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Early Stage Brain Tumor Detection And Classification Using KSVM Algorithm In GUI Window

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Abstract

The brain is central control unit of human body. The tumor is not diagnosed in early stage then it affects the brain means it causes the death of the patient. Magnetic Resonance Image (MRI) doesn't produce any harmful radiation and it is a better method for area calculation as well as classification based on the grade of the tumor. Nowadays there exists no automatic system to detect and identify the grade of the tumor. This paper proposes brain tumor classification which is divided into four phases as pre-processing, segmentation, feature reduction and extraction, classification. Segmentation of brain Tumor is a one of the basic steps in detection and classification of tumor. The noise is eliminated by using Gaussian filter and canny edge detector is used to detect the tumor area and calculation of tumor area. To segment the tumour K means cluster is used. DWT (Discrete wavelet transform) and GLCM (Grey Level co-occurrence matrix) used for transform and spatial feature extraction and PCA (Principal component analysis) reduces the feature vector to maintain the classification accuracy of brain MRI images. For the performance of MRIs classification, the significant features have been submitted to KSVM (kernel support vector machine). The proposed method is validated on BRATS 2015 dataset and Kaggle dataset. The proposed system will reduce processing time and achieved 99% classification accuracy,98% of sensitivity and 100% of specificity.

Keywords— Gaussian filter, Canny edge detector, DWT, PCA, GLCM, Segmentation, MRI image, tumor detection, KSVM.

I.INTRODUCTION

The brain tumor means formation of abnormal cells in the brain. There are two main kinds of tumor those are Benign and malignant. The benign tumor is also called primary tumor and malignant tumor is called secondary tumor. The American Brain Tumor Association and World Health Organization consider the tumor in four grades those are grade I and grade II and are also known as low-grade tumors and grade III and grade IV and are called high-grade tumors. The low-grade tumors are also called benign tumor which grow slowly and the high-grade tumors are also called malignant which grow rapidly [2]. It is significant to detect brain tumor at the early stage and it is necessary to identify the tumor area and segment the tumor images.

Identification of brain tumor includes physician enquires regarding the medical history of the patient, both family history as well as personal history and carries out full physical examination that includes muscular strength, alertness of the body, reflexes, coordination of mind and body and responses to pain and eye check-up, etc. The physician performs a neurological examination by checking the common signs of health.

A specific treatment is suggested based on tumor type location and its size, as well as patient health condition and age. The options for the treatment include radiation therapy, chemotherapy and surgery. Image modalities is also diagnostic physical test for the patient which have been discussed in the below section [7].

With the recent technological developments made in the field of medical imaging, brain tumor imaging has emerged out as a significant component in diagnosis, planning of treatment, and monitoring of the response received for the treatment Computed Tomography (CT), Single-Photon Emission Computed Tomography (SPECT), Positron Emission Tomography (PET), Functional Magnetic Resonance Imaging (fMRI) and Magnetic Resonance Imaging (MRI) are Medical Imaging techniques[8]. These techniques provide valuable information about shape, size, location and metabolism of brain tumors assisting in diagnosis. Magnetic resonance imaging (MRI) and computed tomography (CT) scans are two diagnostic modes which show the internal structure of the brain. Operator performance causes noise in MRI images and this noise leads to inaccuracies classification. MRI is considered as the standard technique due to its high-quality soft tissue contrast resolution and, image manipulation, uses non-ionizing radiation and multi plane imaging technique [5]. Magnetic resonance imaging (MRI) and computed tomography (CT) scans are two diagnostic modes which show the internal structure of the brain. Operator performance causes noise in MRI images and this noise leads to inaccuracies classification. MRI is considered as the standard technique due to its high-quality soft tissue contrast resolution and, image manipulation, uses non-ionizing radiation and multi plane imaging technique.[6]

