Ensemble Classifier for Brain Tumor MRI Segmentation and Classification

A DISSERTATION

Submitted in partial fulfillment of the requirement for the award of Degree of Master of Technology in Information Technology Discipline

Submitted To

Rajiv Gandhi Prodyogiki Vishwavidyalaya, Bhopal (M.P.)

Submitted By

Purna Raghuwanshi

Enrollment No:

0111CS18MT15

Under The Supervision of:

Prof. Vivek Sharma
Assistant Professor

Technocrats Institute of Technology, Bhopal (M.P.)

ESTD:1
999

Department of Computer Science & Engineering

TECHNOCRATS INSTITUTE OF TECHNOLOGY, BHOPAL

June-2022

Ensemble Classifier for Brain Tumor MRI Segmentation and Classification

Dr. Vivek Sharma, Professor Dept of Computer Science & Engineering, Technocrats Institute of Technology Bhopal Vivek.sharma@gmail.com	Purna Raghuwanshi Research Scholar-M.Tech Dept of Computer Science & Engineering, Technocrats Institute of Technology Bhopal pragh27@gmail.com

Abstract---Brain tumor is a group of tissue that is prearrange by a slow addition of irregular cells. It occurs when cell get abnormal formation within the brain. Recently it is becoming a major cause of death of many people. The seriousness of brain tumor is very big among all the variety of cancers, so to save a life immediate detection and proper treatment to be done. Detection of these cells is a difficult problem, because of the formation of the tumor cells. It is very essential to compare brain tumor from the MRI treatment. It is very difficult to have vision about the abnormal structures of human brain using simple imaging techniques. Ensemble methods have been called the most influential development in Data Mining and Machine Learning in the past decade. They combine multiple models into one usually more accurate than the best of its components. Ensemble methods combine the procedure of neural network, extreme learning machine (ELM) and support vector machine classifiers. The proposed system consists of manifold phases. Preprocessing, segmentation, feature extraction, and classification. At initially preprocessing is performed by using filtering algorithm. Secondly segmentation is performed by using clustering algorithm. Thirdly feature extraction is performed by Gray Level Co-Occurrence Matrix (GLCM). Automatic brain tumor stage is performed by using ensemble classification. This phase classifies brain images into tumor and non-tumors using Feed Forwarded Artificial neural network based classifier. Experiments have exposed that the method was more robust to initialization, faster and accurate.

Keywords-- Ensemble classifiers, GLCM, ELM, SVM, Feed Forward Artificial Neural Network and Fuzzy C-means Clustering

INTRODUCTION

In recent times, the introduction of information technology and e-health care system in the medical field helps clinical experts to provide better health care to the patient. Brain tumors affect the humans badly, because of the abnormal growth of cells within the brain. It can disrupt proper brain function and be life-threatening. Two types of brain tumors have been identified as benign tumors and malignant tumors. Benign tumors are less harmful than malignant tumors as malignant are fast developing and harmful while benign are slow growing and less harmful. The various types of medical imaging technologies based on noninvasive approach like; MRI, CT scan, Ultrasound, SPECT, PET and X-ray [1]. When compared to other medical imaging techniques, Magnetic Resonance Imaging (MRI) is majorly used and it provides greater contrast images of the brain and cancerous tissues. Therefore, brain tumor identification can be done through MRI images [2]. This paper focuses on the identification of brain tumor using image processing techniques. The detection of a brain tumor at an early stage is a key issue for providing improved treatment. Once a brain tumor is clinically suspected, radiological evaluation is required to determine its location, its size, and impact on the surrounding areas. On the basis of this information the best therapy, surgery, radiation, or chemotherapy, is decided. It is evident that the chances of survival of a tumor-infected patient can be increased significantly if the tumor is detected accurately in its early stage [3]. As a result, the study of brain tumors using imaging modalities has gained importance in the radiology department. In this paper the brain tumor identification is done by an image processing.

