A FRAMEWORK FOR BUILDING AN AUTOMATIC BRAIN TUMOR DIAGNOSTIC TOOL USING MAGNETIC RESOUNANCE IMAGING

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ABSTRACT: The main objective of the project was to develop an automatic diagnostic tool using magnetic resonance imaging (MRI), in order to facilitate the medical doctors in their decision making process, about the existence of brain tumor at its earlier stage. The proposed framework is a step towards building a clinical decision support system to automate the detection of brain tumor. The tool worked on magnetic resonance images (MRI), therefore training and testing dataset of images were obtained from an open- source Harvard medical school online repository. The algorithm comprised of following five steps, i.e. pre-processing, features extraction, training the classifiers, testing and final evaluation of framework. Two types of features were extracted after pre-processing the MRIs. The extracted features were utilized for training the classifiers i.e. support vector machine (SVM), K nearest neighbor (KNN) and naive bayes. KNN and naive bayes showed 100% accuracy, specificity and sensitivity, where as SVM was 70% accurate. The proposed tool helps the accurate decision making capability regarding brain tumors.

Keywords: Clinical decision support system, pattern recognition, automated brain tumor diagnosis, Feature classification, magnetic resonance imaging.

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INTRODUCTION

Decision support system is a computerized information system, which helps in decisions making process. A clinical decision support system is described as a health care diagnostic software that assists medical doctors, clinical staff and patients in understanding the person's specific case and make the diagnostic decision accordingly. Growth and development of biological cells in a human body is a natural process but sometimes complex biological phenomenon results in rapid and abnormal division of cells which leads to an abundance of unwanted cells. This activity can also take place in the brain thus making its structure bulky and irregular. This outgrowth of brain tissue is called brain tumor. Tumor can be benign or malignant, however early diagnostics of the ailment increases the patient's survival rate (Musen *et al.*, 2014). Clinical decision support system uses its intelligent knowledge base to provide recommendation for client's specific advices. It assists medical professionals in decision making, using image processing and machine learning techniques (Kawamoto *et al.*, 2005). Proposed clinical decision support system depicted a novel approach for early diagnosis of brain tumor based on magnetic resonance imaging (MRI).

Some of the recent clinical decision support system utilized image processing and machine learning techniques for the diagnosis. Support vector machine SVM was trained by the following features like grey level co-occurrences matrix, means, and discrete cosine transform and reported accuracy was 99% (Srinivasan *et al.*, 2015).

Bayesian network based estimation gives an idea of the stage of cancer and predicts the survival time. In reported algorithm magnetic resonance images of English Lung Cancer Database LUCADA was used as dataset. Reported algorithm also prescribe patients having lungs cancer to follow their treatment plan. The accuracy of system is 76% (Sesen *et al.*, 2013). LUCADA dataset was compiled and reported in study by (Rich, et al., 2011).

In a study, discrete wavelet transform is used for feature extraction. To select foremost features, principal component analysis (PCA) was employed and these features set were input in to classifier. Back Propagation Neural Network (BPNN) is used as a classifier to determine whether an image has tumor tissues or not. The accuracy, specificity and sensitivity rate of their system is 92.8%, 99% and 100% respectively (El-Dahshan, *et al.*, 2014).

The proposed framework would overcome the limitations of the existing approaches/techniques, especially, it would aid in the manually generated reports by the radiologists/ physicians and increases the accurate diagnosis of

brain tumor even at home. The software developed with proposed framework would be able to extract features accurately and thus identifying the tumor and its development by the course of time.

MATERIALS AND METHODS

Proposed Framework: Development of an automatic brain tumor diagnostic tool employ following vital processes, i.e. constituting the medical imaging database storage for normal and tumorous medical images, features extraction of the medical image, storage of extracted features in knowledge base, knowledge base is then used to train the classifiers to identify the pattern, and finally the development of the an expert system that make a comparison based on identified pattern of statistical model for both ,normal and tumorous, images would lead to the diagnoses of tumor. Schematic diagram of an automatic Brain MRI system is shown in Fig-1.

