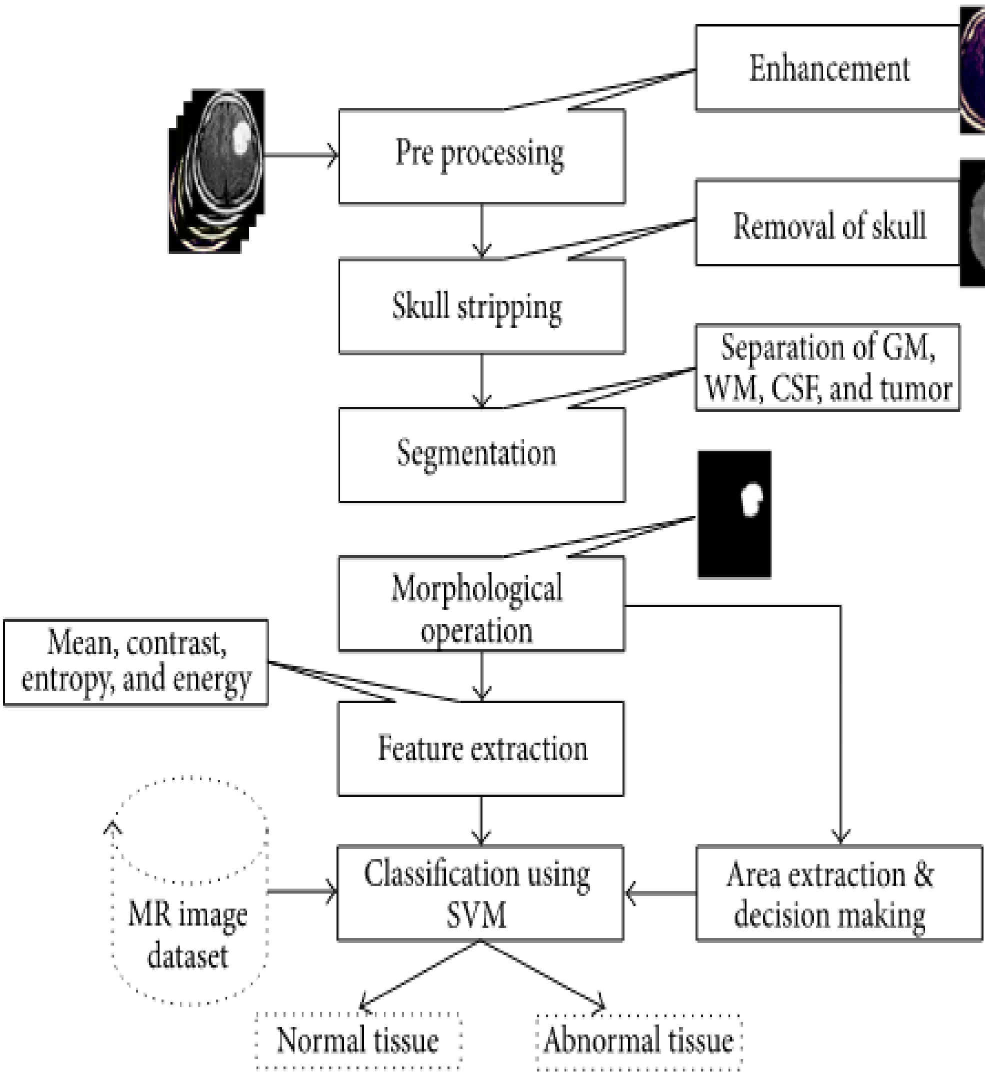


Figure (4.4) SVM classification.

4.3 ANN (ARTIFICIAL NEURAL NETWORK)

Artificial neural network is an approach to use of prediction and classification of large data in machine learning. Basically ANN is a subset of deep learning. This approach based on layer architecture like input layer, hidden layer and output layer. This approach functionality similar to biomedical human brain system. ANN is also called of Mini human brain system. Fundamental ANN system model is consists some components -

1. Computational hidden layer

2. Computational Input layer

3. Computational Output layer

4. Number of neuron.

a. Computational hidden layer: Basically this is a network generation stage to given weighting functions and selection of best fit computational cost functions with respect to given input layer training data [18].

b. Computational Input layer: The input layer is also called of import data stage. The training data and prediction class is import through for analysis software [19].

c. Computational Output layer: This layer is generate prediction out comes in form of training, validation and test. This layer out comes are also give an accuracy, training MSE and performance parameters [20].

