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MRI Based Brain Tumor Detection and Classification

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ABSTRACT

Automatic detection of tumors in medical images is motivated by the necessity of high accuracy when dealing with a human life. Also, the computer assistance is demanded in medical institutions due to the fact that it could improve the results of humans in such a domain where the false negative cases must be at a very low rate. Processing of MRI (Magnetic Resonance Imaging) images is one of the techniques to diagnose the brain tumor. The segmentation, detection, and extraction of infected tumor area from MRI images are a primary concern but a tedious and time taking task performed by radiologists or clinical experts, and their accuracy depends on their experience only. So, the use of computer aided technology becomes very necessary to overcome these limitations. This paper describes the strategy to detect and classify brain tumor from patient's MRI scan images and hence compare the performance of SVM (Support Vector Machine) and CNN (Convolutional Neural Network) algorithms used in classification.

Keywords:-Magnetic Resonance Image(MRI), Support Vector Machine(SVM), Convolutional Neural Network(CNN), Gray-Level Co-Occurrence Matrix(GLCM), Computed Tomog- raphy(CT), Rectified Linear Unit (ReLU)

I. INTRODUCTION

Nowadays biomedical imaging and its diagnosis is important for many applications in patient treatment related problems. At present, imaging technology is a must for patient diagnosis. The various medical images like MRI, Ultrasound, CT (Computed Tomography), X-ray etc play an important role in diagnosing and treating diseases. The recent revolution in medical imaging resulting from techniques such as CT and MRI provides detailed information about the disease and can identify many pathological conditions which helps in giving an accurate diagnosis. Furthermore, the new techniques are helping to advance fundamental biomedical research. Medical imaging is one of the most common techniques used to improve the diagnosis and treatment of a large variety of diseases. The brain image analysis is the main objective in the field of medical image analysis. MRI images have many benefits over other techniques such as, it is a useful non- invasive technique for assisting in clinical diagnosis and its high level of contrast resolution, multispectral characteristics increases its ability to provide rich information about human soft tissue. MRI provides useful information in the field of surgery, radiotherapy, treatment planning and stereotactic neurosurgery. In the proposed system, a machine learning based system using Matlab has been developed for automatic detection and classification of brain tumor from MRI. The detected tumor is classified into benign or malignant. Benign tumors are a lump of abnormal non-cancerous cells which does not spread, whereas malignant tumors are cancerous cells which may spread further. Improving the ability to identify early-stage tumors is an important goal for physicians, because early detection is a key factor in producing successful treatments. An interactive user interface using Matlab GUI has also been developed to make the system user-friendly. To create the proposed system, the integration of various image processing techniques such as preprocessing, segmentation, feature extraction and classification are essential. For clas- sification, SVM and CNN based classifier is used and their performances are compared.

II. LITERATURE SURVEY

S. Damodharan and D. Raghavan [1] "Combining tissue segmentation and neural network for brain tumor detection" International Arab Journal of Information Technology, vol. 12, no. 1, pp. 42–52, 2015, have presented a neural network based technique for brain tumor detection and classification. In this method, the quality rate is produced separately for segmentation of WM, GM, CSF, and tumor region and claims an accuracy of 83% using neural network based classifier.

P. Kumar and B. Vijayakumar [2] "Brain tumour MR image segmentation and classification using by PCA and RBF kernel based support vector machine," Middle-East Journal of Scien- tific Research, vol. 23, no. 9, pp. 2106–2116,2015, introduced brain tumor segmentation and classification based on principal component analysis (PCA) and radial basis function (RBF) kernel based SVM and claims similarity index of 96.20%, overlap fraction of 95%, and an extra fraction of 0.025%. The classification accuracy to identify tumor type of this method is 94% with total errors detected of 7.5%.

Nilesh Bhaskarrao Bahadure, Arun Kumar Ray and Har Pal Thethi [3] " Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction Using Biologically Inspired BWT and SVM" this method a combination of biologically inspired Berkeley wavelet transformation (BWT) and SVM as a classifier tool to improve diagnostic accuracy. The exper- imental results achieved 96.51% accuracy demonstrating the effectiveness of the proposed technique for identifying normal and abnormal tissues from MR images.