Dataset: Around one thousand magnetic resonance images were used for training and testing of proposed system. All images were axial, T-2 weighted, 256 x 256 pixels. These images were collected from open source dataset of Harvard medical school (http://med.harvard.edu/AANLIB).

Pre-processing Stage: In this stage finer details of MRI were enhanced through removing noise and normalizing techniques. Image noise was reduced by applying the median filter, which resulted in sharpening of edges and increased overall quality of images.

Segmentation for Region of Interest: Image segmentation was used which divided an image into parts and defined its region of interest. Segmentation was done by two approaches, firstly by pulse coupled neural network and secondly by thresholding. Pulse coupled neural network was used to extract edges information, remove noise, define region of interest and segment the image according to cell texture in a digital image. It was one of the generic pattern recognition engines. Pulse coupled neural network was biologically inspired powerful front-end processor. Some changes in the value of pulse coupled neural networks gave different information. Unwanted background was removed from foreground by thresholding. This helped in brain segmentation from skull by Grey level histogram.

Feature Extraction: Two types of features were extracted from MRI to train the classifiers. Watershed segmentation and discrete wavelet transform.

Watershed Segmentation: Watershed segmentation reported as one of best tool for image segmentation (*Mustaqeem et al.,* 2012). It groups the pixels of image according to similar intensity value. It was used for contour detection and region based segmentation. Marker-controlled watershed segmentation considered as a very robust and flexible for object segmentation with close contours, where boundaries were represented in the form of ridges (*Mustaqeem et al.,* 2012). Proposed Algorithm also utilized the 'Watershed gradient' to obtain the segmentation characteristic information of images. These features helped to train classifiers to differentiate between tumor and normal functioning brain.

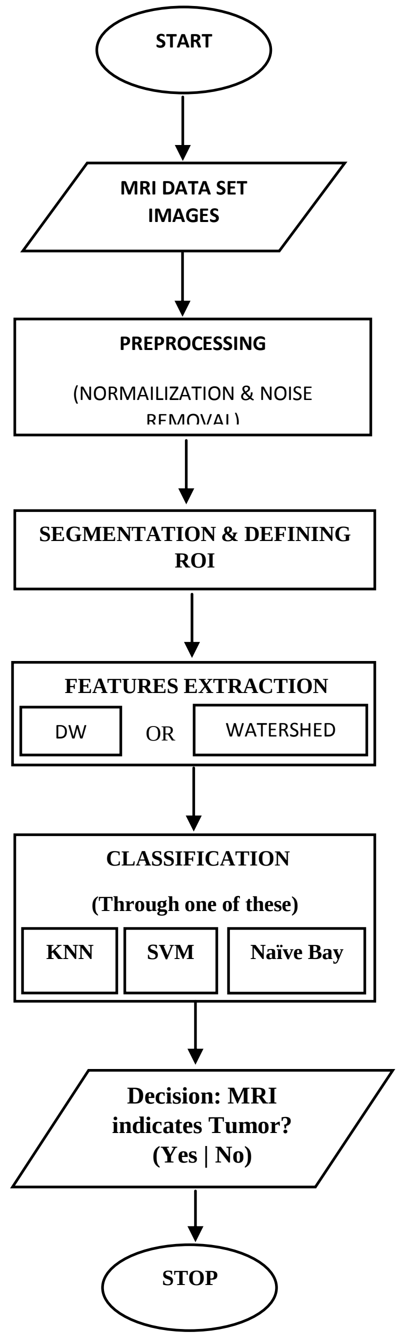

Fig-1: Flow Chart of Tumor Detection.

Discrete Wavelet Transform: Discrete wavelet decomposition was used for feature extraction. It consisted of cascade filter bank of low and high pass filters. In this system 'Haar' Wavelet decomposition at second level was used, to obtain feature vector of magnetic resonance images. All four co-efficients of discrete wavelet decomposition were utilized for feature extraction. These were used to obtain the location and frequency information of images. Extracted prime features were discrete wavelet approximate coefficients, discrete wavelet horizontal coefficient, discrete wavelet vertical coefficient, discrete wavelet diagonal coefficient and watershed gradient. These five prime features further processed to extract derived features, by computing entropy, variances, standard deviation and mean prime feature.