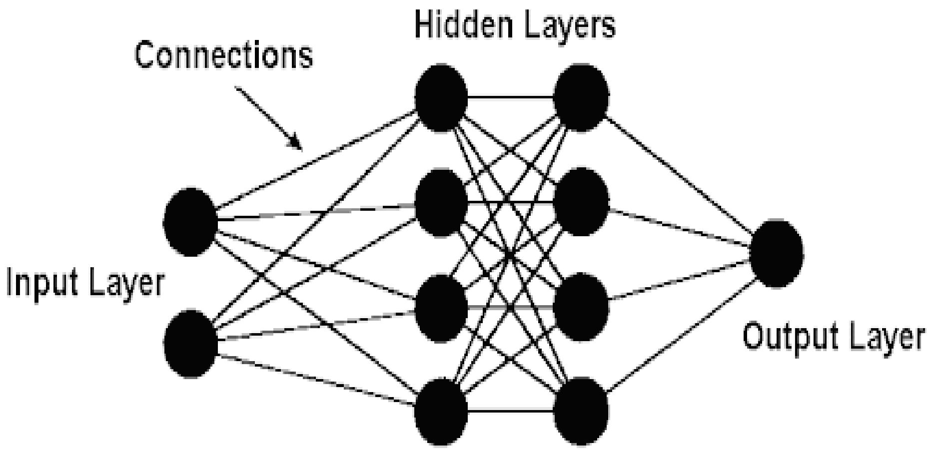


Figure (4.5) ANN Classification layers modelling.

d. Number of neuron: number of neuron are given a inter connection between computational input and output layers. In simulation and analysis situation number of iteration depends on given number of neuron.

Neural Network Algorithms – Artificial Neural Networks arguably works close enough to the human brain. Conceptually artificial neural networks are inspired by neural networks in the brain but the actual implementation in machine learning is way far from reality. ANN take in multiple inputs and produce a single output. Point to note ANN's are inspired by the animal brain, but nowhere close to biological neural networks.

Neural Network Architecture

Neural networks consist of input, output layers hidden layers. Transformation of input into valuable output unit is the main job. They are excellent examples of mathematical constructs. Information flows in neural network happens in two ways.

Feedforward Networks – In these signals only travel in one direction without any loop i.e. towards the output layer. Extensively used in pattern recognition. This network with a single input layer and a single output layer can have zero or multiple hidden layers though. This method has two common designs as below

- At the time of it's learning or "being trained"
- At the time of operating normally or "after being trained"

Feedback Networks – In this recurrent or interactive networks can use their internal state (memory) to process sequences of inputs. Signals can travel in both directions with loops in the network. As of now limited to time-series/sequential tasks. Typical human brain model.

Neural Network Algorithms works on three main layers of its architecture i.e input layer, hidden layer (though there can be many hidden layers) and output layer.

Architectural Components

Input Layers, Neurons, and Weights – The basic unit in a neural network is called as the neuron or node. These units receive input from the external source or some ANNother nodes. The idea here is to compute an output based associated weight. Weights to the neuron are assigned based on its relative importance compared with other inputs. Now finally function is applied to this for computations.

Let's assume our task to it to make tea so our ingredients will represent the "neurons" or input neurons as these are building blocks or starting points. The amount of each ingredient is called a "weight." After dumping tea, sugar, species, milk and water in a pan and then mixing will transform it another state and colour. This process of transformation can be called an "activation function.

Hidden Layers and Output Layers – The hidden layer is always isolated from the external world hence its called as hidden. The main job of the hidden layer to take inputs from the input layer and perform its job i.e calculation and transform the result to output nodes. Bunch of hidden nodes can be called a hidden layer.

Continuing the same example above – In our tea making task, now using the mixture of our ingredients coming out of the input layer, the solution upon heating (computation process) starts changing colour. The layers made up by the intermediate products are called "hidden layers". Heating can be compared with the activation process at the end we get our final tea as output.