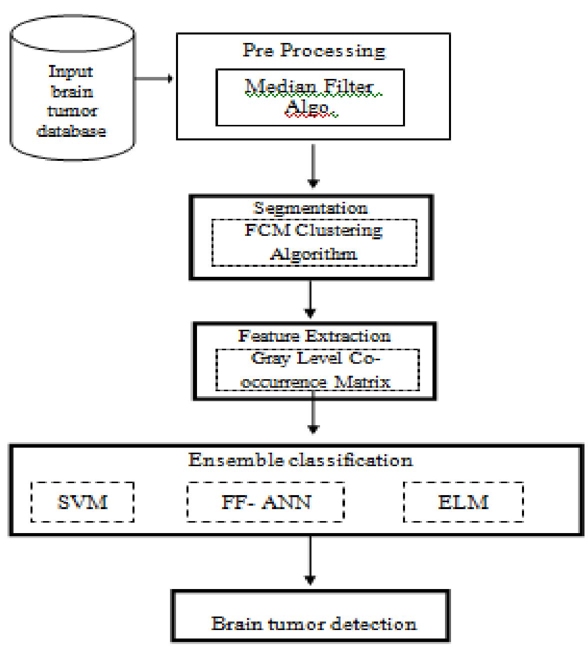
In this paper, there are four process are done to identify the brain tumors. The first process is pre processing the image data from the collection of database using median filtering, second stage is segmentation using Fuzzy C-means Clustering Algorithm [4], third stage is feature extraction using Gray Level Co- Occurrence Matrix (GLCM), [5] and the fourth stage is classification using ensemble classifiers is the combination of neural network, Extreme Learning Machine (ELM) and Support Vector Machine classifier (SVM). This will be discussed briefly in this following section.

LITERATURE REVIEW

Saleck et al [4] introduced a new approach using FCM algorithm, in order to extract the mass from region-of interested (ROI). The proposed method aims at avoiding problematic of the estimation of the cluster number in FCM by selecting as input data, the set of pixels which are able to provide us the information required to perform the mass segmentation by fixing two clusters only. The Gray Level Occurrence Matrix (GLCM) is used to extract the texture features for getting the optimal threshold, which separate between selected set and the other sets of the pixels that influences on the mass boundary accuracy. The performance of the proposed method is evaluated by specificity, sensitivity and accuracy.

Bhima and Jagan [6] demonstrated the superior accuracy for brain tumor detection in compared to the presented methodologies. Also the major identified bottleneck of the recent research outcomes are limited to detection of brain tumor and the overall analyses of internal structure of the brain is mostly ignored being one of the most important factor for disorder detection. Vrji and Jayakumari [7] improved brain tumor approximation after a manual segmentation procedure and 2D & 3D visualization for surgical planning and assessing tumor. thetumor identification, the investigations has been made for the potential use of MRI data for improving brain tumor shape approximation. In Preprocessing and Enhancement stage, medical image is converted into standard formatted image. Segmentation subdivides an image into its constituent regions or objects. Rashid et al [8] investigated the chosen brain MRI image and a method is targeted for more clear view of the location attacked by tumor. An MRI abnormal brain images as input in the introduced method, Anisotropic filtering for noise removal, SVM classifier for segmentation and morphological operations for separating the affected area from normal one are the key stages if the presented method. Attaining clear MRI images of the brain are the base of this method. The classification of the intensities of the pixels on the filtered image identifies the tumor.Sudharani et al [9] the present paper proposed the c1assification and identification scores of brain tumor by using k-NN algorithm which is based on training of k. In this work Manhattan metric has applied and calculated the distance ofthe c1assifier. The algorithm has been implemented using the Lab View. Vidyarthi, A., &Mittal[10] proposed a hybrid model which identifies the region of interest using fused results of threshold segmentation and morphological operations. Initially, an abnormal brain MR image is processed with Otsu threshold based segmentation and morphological operations like erosion. Further, both the segmented resultant images are fused with the original MR image to preserve the background and correctly identification of the tumor region.