During image acquisition, coding and transmission the noise is always present in digital images. So, in image processing filter methods are mainly used to suppress either the high frequencies in the image means smoothing the image or low frequencies in the image means detecting the edges in the image. There are different types of image noise filtering methods in image processing those are Median filter, mean filter, bilateral filter, weiner filter, Anisotropic filter and Gaussian filter. If salt and pepper noise is present in image then meadian filter is good methods, poisson noise is present in image then mean filter is good method and speckle noise is resent in image then weiner filter method is good. [14]. Averaging filter gives the good result by computing MSE. Median filter removes the noise based on PSNR. A Gaussian filtering is applied. It is a linear filter and it is used to blur the image or to reduce noise as well as for edge detection or enhance the boundaries of the object. It is not easy to detect and classify the brain tumors. Due to the misplaced edges, noise, low contrast of medical images it is hard to get information from these images [16]. It includes few processes, such as image segmentation, enhancement, feature selection and extraction, feature classification and reduction.

Image segmentation is partitioning a brain image into multiple segments which are uniform and homogenous with respect to some characteristics such as colour, intensity or texture. Segmentation techniques are threshold method, edge-based segmentation, region-based segmentation, clustering based segmentation, watershed-based segmentation and artificial neural network based segmentation.

Clustering is grouping similar data together and reduces data dimension and it learns the shape of dataset by repeatedly moving its neurons closer to the data points. Clustering methods are k-mean clustering, improved k-mean clustering, Fuzzy C-mean and improved Fuzzy C-mean clustering. In K-means, data will be included in one particular cluster. In FCM, data can be included in all existing clusters, but with varying degrees of membership in a range of values [01]. the execution time is less in K-Means compared to Fuzzy C Means clustering technique, because the number of iterations of K-Means is less than Fuzzy C Means clustering[3]. Clustering is one of the unsupervised segmentation methods. K-means and Fuzzy C-means algorithm are two mostly used clustering techniques. K-means clustering is an effective way that uses a fixed number of clusters prior to classify a set of data [16].

The feature extraction can be done by using Gray Level Co-occurrence Matrix (GLCM) and Discrete wavelet transform (DWT). Spatial feature extraction can be done by using GLCM and transform feature extraction can be done by DWT. The high dimensional space patterns can be made by statistical method known as principal component analysis (PCA). The multidimensionality and number of variables can be reduced by PCA and it enables the exploring of date in an easy way [20]. The classifier on the basis of machine learning comprising of supervised and unsupervised learning has become popular in recent years. K-NN, SVM and ANN are included in supervised learning. Self-organization feature map (SOFM) and fuzzy c-means are included in unsupervised [4]. The advantageous features of SVM are regularization, low test error rate, kernel trick and absence of local minima.

The tumor classification and detection has been done by employing various techniques till now. But these techniques have drawbacks such as lack of accuracy, intensity inhomogeneity, noise, time complexity, computational complexity, feature selection, extraction and reduction, etc. DWT with KSVM classifier is proposed to overcome these limitations and also classification of the tumor is done with high accuracy by using this classifier, which denoising and segment the image, extract and reduce the feature, select the proper features for accurate classification of the tumor as benign and malignant tumor from MRI image. The international Association of cancer registries (IARC) reported that brain tumor cases in India in this is 24,530 (13,840 men and 10,690 women) and 3,08,102 (1,68,346 male cases and 1,32,414 female cases) in worldwide.

II. LITERATURE SURVEY

Hemanth et al., [21] Proposed Convolutional neural network for classification of brain tumor. For denoising the MRI image, they applied Average and Bilateral Filtering methods and for Segmentation, pixel-based segmentation is used and PSNR, MEAN, Entropy, standard deviations are selected for machine learning model. They achieved 91% of classification accuracy by using CNN classification method.

Saurabh Kumar et al. [22] Proposed Support Vector Machine (SVM) classification for of brain tumor. The MRI images denoised by using Gaussian filter method and segmentation is done by Self-Organized Mapping method. They collected MRI dataset from Digital imaging and communications in medicine and they achieved 97% of accuracy.

Chong Zhang et al. [23] Proposed K-means clustering to segment the brain tumor. Adaptive Wiener filtering is utilized for denoising, and morphological operations are used for removing nonbrain tissue, effectively reducing the method's sensitivity to noise. Secondly, K-means++ clustering is combined with the Gaussian kernel-based fuzzy C-means algorithm to segment images. This clustering not only improves the algorithm's stability, but also reduces the sensitivity of clustering parameters. Finally, the extracted tumor images are postprocessed using morphological operations and median filtering to obtain accurate representations of brain tumors.