The network described here is much simpler for ease of understanding compared to the one you will find in real life. All computations in the forward propagation step and backpropagation step are done in the same way (at each node) as discussed before. Neural Network Algorithms.

Neural Network Work Flow – Layers of Learning

Neural networks learning process is not very different from humans, humans learn from experience in lives while neural networks require data to gain experience and learn. Accuracy increases with the amount of data over time. Similarly, humans also perform the same task better and better by doing any task you do over and over.

Neural Network Algorithms' underlying foundation of neural networks is a layer and layers of connections. The entire neural network model is based on a layered architecture. Each layer has its own responsibility. These networks are designed to make use of layers of "neurons" to process raw data, find patterns into it and objects which are usually hidden to naked eyes. To train a neural network, data scientist put their data in three different baskets.

Training data set – This helps networks to understand and know the various weights between nodes.

Validation data set – To fine-tune the data sets.

Test data set – To evaluate the accuracy and records margin of error.

Layer takes input, extract feature and feed into the next layer i.e. each layer work as an input layer to another layer. This is to receive information and last layer job is to throw output of the required information. Hidden layers or core layers process all the information in between.

- Assign a random weight to all the links to start the algorithm.
- Find links the activation rate of all hidden nodes by using the input and links.
- Find the activation rate of output nodes with the activation rate of hidden nodes and link to output.
- Errors are discovered at the output node and to recalibrate all the links between hidden & output nodes.
- Using the weights and error at the output; cascade down errors to hidden & output nodes. Weights get applied on connections as the best friend for neural networks.
- Recalibrate & repeat the process of weights between hidden and input nodes until the convergence criteria are met.
- Finally the output value of the predicted value or the sum of the three output values of each neuron. This is the output.
- Patterns of information are fed into the network via the input units, which trigger the layers of hidden units, and these, in turn, arrive at the output units.

We outline a few main algorithms with an overview to create our basic understanding and the big picture on behind the scene of this excellent networks.

- Feedforward algorithm
- Sigmoid – A common activation algorithm
- Cost function
- Backpropagation
- Gradient descent – Applying the learning rate

4.4 PROPOSED SYSTEM MODELING STEPS

1.Genetare a input training data sets at n_1…….n_j to different collection of input class c_1……….c_n.

2. The next step is a resize of input image for ideal .jpg/.png 256x256 formats. In this steps image quality are same to input original image.

3. In prepressing stage image to convert at binaries image. The image is also convert to gray scale for variable threshold level.

4. In this hybrid system model SVM generate a hyper plan to given data set n1…….nj. This hyper plan maximum range to depend on image threshold level. Now show nonlinear hyper plan equation is-

$$[\frac{1}{nt}\max\left(0,1-ct(wt-ni-b)\right)]+\sigma\,||\mathrm{wt}||^2$$

Where wt is a Computational normal support vector hyper plane, σ is a normalized Computational hard margin hyper plan given input data and nt is input data training image sample.

5. The SVM classified image is come to thresholding segmentation stage. In this approach pixel contrast level based generate a soft threshold. In this stage image quality is improve and reduction of all image noise.

6. Now last stage is ANN predictor modelling in step input image is generate a input layer data sets and each class is target sets. Hence neural network model gives a training, validation and test form prediction value and its accuracy.