A. Chaddad [4] "Automated feature extraction in brain tumor by magnetic resonance imaging using gaussian mixture models," International Journal of Biomedical Imaging, vol. 2015, Article ID 868031, 11 pages, 2015, has proposed a technique of automatic feature extraction for brain tumor detection based on Gaussian mixture model(GMM) using MR images. In this method, using principal component analysis (PCA) and wavelet based features, the performance of the

GMM feature extraction is enhanced. An accuracy of 97.05% for the T1-weighted and T2-weighted and 94.11% for FLAIR- weighted MR images are obtained.

N. Deepa and B. Arunadevi [5] "Extreme learning machine for classification of brain tumor in 3D MR images," Infor- matologia, vol. 46, no. 2, pp.111–121, 2013, have proposed a technique of extreme learning machine for classification of brain tumor from 3D MR images. This method obtained an accuracy of 93.2%, the sensitivity of 91.6%, and specificity of 97.8%.

J. Sachdeva, V. Kumar, I. Gupta, N. Khandelwal, and C. K. Ahuja [6] "Segmentation, feature extraction, and multiclass brain tumor classification," Journal of Digital Imaging, vol. 26, no. 6, pp. 1141–1150, 2013, have presented a multiclass brain tumor classification, segmentation, and feature extraction performed using a dataset of 428 MR images. In this method, authors used ANN and then PCA-ANN and observed the increment in classification accuracy from 77% to 91%.

Pavel Dvorak, Walter Kropatsch, and Karel Bartusek [7] "Automatic Detection of Brain Tumors in MR Images", have proposed method that works with T2-weighted magnetic res- onance images, where the head is vertically aligned. The detection is based on checking the left-right symmetry of the brain, which is the assumption for healthy brain.The proposed method reaches the true positive rate of 91.16% and the true negative rate of 94.68%.

Sonu Suhag, L. M. Saini [8] "Automatic Detection Of Brain Tumor By Image Processing In Matlab". This method involves Preprocessing, Segmentation, feature extraction and detection of tumor from MRI scanned brain images. Magnetic Reso- nance Imaging (MRI) is a non-invasive imaging modalities which is best suited for the detection of brain tumor.The method proposed in this paper is fuzzy c-means (FCM) Segmentation which can improve medical image segmentation. The accuracy of this classification is 94 percent.

Sajjad Mohsin, Sadaf Sajjad, Zeeshan Malik, and Abdul Hanan Abdullah [9] "Efficient Way of Skull Stripping in MRI to Detect Brain Tumor by Applying Morphological Opera- tions, after Detection of False Background" Results show that the accuracy rate upto 95% is obtained and 43% efficiency is increased as compared to the different morphological tech- niques used previously.

III. PROPOSED SYSTEM ARCHITECTURE

As per literature survey, it was found that automated brain tumor detection is very necessary as high accuracy is needed when human life is involved. Automated detection of tumor in MR images involves feature extraction and classification using machine learning algorithm. In this paper, a system to automatically detect tumor in MR images is proposed as shown in figure 1.

1. Input Image

MRI scan is given as input to the system. MRI scan is preferred as it gives the detailed picture of nervous tissues and brain in different planes without obstacle and it gives better result than CT scan. MRI scanners use strong magnetic fields, electric field gradients, and radio waves to generate images of the organs in the body. MRI does not involve X-rays and the use of ionizing radiation, which distinguishes it from CT or CAT scans [16].

2. Image Preprocessing

The primary task is to improve the quality of the MR images and make it in a form suited for further processing by human or machine vision system. In addition, it helps to improve certain parameters of MR images :

- Improving signal-to-noise ratio
- Enhancing visual appearance of MR image
- Removing irrelevant noise & undesired parts in the back- ground [3].

In Matlab image preprocessing is done using a process called Median filtering. It is a nonlinear process useful in reducing impulsive, or salt-and-pepper noise. It is also useful in preserv- ing edges in an image while reducing random noise. Impulsive or salt-and pepper noise can occur due to a random bit error in a communication channel. In a median filter, a window slides along the image, and the median intensity value of the pixels within the window becomes the output intensity of the pixel being processed.

3. Segmentation

K-means clustering is one of the popular algorithms in clustering and segmentation. K-means segmentation treats each image pixel (with RGB values) as a feature point having a location in space. The basic K-means algorithm then arbitrarily locates the number of cluster centers in multidimensional measurement space.

K Means Algorithm :

Let $X = \{x_1,x_2,x_3,\ldots\ldots\ldots,x_n\}$ be the set of data points and

$V = \{v_1,v_2,\ldots,v_k\}$ be the set of centers.