Hüseyin Kiraz et al. [24] Proposed KNN (K Nearest Neighbours) Algorithms for classification of tumor. For noise removing of preserving edges Bilateral Filtering is used and for sharping High-pass filtering is used. Segmentation of tumor is done by using Thresholding Segmentation ant they collected 50 MRI images which is publicly available dataset. They achieved 89.9% classification accuracy by using KNN.

Doshi Jeel Alpeshkumar et al.,[25] Proposed Convolution Neural Network for classification of brain tumor. The MRI images denoised by using Gaussian blur filter method and segmentation is done by binary thresholding and for features extraction they used morphological operations. They collected 255 brain MRI from it 155 contains tumor and 98 images of healthy brain to train the model from Kaggle Dataset and they achieved 97% classification accuracy by using CNN.

Chaudhary *et al.*,[26] They proposed K-Means for segmentation and DWT is used to extract features. For the classification between malignant and benign tumor SVM is applied at last. They used 6 images for testing their code from Rajendra institute of medical science and they achieved 94.6% of accuracy.

Vijh *et al.*, [27] To find the optimal threshold value, adaptive particle swarm optimization including OTSU is proposed. In order to eliminate the noise and enhance the image quality anisotropic diffusion filtering is employed on brain MRI. For performing classification and guiding the convolutional neural network, data is provided by extracted features. They collected 40 MR-free non-tumored images and 61 IBSR (Internet Brain Segmentation Repository) tumored images of magnetic resonance and gained 98% of accuracy.

Ansari M *et al.*, [28] proposed median filtering to denoise the image and Morphological Operation for Image Segmentation. The DWT and GLCM is utilized for feature extraction and SVM are utilized for segmentation of brain tumor as benign and malignant. They used 5 MRI images for testing their code these images are JPEG/JPG format and they achieved 98.91% of accuracy.

Gokulalakshmi *et al.*, [29] proposed SVM classifier and K-means clustering for classification. For feature extraction Grey-Level Co-occurrence Matrix (GLCM) and Discrete Wavelet Transformation (DWT) are used. They collected 750 samples of 30 images from DICOM dataset and They achieved 94% of accuracy.

Chander P *et al.*, [30] proposed adaptive K-Means clustering algorithm for segmentation and SVM classifier is used for classification. Discrete Wavelet Transformation (DWT) and Grey-Level Co-occurrence Matrix (GLCM) are utilized for feature extraction. Forty MR images of malignant and Benign tumor are collected from Harvard University medical Image Repository. They achieved 99.7% of segmentation accuracy and 93% of Classification accuracy.

Deb et al., [31] Proposed bilateral filtering method to remove the noise, GLCM is used for feature extraction, Adaptive Squirrel search algorithm (ASSA) is used for segmentation and AFDNN (Adaptive Fuzzy Deep Neural Network) is used for classification of brain tumor. They collected data from BRATS 2012, BRATS 2015 and BRATS 2016 and they achieved 99.6% classification accuracy by using BRATS 2016 dataset.

Rai et al.,[32] Proposed Low Layered U-Net (LU-Net), Le-Net and VGG-16 CCN model for detection and segmentation of brain tumor. They collected of 253 images of high pixels from publicly available open-source dataset and they achieved 98.00% of accuracy.

Sathish et al.,[33] Proposed gaussian hybrid fuzzy clustering (GHFC) for segmentation and Exponential cuckoo based Radial Basis Neural Network (Exponential cuckoo based RBNN) classifier for classification of brain tumor. They collected 65 images from BRATS and 50 MRI images from Sim BRATS database. They achieved 87.19% classification accuracy.