Li et al [11] proposed framework employs local binary patterns (LBPs) to extract local image features, such as edges, corners, and spots. Two levels of fusion (i.e., feature- level fusion and decision-level fusion) are applied to the extracted LBP features along with global Gabor features and original spectral features, where feature-level fusion involves concatenation of multiple features before the pattern classification process while decision-level fusion performs on probability outputs of each individual classification pipeline and soft-decision fusion rule is adopted to merge results from the classifier ensemble. Moreover, the efficient extreme learning machine with a very simple structure is employed as the classifier. Dhanaseely et al [12] presented and investigated two different architectures in this work. The cascade architecture (CASNN) and feed forward neural architecture (FFNN) are investigated. The feature extraction is performed using principal component analysis (PCA) as it reduces the computational burden. For a given database the features are extracted using PCA. The Olivetti Research Lab (ORL) database is used.The extracted features are divided into training set and testing set. The training data set is used to train both the neural network architectures. Both are tested extensively using testing data. Liu and Liu [13] proposed an algorithm of HV microscopic image feature extraction and recognition using gray level co-occurrence matrix (GLCM) in order to effectively extract the feature information



of human viruses (HV) microscopic images. Firstly, 20 pieces of microscopic images of human virus are obtained by using GLCM, and then the four texture feature parameters, entropy, energy inertia moment and correlation are extracted utilizing the GLCM, and then HV image recognition is carried out.

Parveen and Singh [14] proposed a new hybrid technique based on the support vector machine (SVM) and fuzzy c- means for brain tumor classification[150.

PROPOSED METHODOLOGY

The proposed work is mainly focused on the identification of brain tumor to reduce the death rate. The identification of brain tumor is done by MRI segmentation and by using Ensemble Classifiers. The proposed methodology consists of four stages. The first stage is pre-processing by using filtering algorithm, the second stage is Segmentation is done by clustering algorithm, third process is feature extraction which is done by Gray – Level Co-occurrence Matrix(GLCM) [40] and the fourth stage of work is Classification by using Ensemble classifier which is a combiner process of neural network, Extreme Learning Machine (ELM) and Support Vector Machine (SVM) and here an automatic brain tumor stage by ensemble classifier by forwarded Artificial Neural Network. Image segmentation is an essential preprocessing trend in a complicated and composite image dealing algorithm in Brain magnetic resonance imaging (MRI). Segmentation plays a fine role in the medical image segmentation. The overview of proposed methodology is shown in figure 1.

Figure 1:Overview of Proposed Methodology

Pre-Processing

It is very difficult to process an image. Before any image is processed, it is very significant to remove unnecessary items it may hold. After removing unnecessary artifacts, the image can be processed successfully. The initial step of image processing is Image Pre-Processing [16].Pre- Processing involves processes like conversion to grayscale image, noise removal and image reconstruction. Conversion to grey scale image is the most common pre-processing practice [17]. After the image is converted to grayscale, then remove excess noise using different filtering methods.

Median Filter

This most common technique which used for noise elimination, It is a „non-linear‟ filtering technique. This is used to eliminate „Salt and Pepper noise‟ form the grayscale image [18]. Median filter is based on average value of pixels. The advantages of median filter are efficient in reducing Salt and Pepper noise and Speckle noise. Also, the edges and boundaries are preserved. The main disadvantages are complexity and time consumption as compared to mean filter. [19]

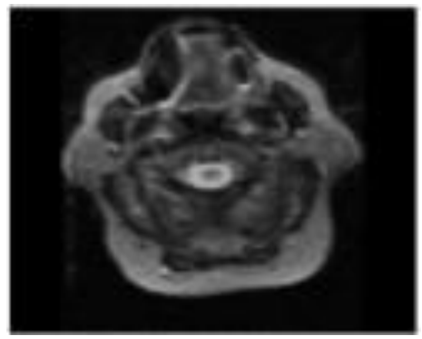


Figure 2: Median filter

In our proposed work we are going to use median filter for less computation complexity and better smoothing of images. However, it is better in preserving useful detail in the image than the mean filter. Like the mean filter, the median filter considers each pixel in the image and replaces it with the median of the neighborhood pixel values. The median filter has two main advantages over the mean filter [20]:

- It is a more robust estimation than the mean. A single unrepresentative pixel in a neighborhood will not affect the median significantly.
- It does not create new unrealistic pixel values, since the median must actually be the value of one of the pixels in the neighborhood.

Segmentation

Segmentation of images is important as large numbers of images are generated during the scan and it is unlikely for clinical experts to manually divide these images in a reasonable time. Image segmentation refers to segregation of given image into multiple non-overlapping regions. Segmentation represents the image into sets of pixels that are more significant and easier for analysis. It is applied to approximately locate the boundaries or objects in an image and the resulting segments collectively cover the complete image [21]. The segmentation algorithms works on one of the two basic characteristics of image intensity; similarity and discontinuity [22].