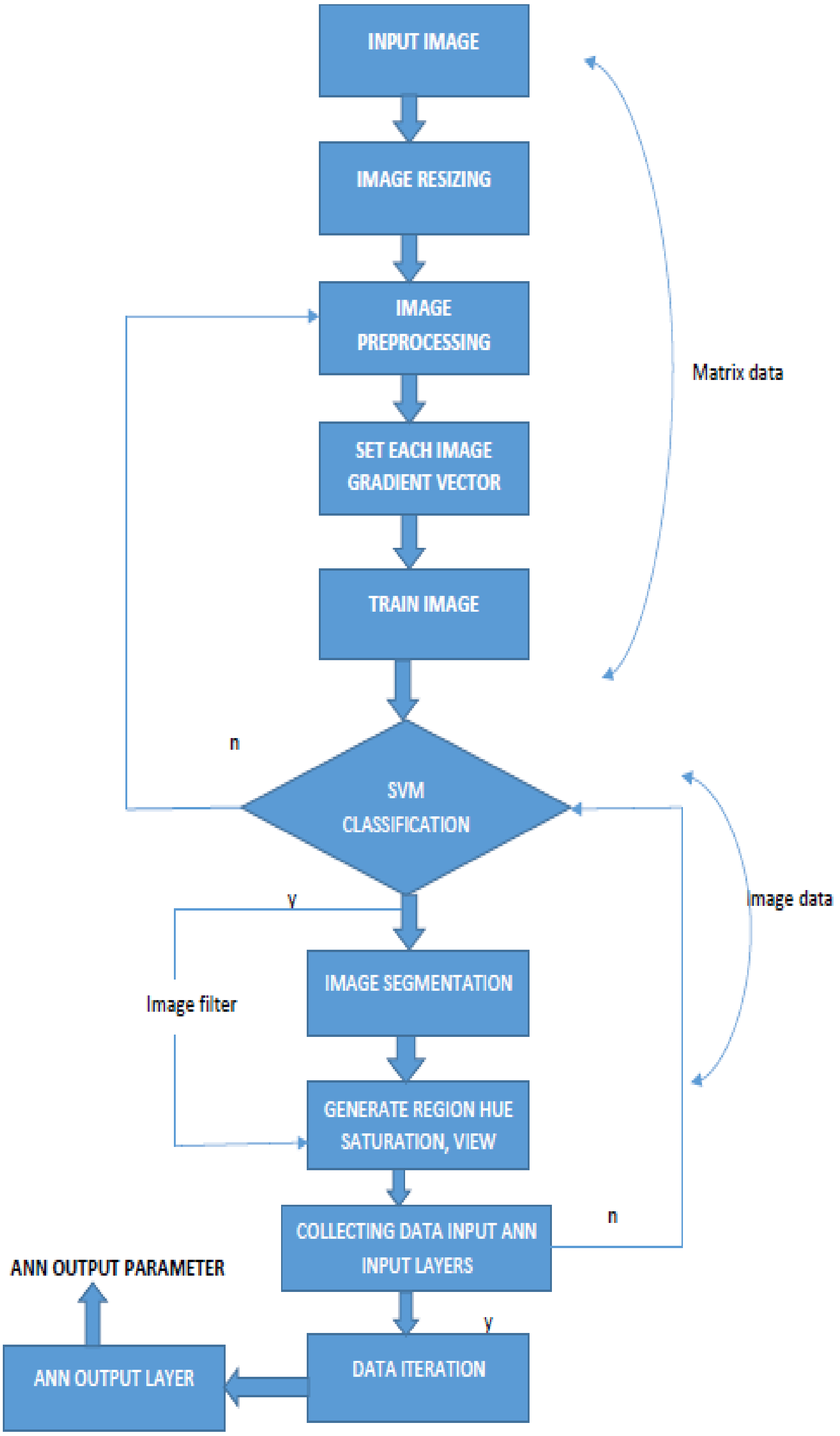


Figure (4.6) Flow chart proposed algorithm.

SIMULATION AND RESULT

5.1 DATA BASE COLLECTION

In this section are identified of proposed system modelling result by using MATLAB 2015A software. This result are obtained in MATLAB image processing toolbox and machine learning toolbox.

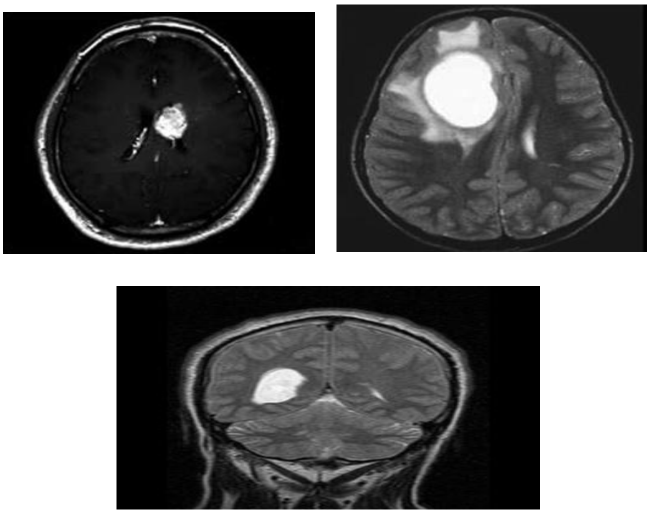


Figure (5.1) Data base.