Knowledge Base: The derived features extracted from the MRI was stored in database. All the thousand training images derived features were extracted and stored for further processing.

Classification: An automated decision making about a brain MRI to detect brain tumor of a subject, through analysis of the characteristics of an image, based on statistical model to differentiate between classes is known as classification (*El-Dahshan et al.*, 2014). In this study three classifiers were utilized, namely support vector machine, naive bayes and K-nearest neighbor. The proposed system analyzed and compared the performance of these classifiers.

RESULTS AND DISCUSSION

A framework for building an automatic brain tumor diagnostic tool at earlier stage was developed. MRI images were input in the system, to extract the features, which were stored in the knowledge base of the decision support system. This Knowledge based data was utilized to train the classifiers. The classifiers used the training images and established a statistic model based on features to differentiate between various classes of tumorous and normal brain. After training the classifiers on two type of dataset, tested images were processed by classifiers and the results obtained are listed in Table 1.

The proposed framework was executed six times for evaluation of the system. After each execution, evaluated parameters were recorded for accuracy, sensitivity and specificity. These parameters ensured the credibility of the results obtained from classification systems (Mustaqeem et al., 2012). Sensitivity was the parameter to calculate the ratio of positive identification of tumorous brain, whereas, specificity was the parameter to calculate the ratio of normal brain MRI which was correctly identified.

The accuracy of the classifiers was the rate of correct diagnosis based on positive predication rate. This error rate could be described as a ratio between the terms, 'true positive' and 'false positive' by true negative and false negative. True Positive (TP) was the test result of positive in the presence of the clinical abnormality. True Negative (TN) was the test result of the negative in the absence of the clinical abnormality. False Positive (FP) was the test result of positive in the absence of the clinical abnormality. False Negative (FN) was the test result of negative in the presence of the clinical abnormality as given below.

$$\textbf{Sensitivity} = \frac{TP}{(TP+FN)} \qquad \textbf{(1)}$$

$$\textbf{Specificity} = \frac{TN}{(TN+FP)} \qquad \textbf{(2)}$$

$$\textbf{Accuracy} = \frac{TP+TN}{(T+N)} \qquad \textbf{(3)}$$

Mathematical expression (1-3) represents, the parameters for the evaluation of supervised learning classifiers (Wilson *et al.*, 1995). Better the percentage of these parameters better would be the training of the classifier in the given feature of the dataset (Ivanov *et al.*, 2002). Comprehensive review of the recent automated tools for brain tumor diagnosis was reported in a study and suggested that the accuracy, specificity and sensitivity were the parameters for the evaluation of classifiers (El-Dahshan, *et al.*, 2014).

Table 1. Performance of Different Classifiers

Classifier Type	Discrete Wavelet Transform			Watershed Segmentation		
	Accuracy %	Sensitivity %	Specificity %	Accuracy %	Sensitivity %	Specificity %
KNN	100	100	100	100	98	100
Naïve Bayes	100	100	95	72	100	70
SVM	70	93	84	70	100	72

It was observed, that the feature set of discrete wavelet decomposition showed the tumorous and normal images accurately. K nearest neighbour and naive bayes gave 100% results while support vector machine gave 70% accurate results. Using watershed segmentation features, K nearest neighbour gave 100% accurate results, support vector machine 72% and naive bayes 70% results. Table 1 show the results obtained by testing the images to classify the normal or tumorous categories by the respective classifiers.

In a study (Srinivasan *et al.*, 2015) reported an accuracy of algorithm as 99%. (Hamdaoui *et al.*, 2014) reported an approach based on "fuzzy c", mean clustering soft computing technique' for tumor segmentation from healthy tissues. Using "fuzzy c" mean produced 80% accurate diagnosis of brain tumor 88% accuracy was reported by (Zeljkovic, *et al.*, 2014), 95% accuracy was reported by (Kim and Soo-Young, 2014) and 76% accuracy was reported by (Sesen *et al.*, 2013).