Clustering methods are most promising technique for processing the medical images. Cluster analysis can be set out as a pre-processing stage for other methods, namely classifiers that would then run on selected clusters [26]. Therefore in our system, we have used clustering segmentation techniques for diagnosis of tumor and calculating tumor area in MRI images

Fuzzy C – means algorithm is used for proposed work which divide the set of pixels X= {x1, x2, . . .,xN} into C fuzzy clusters where each point has a degree of belonging to clusters. It allows a point to belong to more than one cluster as per its membership value. It is an iterative process for minimizing objective function, related to fuzzy membership set U of cluster centers C: 3.*If* $|| U^{(k+1)} - U^{(k)} || < \varepsilon$ *then STOP; otherwise return to step 2.*

Feature Extraction

Feature extraction [28] is an important step in the construction of any pattern classification and aims at the extraction of the relevant information that characterizes each class. In this process relevant features are extracted from objects/ alphabets to form feature vectors. These feature vectors are then used by classifiers to recognize the input unit with target output unit. It becomes easier for the classifier to classify between different classes by looking at these features as it allows fairly easy to distinguish. Feature extraction is the process to retrieve the most important data from the raw data. In our work feature extraction is based on GLCM will be briefly discussed in this following section [40].

Gray-level co-occurrence matrix (GLCM) [28] is the statistical method of examining the The data points nearer to center of cluster have highest degree of membership than the points on edge [27]. FCM initially guess the cluster centers and assigns every point a membership grade for each clusters. Then, it moves the cluster center to right location by iteratively updating the centers within a data set.

- ***Color:*** is a component of light which is separated when it is reflected off of an object. Colors can be identified numerically by their coordinates.
- ***Intensity:*** Intensity is a purity or strength of color.
- ***Texture:*** It is the visual characteristic of a surface. For example, a surface can be rough or smooth.

Classification

Classification is used to classify each item in a set of data into one of predefined set of classes or groups. In other words, classification is an important technique used widely to differentiate normal and tumor brain images.

The data analysis task classification is where a model or classifier is constructed to predict categorical labels (the class label attributes). Classification is a data mining function that assigns items in a collection to target categories or classes. The goal of classification is to accurately predict the target class for each case in the data. In this proposed work the classification is done by the combined process of three different algorithms is known as ensemble classification.

Ensemble Classification

Ensemble based methods have recently enjoyed great attention [30] due to their reported superiority over single method based system generalization performance [31], [32].

The aim of classification is to combine multiple models (classifiers or features) to solve particular problems [33].

Ensemble methods can be divided into a number of categories, such as ensemble classifiers [34]; ensemble features [35]; and ensemble feature and classifiers [36]. To demonstrate the full and practical importance of using a multiple classifier system, an analogy can be made with decision making in everyday life.

Extreme Learning Machine

Extreme Learning Machine (ELM) is a single hidden layer feed forward neural network (SLFNN) which randomly selects input weights and hidden neuron biases without training. The outputs weights are analytically are analytically determined using the norm least-square solution and Moore-Penrose inverse of a general linear system, thus allowing a significant training time reduction. The activation function like sine, Gaussian, sigmoid etc., can be chosen for hidden neuron layer and linear activation functions for the output neurons .The SLFNN evaluated here uses additive neuron design instead of kernel based [39], hence random parameter selection. SLFNs are considered as a linear system. The aim of the approach is to generate high resolution images from inputs with low-resolution. In the training process, the input was extracted from the image features. Furthermore, the high frequency components that were taken from the original images with high-resolution were utilized as the target values. Then, ELM learns a model that is capable of mapping the interpolated image and imposing it on the high frequency components. Once training is done, the learned model can predict the high- frequency components using low resolution images [36].