1) Randomly select 'k' cluster centers.

2) Calculate the distance between each data point and cluster centers.

3) Assign the data point to the cluster center whose distance from the cluster center is minimum of all the cluster centers.

4) Recalculate the new cluster center using :

$$\mathbf{v}_i = (1/c_i)\sum_{i=1}^{c_i} x_i$$

where, 'c_i' represents the number of data points in i^{th} cluster.

5) Recalculate the distance between each data point and new obtained cluster centers.

6) If no data point was reassigned then stop, otherwise repeat from step 3 [14].

4. Feature Extraction

The function of feature extraction is to reduce the original dataset by evaluating some specific features that differentiate one input pattern from another. The extracted features pro- vide the characteristics of the input type to the classifier by considering the depiction of the significant properties of the image. The analyzing methods that have been done so far has used the values of pixel intensities, pixel coordinates and some other statistic features namely mean, variance or median, which have error in determination process, low precision and low efficiency in classification [11]. In the proposed system the GLCM (Gray-Level Co-Occurrence Matrix) texture features chosen are contrast, correlation, energy, homogeneity

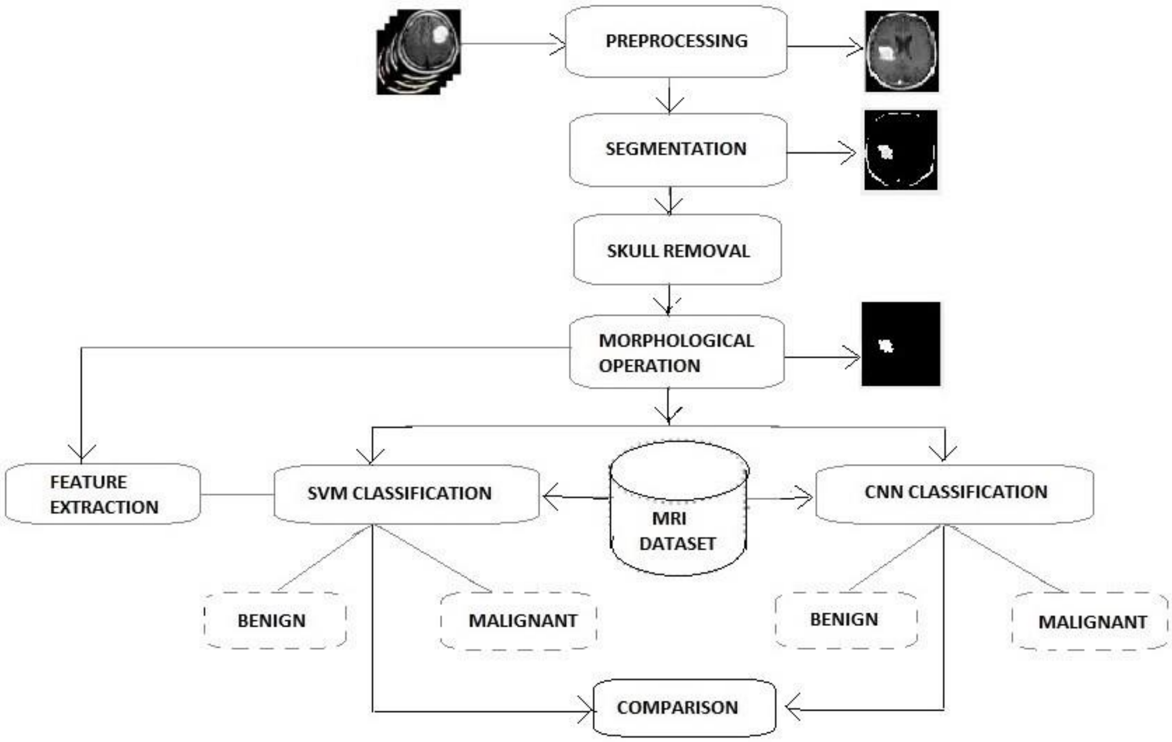

Fig. 1. Steps used in proposed algorithm[3].