Toğaçar et al.,[34] Proposed Brain MRNet is new convolutional neural network model for detection of brain tumor. They collected 253 images in which 155 images are abnormal and 98 images are normal. Here images are in JPEG format and they achieved 96.05% of accuracy.
Toğaçar et al., [35] Proposed novel convolutional neural network (CNN) model that is combined with the hyper column technique for feature extraction, feature selection is done by using recursive feature elimination (RFE) and SVM is used for classification of brain tumor. They collected 253 images in which 155 images are abnormal and 98 images are normal. Here images are in JPEG format and they achieved 96.77% of accuracy.
Gokulalakshmi et al.,[36] Proposed K-means clustering for segmentation, Discrete wavelet transformation (DWT) and gray-level co-occurrence matrix (GLCM) is used for feature extraction, and SVM is used for classification of brain tumor. They collected 750 samples from DICOM dataset and they achieved 93.3% of accuracy.
Kalaiselvi et al.,[37] Proposed Convolutional Neural Networks (CNN) for classification. They collected dataset from BRATS 2013 dataset and a clinical dataset collected from The Whole Brain Atlas (WBA), by Women's Hospital, Harvard Medical School, Boston, USA. They used 6 models of CNN and they achieved 96-99% of classification accuracy.
Kumar et al.,[38] Proposed adaptive k-nearest neighbor classifier to classify the tumor as normal or abnormal and for segmentation they proposed the optimal possibilistic fuzzy C-means clustering algorithm. They collected 1000 images from BRATS MICCAI brain tumor dataset and another one is publically available dataset images which are collected from internet. They achieved 96.5% classification accuracy ,100% Sensitivity, 93%% of Specificity.
Amarapur et al., [39] They proposed Cognition based Modified Level Set Segmentation method for segmentation of brain MRI images and for classification of brain tumor is done by using Adaptive Artificial Neural Network (AANN) classification method. They collected data from BRATS-2015 database and they achieved 98% of classification accuracy.
Bhandari et al., [40] They proposed convolutional neural networks (CNNs) to segment the brain tumor. They collected training dataset from Multimodal Brain Tumor Segmentation (BraTS) benchmark and from their own university. They achieved segmentation accuracy from 82 to 89%.
Abd Alreda et al., [41] They proposed Feed Forward Back Propagation neural network (FFBPNN) and support vector machine (SVM) for brain tumors classification and Discrete wavelet transform and gray level co- occurrence matrix (GLCM) for feature extraction. They collected 308 images of 83 cases for training and 37 cases for testing from the cancer imaging archive (TCIA) and 59 cases for training and 29 cases for testing from Harvard medical brain databases and they collected 66 cases for training and 34 cases for testing from General Hospital of Baquba-Iraq of MRI brain images and they achieved 97% of classification accuracy.
SivaSai et al.,[42] Proposed Adaptive Bilateral Filter to remove the noise and Fuzzy Recurrent Neural Network (FR-Net) is used for segmentation of brain tumor. They collected 1900 MRI images from Kaggle and they achieved 87.8% of accuracy.
Ramdas Vankdothu et al.,[43] proposed recurrent convolutional neural networks (RCNN) classification method to classify brain tumors with low complexity and high accuracy. Pre-processing stage applied adaptive filtering algorithm to denoise the MRI images and Image segmentation is performed using the improved K-means clustering (IKMC) algorithm, and the Gray level co-occurrence matrix (GLCM) is used for feature extraction to extract features and extracted features were applied to RCNN classifier to classify the tumor. They collected the Kaggle dataset with 394 testing sets and 2870 training set MRI images and they achieved 95.17% classification accuracy.

III. METHODOLOGY

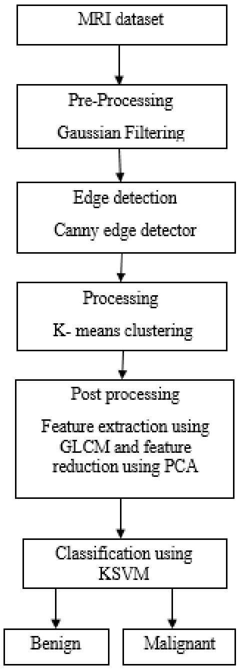

Figure 1: Steps for tumor detection and classification using KSVM

The analysis of proposed system consists of various steps such as pre-processing, Edge detection, segmentation, feature extraction and classification. In the preprocessing stage, for extracting the noise, Gaussian filter is applied to the image. In the segmentation stage, for the purpose of segmenting tumor, K-means clustering is applied. In the third stage different types of features are extracted. Finally, in the classification stage the type of tumor images can be identified [6].