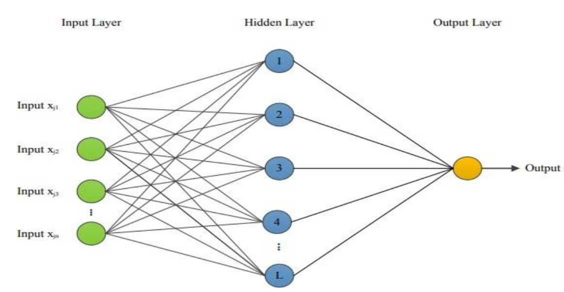


Figure 4: Overview of ELM

Feed Forwarded Neural Network

In more practical terms neural networks are nonlinear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in Data. Using neural networks as a tool, data warehousing firms are harvesting information from datasets in the process known as data mining.

ISSN 2229-5518

The difference between these data warehouses and an ordinary database is that there is actual manipulation and cross-fertilization of the data helping users makes more informed decisions.

Feed forward Neural Network One of the simplest feed forward neural networks (FFNN) [38], such as in Figure 5, consists of three layers: an input layer, hidden layer and output layer. In each layer there are one or more Processing Elements (PEs). PEs is meant to simulate the neurons in the brain and this is why they are often referred to as neurons or nodes.

PE receives inputs from either the outside world or the previous layer. There are connections between the PEs in each layer that have a weight (parameter) associated with them. This weight is adjusted during training. Information only travels in the forward direction through the network - there are no feedback loops.

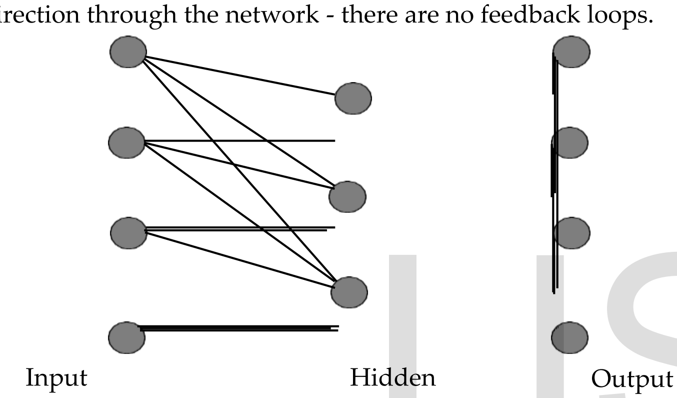


Figure 5: FIFO in Neural Networks

Experiments and Results

Curvelet, its implementation and feature extraction process. Based on those analyses, we find that curvelet is powerful and effective in capturing edge information accurately which is a key to texture features based CADx. In this chapter, we test the performance of medical image diagnosis system using curvelet texture features. We also test curvelet features performance on the scale distorted image diagnosis. In the literature, wavelet texture feature is the effective bench mark for MRI brain image classification. In order to benchmark the wrapping based curvelet texture diagnosis performance, we compare its performance with that of existing wavelet texture features.

MRI Database

The dataset used in this thesis consists of T2-weighted MR brain images in axial plane and were downloaded from the website of Harvard Medical School (URL: http://med.harvard.edu/AANLIB/) [32]. The benchmark dataset (Dataset-160) consists of 160 (20 normal and 140 abnormal) brain MR images.

Dataset (160)		Training (128)		Testing (32)	
Normal	Abnormal	Normal	Abnormal	Normal	Abnormal
20	140	16	112	4	28

Table 1: The experiments dataset

Performance Evaluation Metrics

Sensitivity (true positive fraction) is the probability that a diagnostic test is positive, given that the person has the disease

Specificity (true negative fraction) is the probability that a diagnostic test is negative, given that the person does not have the disease

Accuracy is the probability that a diagnostic test is correctly performed

Sensitivity, Specificity, and Accuracy Evaluation

In order to assess the efficiency of the proposed technique described in the previous chapter, a series of experiments were carried out using all datasets separately. Therefore, for each 256x256, 128x128 and 64x64 dataset, 128 images were used for training and 32 images for testing. In this experiment and for each dataset, training images were submitted to proposed system. These images are decomposed using curvelet transform at different scales and orientations

Image Size	Scale no	TP	TN	FP	FN	S%	Sp%	A%
256x256	5	27	4	0	1	96.4	100	96.9
128x128	4	27	4	0	1	96.4	100	96.9
64x64	3	26	4	0	2	92.8	100	93.7

Table 2: Sensitivity (S), specificity (Sp) and accuracy (A) values for the classification of MR images as normal and abnormal via curvelet transform with PCA.