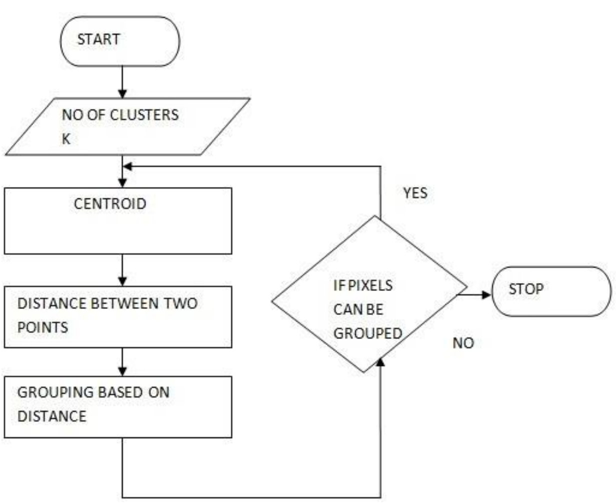

Fig. 2. Flowchart of K Means Algorithm

and morphological features like shape, area etc and features like standard deviation, RMS (Root Mean Square), entropy, smoothness, kurtosis, skewness, IDM. The feature extraction process is carried out with some initial preprocessing. Each tissue segmented image is split into a limited number of blocks and the feature values are calculated for every block.

To create a GLCM, use the graycomatrix function. The graycomatrix function creates a GLCM matrix by calculating how often a pixel with the intensity (gray-level) value *i* occurs in a specific spatial relationship to a pixel with the value *j*. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right. Each element (*i*, *j*) in the resultant GLCM is simply the sum of the number of times that the pixel with value *i* occurred in the specified spatial relationship to a pixel with value *j* in the input image.

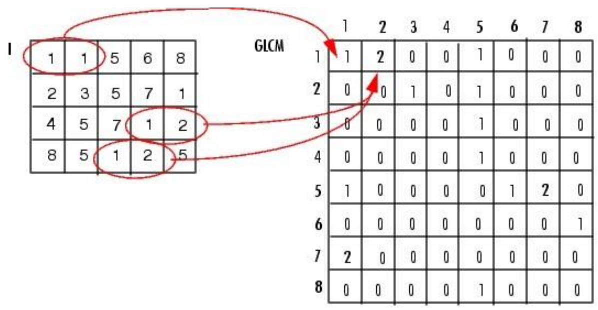

Fig. 3. Process Used to Create the GLCM

GLCM Features :

- Contrast : Measures the local variations in the gray-level co-occurrence matrix.
- Correlation : Measures the joint probability occurrence of the specified pixel pairs.
- Energy : Provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment. Homogeneity : Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal [15].

5. Classification Of Tumor

In this system, Support vector machine and Convolutional Neural Network is used to classify the tumors. SVM is the linear learning algorithm used for classification and is a powerful supervised classifier and accurate learning tech- nique. SVM is used to classify the input image as benign or malignant, a systematic technique for two class problems. The SVM classifier is used in many research areas because it gives high performance in pattern recognition and image processing tasks. SVM is most likely used in problems with small training dataset and high dimensional feature space. Like neural networks, SVM needs two stages, training and testing. The SVM can be trained by features given as an input to its learning algorithm. During training, the SVM finds the suitable margins between two classes. Features are named according to class associative with specific class. In SVM, input data is mapped into higher dimensional internal product space called feature space in this transformed space, a hyper plane linear classifier is applied utilizing those patterns vectors that are closest to the decision boundary. During the testing phase if an unknown image is given as an input to the trained classifier, it classifies the test image to the corresponding class to which it actually belongs.

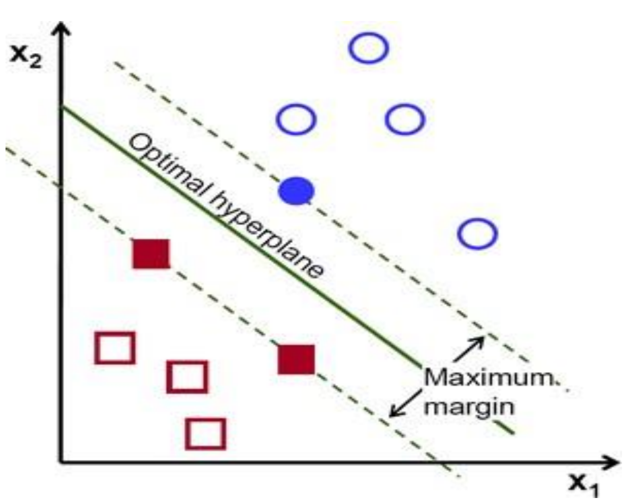

Fig. 4. SVM

Here the inputs x_i (i= 1, . . . ,M) belong to Class 1 or Class 2 and the associated labels be y_i = 1 for Class 1 and 1 for Class 2.