Fig.5.1 are shows data sets image segmentation and feature extraction results in gray scale image.

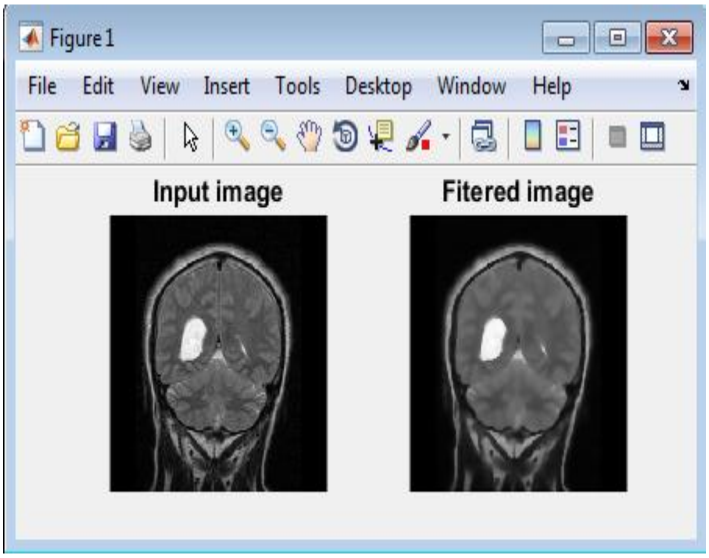


Figure (5.2) Input image and filter image.

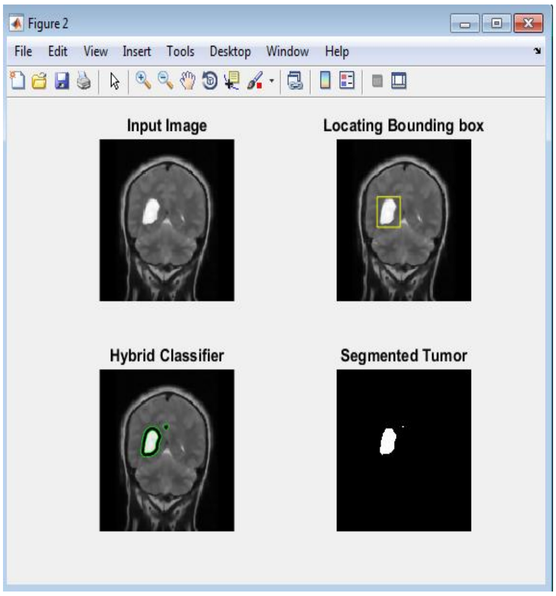


Figure (5.3) Tumor area Classification.

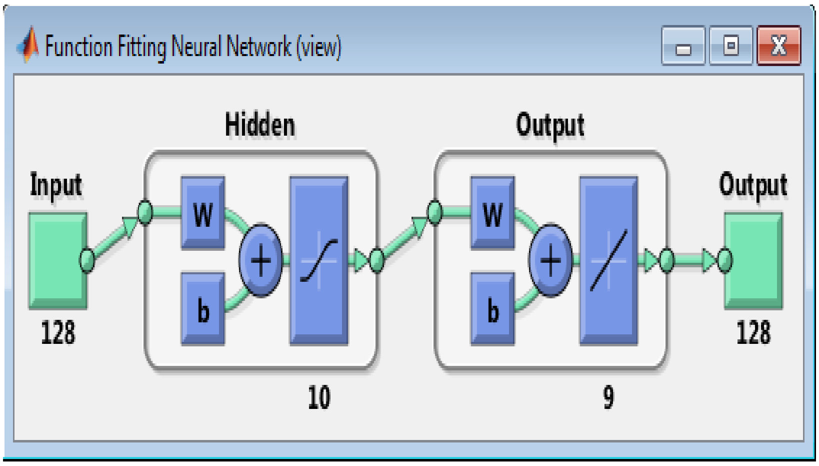


Figure (5.4) Layer of ANN.