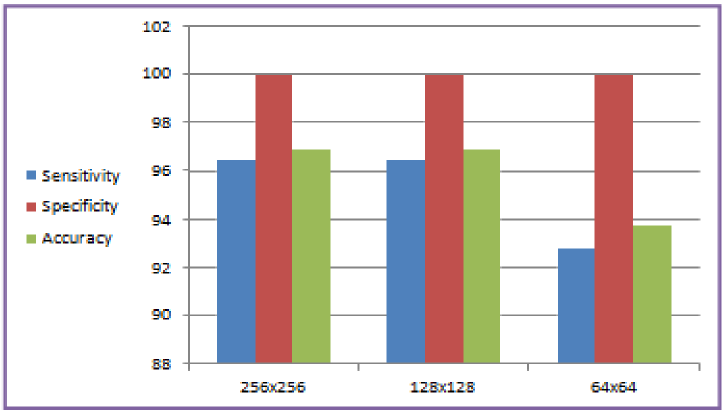


Figure 6 Sensitivity, Specificity, and Accuracy of different dataset resolution

The dimension of the feature vector was reduced to 60 features with the PCA algorithm. Limiting the feature vectors to the component selected by the PCA leads to an increase in accuracy rates. In this experimental, MRI dataset that have healthy and diseased brain are classified by the proposed classifiers. The analysis of the experimental results shows that classification accuracy 96.9% is achieved with the FF-ANN classifier.

Comparison of Proposed System with Other Systems

Compare the performance of the proposed system with some state-of-the-art brain MR image classification schemes.

To evaluate the effectiveness of our method we compare our

Scheme	Accuracy (%)
DWT + PCA + ANN	95.7
Gabor +PCA+ ANN	91.8
DWT+PCA+SOM	93.2
Proposed Method	96.9

results with recently results [47, 49, and 50] for the same MRI datasets. The comparison results in table 5.4. shows the classification accuracies of our method and state of arts methods. This comparison shows that our system has higher classification accuracy

Table 3 Comparison of Proposed System with Other Systems

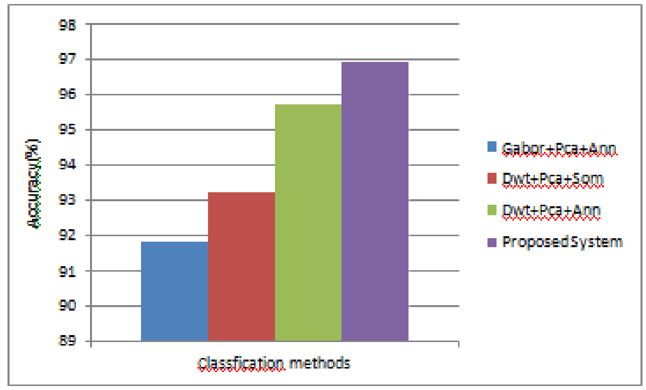


Figure 7: Comparison of different classification systems

CONCLUSION

Cancer is the second leading cause of death for both men and women worldwide and is expected to become the leading cause of death in the next several decades. early detection and diagnosis of cancer increase the treatment options.

Magnetic Resonance Imaging (MRI) is one of the best medical Imaging technologies that currently being used for diagnosing brain tumor. The amount of medical images used to for diagnosis purposes has significantly increased due to the increased number of examinations. This increased volume of medical data makes their management difficult for medical centers, which result in an increase in the time needed to access the data, the patient"s stay time in hospitals, the number of unnecessary examinations and the cost of health care.

The ensemble classifier is finally classified the tumor and non-tumor region. Ensemble classifier plays an important role in our work. Ensemble classifier is the combination of different individual or separate classifiers. In our work the ensemble classifier is made up of combined classifiers of feed forward artificial neural network, extreme learning machine and support vector machine classifier. Here the ensemble have an high accuracy and less execution time and it is very efficient when compared to all other classifier.

The future works appear from the limitations and the difficulties when we developedour system. The following developments can be made in the future:

Future enhancements are

- To improve the accuracy results, the system has to take into account the feedbackfrom the user.
- To achieve further performance improvement of the system, we hope to optimize the system architecture and techniques that were used in this research.
- There exist some details setting can be discussed and

optimized with the images classification issues.

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