Here Class 1 denotes Benign and Class 2 denotes Malignant [10].

CNN is a class of deep, feed forward artificial neural networks that have successfully been applied to analyzing visual imagery. CNN requires three parameters for building a classification model which are Batch size, Layers and Options. Batch size is how many training images we use (image data store), Layers of CNN provide the maximum iterations in training the model and Options include fields like 'learning rate' which shows how aggressively a new iteration should change the network. These three parameter s are passed to 'trainNetwork()' function to create the network.

CNN consists of Input layer, Convolution layer, Rectified Linear Unit (ReLU) layer, Pooling layer and Fully connected layer. In addition to these layers this model uses Softmax layer and Classification layer. In convolution neural network, image can be scalable (i.e) it will take 3D input volume to 3D output volume (length, width, height). The input layer inputs image to network and applies data normalization. In the convolution layer, the given input image is separated into various small regions. It applies sliding filters to the input and convolves the input by moving the filters along the input vertically and horizontally, and computing the dot product of the weights and input and finally adds a bias term. Element wise activation function is carried out in ReLU layer that is, it performs a threshold operation to each element of the input where any value less than zero is set to zero. Pooling layer is optional. However, the pooling layer is mainly used for down sampling. It performs down sampling by dividing the input into rectangular pooling regions and computing the maximum of each region. The fully connected layer is used to generate the class score or label score value based on the probability in between 0 to 1. Softmax layer applies a softmax function to the input. Finally, the Classification layer creates the final output layer.

The CNN based brain tumor classification is divided into two phases such as training and testing phases. The number of images is divided into different category by using labels name such as Benign and Malignant. In the training phase, preprocessing is done for image resizing. Further, passing the input dataset to all the layers mentioned above the classifi- cation network undergoes training. Finally, the convolution neural network is used for automatic brain tumor classification and for predicting the class label of a new test image, the network should be loaded and using 'classify()' and 'predict()' functions the prediction is done.

Algorithm for CNN based Classification

1. Input image to Input Layer after preprocessing.
2. Apply convolution filter in first layer.
3. The sensitivity of filter is reduced by smoothing the convolute on filter (i.e) sub sampling.
4. The signal transfers from one layer to another layer is controlled by activation layer.
5. Fasten the training period by using ReLU.
6. The neuron in preceding layer is connected to every neuron in subsequent layer.
7. Apply Pooling layer to perform down sampling.
8. Use fully connected layer to generate class score based on probability.
9. Further, apply Softmax and Classification layers to get the trained network [17].