Fig.5.4 are representing input layer 128 and number of hidden layer 10 and resultant output layer is 9. These figure are layer model of ANN in MATLAB 2015a software.

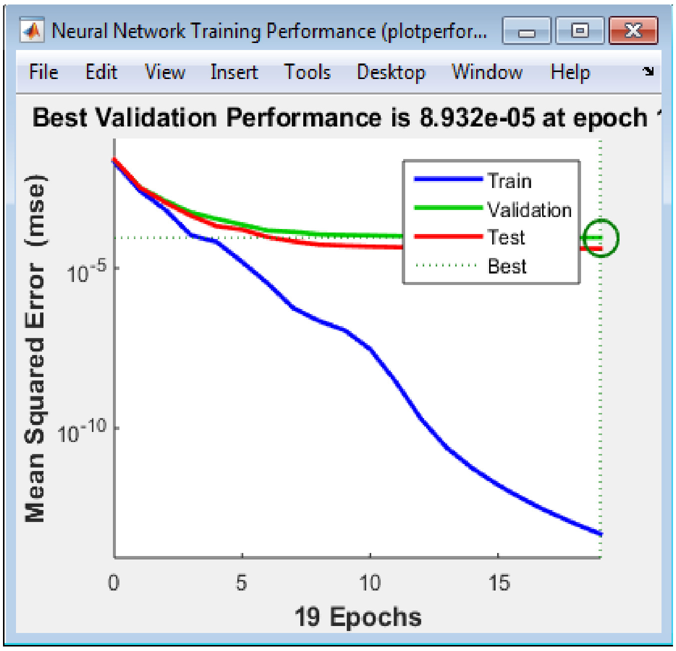


Figure (5.5) MSE criteria based performance evaluation.

Fig.5.5 are shows MSE and iteration curve in training, validation and test stage. Hence training stage obtained best section of error minimization at 10^{-10}.

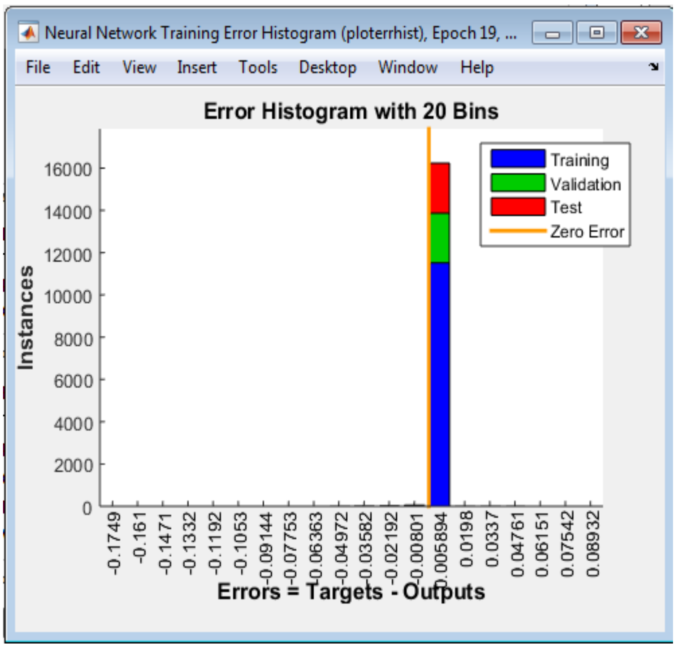


Figure (5.6) Error variation across on train, validation and test.

Fig.5.6 indicating Error of brain tumor detection with respect to number of instance. Hence given hybrid method found 0.0058 error in training stage.