Our proposed framework was quite related with reported algorithm by (El-Dahshan, et al., 2014). They had used Feed Back Pulse Coupled Neural Network (FPCNN) for image segmentation. Whereas, proposed framework was using pulse couple neural network (PCNN) for image segmentation and defining the region of interest.

The discrete wavelet decomposition of second level was employed for features extraction. The accuracy, specificity and sensitivity rate of reported study was 92.8%, 99% and 100% respectively (El-Dahshan, *et al.*, 2014).

By utilizing the two type of features i.e. discrete wavelet transform and watershed segmentation results of supervised classifier were close to perfection. Proposed algorithm has shown 100% accuracy, 100% specificity and 100% sensitivity. The discrete wavelet transform facilitated us with best describing features to discriminate between tumorous and normal brain as compared to watershed.

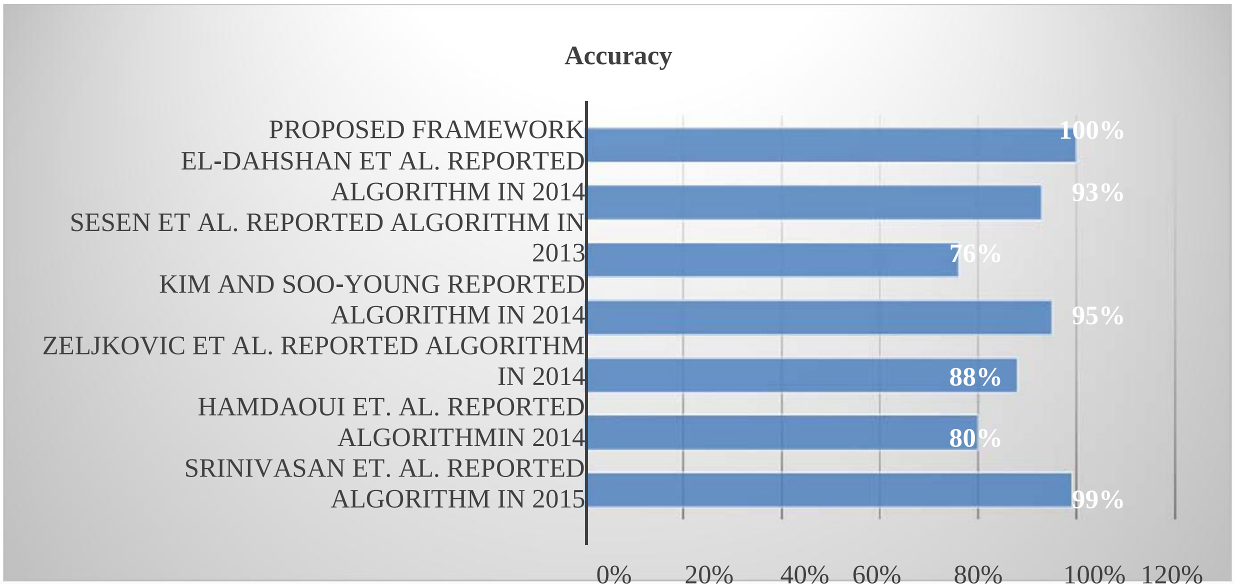

Fig-2. Bar chart to compare accuracy with recent studies

The horizontal bar graph show a statistical comparison among recent studies with proposed framework, depicted in Fig-2. Y axis represented the recent studies while x axis represented discrete values of accuracy of algorithm suggested by the researcher.

This framework would help reduce the burden of medical practitioners, as large amount of MRI data understanding is required for accurate diagnosis, however it is recommended that the final decision should be made after consultation with the specialists. The output of classification of tumorous and normal working brain, diagnosed by the proposed algorithm is represented below in Fig-3.

Fig-3: Output of Tumor Detection.

Future Directions: For future studies it is proposed that the researcher should develop clinical decision support system for the diagnosis and treatment of all types of diseases. This automatic diagnosis tool would be beneficial for the people living in remote areas of the country with poor medical diagnostic facilities.

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