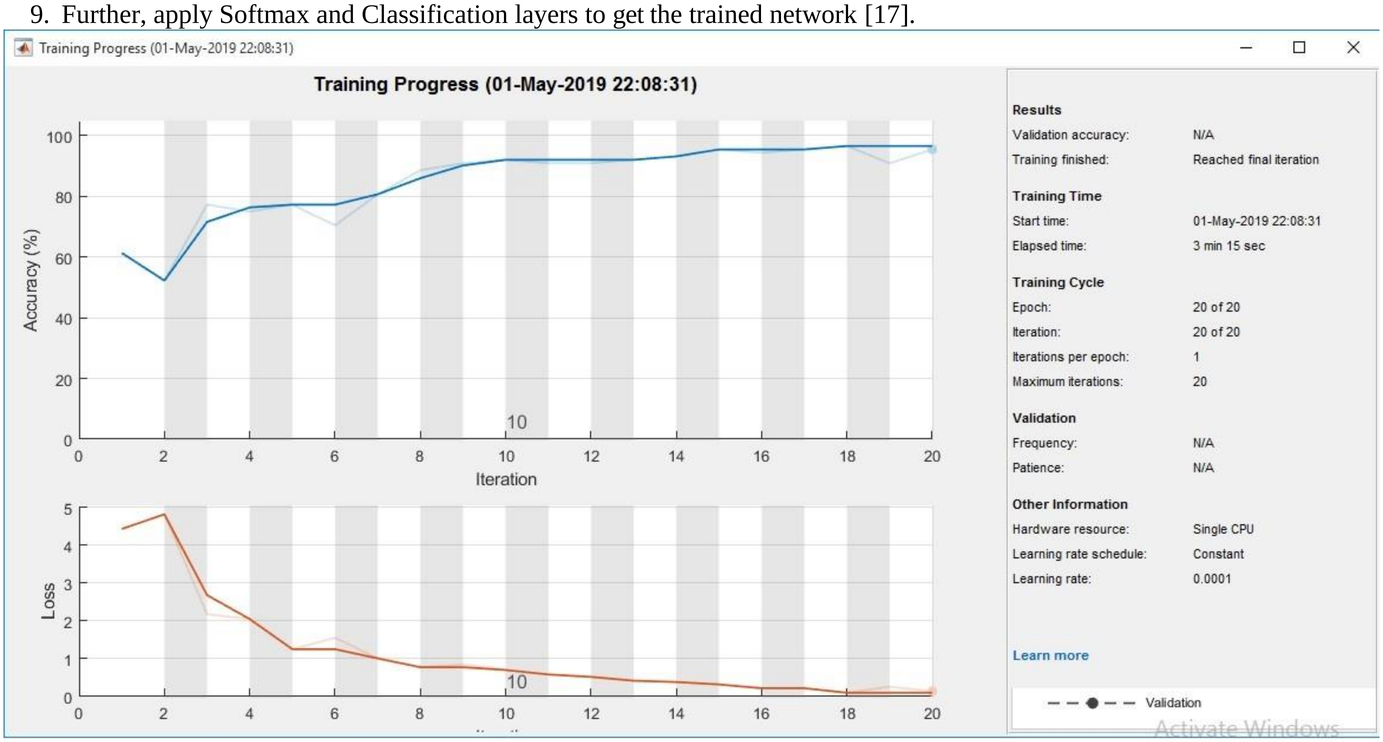

Fig. 5. CNN Training Graph

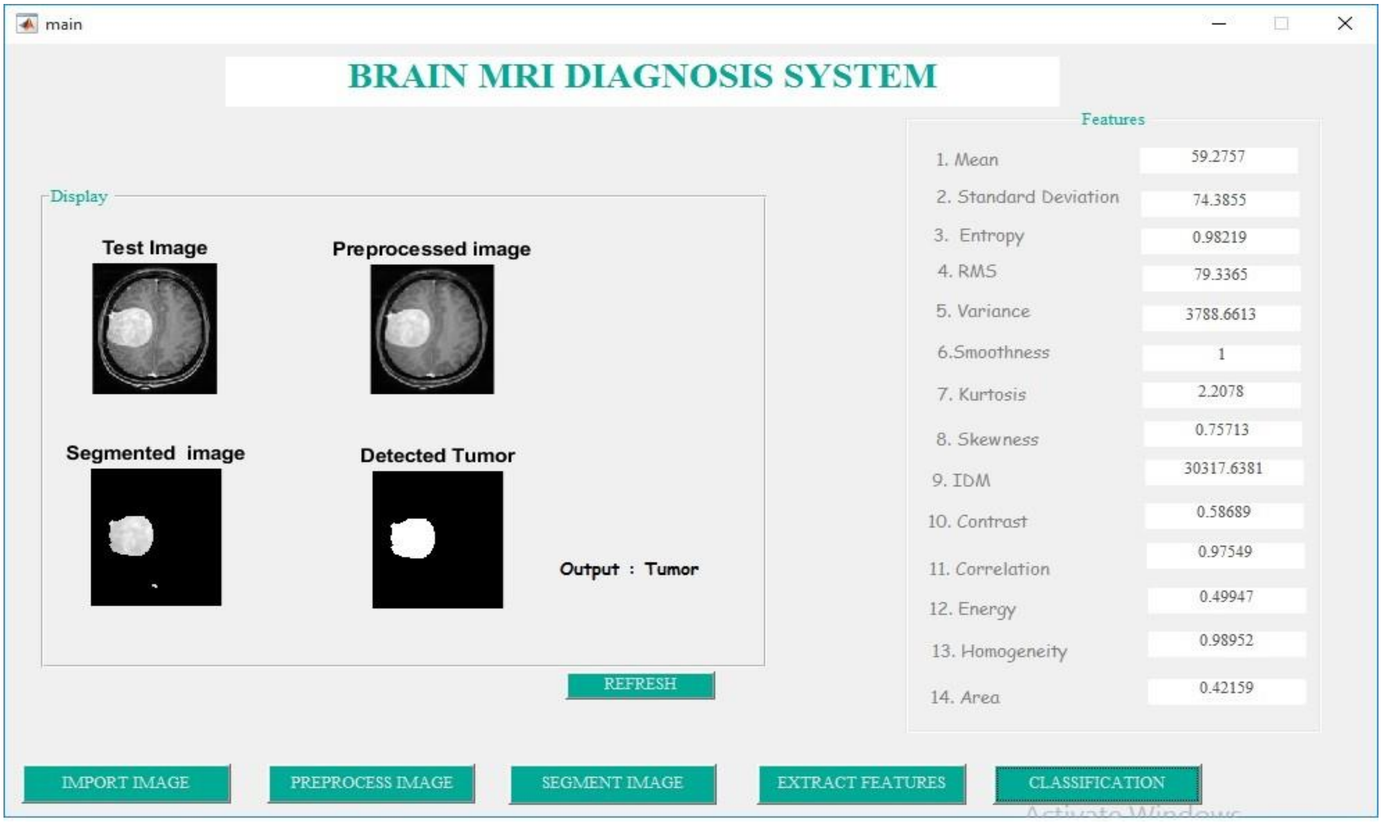

Fig. 6. GUI Initial

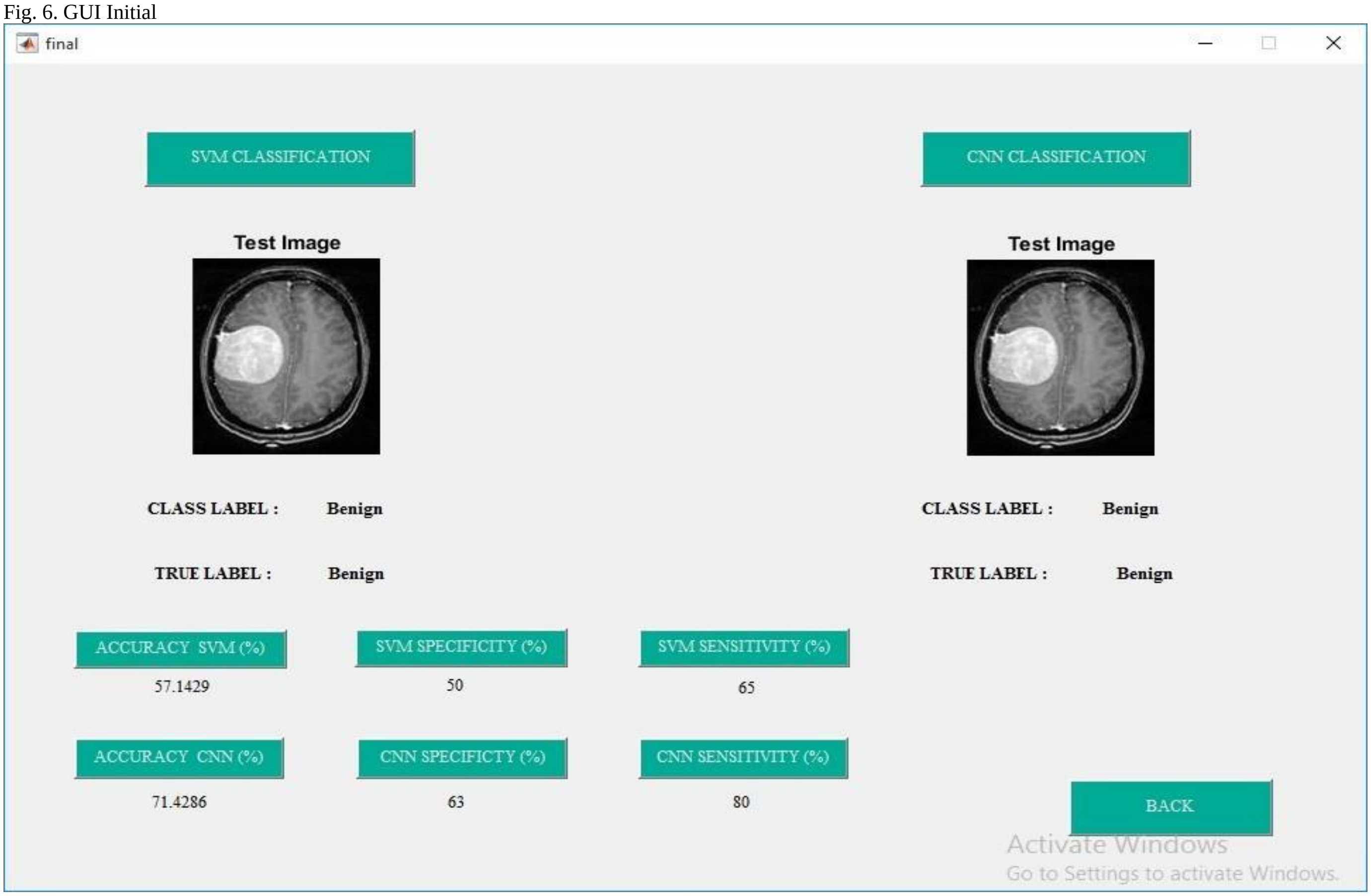

Fig. 7. GUI final

IV. RESULTS AND DISCUSSION

The dataset contains 130 MR images of brain including both Benign and Malignant labels. Out of this, 88 images are used for training and rest 42 are used for testing the classifiers. Training images contain 42 Benign and 46 Malignant images.

For testing, 20 Benign and 22 Malignant images are employed. SVM Classifier is compared with CNN classifier and the classification accuracy is calculated by using confusion matrix.

Table 1 and Table 2 show the confusion matrix for CNN and SVM respectively

TABLE I

CONFUSION MATRIX FOR CNN CLASSIFIER

PREDICTED	Benign	Malignant
ACTUAL		
Benign	TP 16	FN 4
Malignant	FP 8	TN 14

Using data from Table 1, Table 2, we computed sensitivity, specificity, and accuracy for both evaluations. These measures are listed in Table 3.

TABLE II