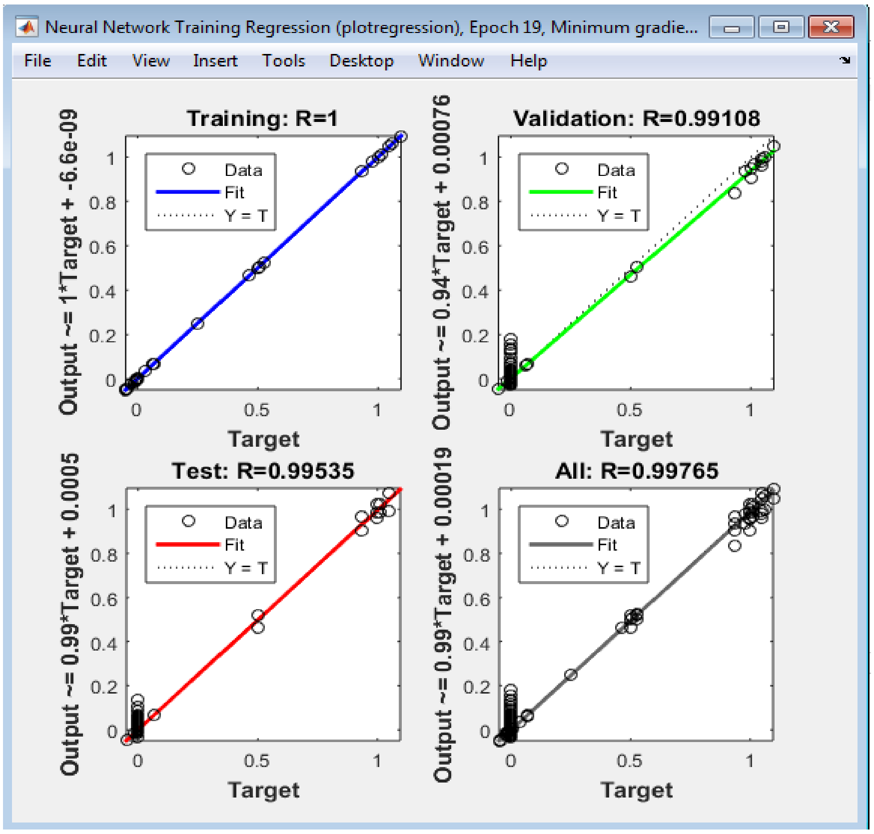


Figure (5.7) Regression curve.

Fig.5.7 are show values of R^2 in training, validation and test stage. In this figure test and validation stage obtain value at 0.99535 and 0.99108.

Table 5.1 Performance observation tabulation.

Parameters	Numerical values
MSE(ΔE)	-0.00801 to 0.0198(±2)
R	0.99765
Neuron	10
Input layer	128
Accuracy	98%

CONCLUSION AND FUTURE SCOPE

6.1 CONCLUSION AND FUTURE SCOPE

In the paper, some research is being done on modern proposed methods for the selection of MR brain imaging. This research work found maximum accuracy 98% and reduced error at 0.0058 in training stage. Accuracy, sensitivity, specificity, and their real-time applications, have been used to ensure the effectiveness of the algorithms used. Finding brain tissue is a difficult and sensitive task, so accuracy and reliability will equally reflect an important part of the chosen approach. Instead of using a machine-readable algorithm to detect brain tumor detection from MRI images, algorithms based on in-depth reading are proposed to automate the extraction of the feature. The proposed work has increased accuracy and reduced losses compared to the existing system. The network that caused the highest accuracy during the test was selected and used as a detector to detect brain tumor.

Further work brain tumor detection to build embedded system using soft core processor to identification of tumor less time period and higher accuracy.

Some highlighted points gives information of future prospect-

[1] Enhancement of image quality using for medical research.

Future research in the segmentation of medical images will strive towards improving the accuracy, precision and computational speed of segmentation methods, as well as reducing the amount of manual interaction. Computational efficiency will be particularly important in real time processing applications.

[2] Suitable Methodology to provide avoidance of any image noise.

Possibly the most important question surrounding the use of image segmentation is its application in clinical settings. Computerized segmentation methods have already demonstrated their utility in research applications and are now increasingly in use for computer aided diagnosis and radiotherapy planning. It is unlikely that automated image.

[3] Proposed work to comparison with segmentation method and clustering method.

Segmentation methods will ever replace physicians but they will likely become crucial elements of medical image analysis. Segmentation methods will be particularly valuable in areas such as computer integrated surgery, where visualization of the anatomy is a critical component

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