CONFUSION MATRIX FOR SVM CLASSIFIER

PREDICTED	Benign	Malignant
ACTUAL		
Benign	TP 13	FN 7
Malignant	FP 11	TN 11

1) Sensitivity = TP/TP+FN

2) Specificity = TN/TN+FP

3) Accuracy = TP+TN/TP+TN+FP+FN where,

- True Positive (TP) - Observation is Benign and is pre- dicted Benign.
- False Positive (FP) - Observation is Malignant and is predicted Benign.
- True Negative (TN) - Observation is Malignant and is predicted Malignant.
- False Negative (FN) - Observation is Benign and is predicted Malignant.

TABLE III

COMPARISON OF CLASSIFIERS

Fig. 8. Comparison of Classifiers

	Sensitivity (%)	Specificity (%)	Accuracy (%)
Evaluation			
Test Classifier			
CNN Classifier	80	63	71.43
SVM Classifier	65	50	57.14

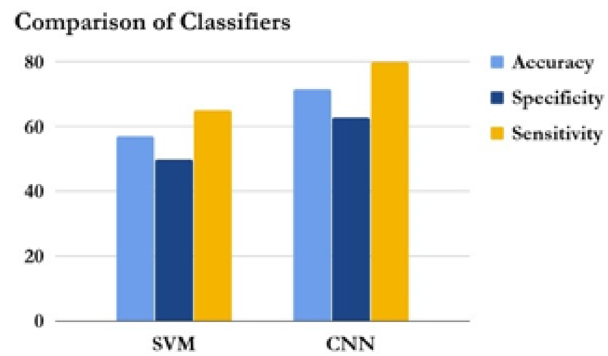

Fig. 8. Comparison of Classifiers

V. CONCLUSION

In this study, Brain Tumor is detected and classified using MRI images of the brain. Preprocessing is used to improve the signal-to-noise ratio and to eliminate the effect of unwanted noise. Furthermore, MRI images of the brain are used to segment brain tissues into normal tissues such as white matter, gray matter, cerebrospinal fluid (background), and tumor- infected tissues and Support Vector Machine and Convolu- tional Neural Network are used to classify the tumor stage into Benign and Malignant by building classification model and network respectively. From the literature survey conducted, it is clear that the brain tumor detection using computer aided technology is fast and accurate when compared with the manual detection performed by radiologists or clinical experts. The various performance factors also indicate that the proposed algorithm provides better result by improving certain parameters such as accuracy, sensitivity, specificity etc. The proposed approach can aid in the accurate and timely detection of brain tumor along with the identification of its exact location. Thus, it is significant for brain tumor detection from MRI images.

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