1) Dataset:

Collected 150 multi-modality MRI images from BRATS 2015 benchmark and Kaggle dataset. MRI scanned images are either color, Gray-scale or intensity images with size of 220×220.if it is Gray-scale image, a Gray-scale converted image is defined by using a large matrix whose entries are numerical values between 0 and 255, where 0 corresponds to black and 255 corresponds to white. Image segmentation and edge detection is considered as two main stages for brain tumor detection.

2) Pre-Processing

The MRI images are taken as the input image data set in which the MRI image gives detail information about the brain. The input dataset is kept in the form as, X= $\{x_1, x_2, \ldots x_n\}$. The images are collected from the BRATS dataset. After preparing the dataset, Preprocessing is the first stage in this system. Magnetic resonance images can be affected by several types of noise and suffer from resolution degradation. [21].

It is the primary stage which is used to remove the unwanted noise from an image like patients name, age, address and other extra details are removed during this process. The image is resized and conversion of RGB to grayscale is performed. Due to thermal effect, there may be noise during MRI scanning, and it is necessary to eliminate this noise. The three components are weighted and averaged with different weights. Because the human eye has the highest sensitivity to green, it is more sensitive to blue. Further processing of MRI images requires conversion to grayscale image, which reduces the computational complexity. The expression for conversion of RGB to grayscale has been given in equation (3.1).

$$G_{gray}= \frac{G_R+G_G+G_B}{3} \tag{3.1}$$

A Gray scale image consist of only two colours, black and white, it is easy to apply filtering. Black represents low frequency part and white represents the high frequency part.

3) Noise removal using Gaussian filter

The gaussian filter blurs the desired area and cuts the noise with higher frequencies. It is a linear filter that remove the gaussian noise and blur the edges effectively. By using gaussian filters (LPF & HPF) the noise present in the input images can be removed. LPF helps out in smoothening of the image and HPF helps out in sharpening of the image. It is a process of weighted average of the entire image, that is, the value of each pixel is obtained by weighted average of itself and other pixel values in the neighbourhood. The essence of filtering is Gaussian Convolution process of normal distribution and image [46]. Gaussian functions are widely used in statistics to describe the normal distributions and hence are often used to represent the probability density function of a normally distributed random variable with expected value σ^2. When working with images we need to use the two-dimensional Gaussian function. The mathematical model of the Gaussian filter is a two-dimensional Gaussian filter function, as shown in below formula:

$$g(x, y)=\frac{1}{2\Pi\sigma^2}e^{\frac{-x^2+y^3}{2\sigma^2}}$$

Among them, g (x, y) is the gray value of the selected pixel (x, y); (x, y) is the pixel coordinate of the two-dimensional plane; x, y is the distance between the pixel point (x, y) and the center point; σ is the standard deviation of Gaussian filtering, which represents the degree of dispersion of data.

4) Edge detection

Edge detection is an image processing technique for finding the boundaries of objects within images. This technique can be a useful way of finding presence of tumor in the brain and It works by detecting discontinuities in brightness. Edge detection of the image segments the brain into several parts, yet there are challenges in the method since, intensity of healthy tissue, tumor and surrounding fluids overlap. Edge detection can be a useful technique to check for any abnormal growth in the brain area.[139]

The challenges of edge detection algorithms are as follows

- Sometimes fake edges are detected, Due to noise
- Missing to detect real edge points and detecting fake edges.
- Multiple responses to each edge in the image should be avoided.
- The changes in lighting conditions and Background is dynamic
- Geometrical features and Position of the detected edge to be shifted from its true location

Edge detection is a most vital part in tumor identification for finding boundaries between regions based on discontinuities in intensity. The edge representation of an image reduces the quantity of data to be processed still yet it contains necessary information. Here we used canny edge detection technique. It is one of the relevant techniques among various edge detection methods in which noise from the image being separated before find edges of image [140].

5) Processing

Image Segmentation is performed by K -means clustering. Selecting proper segmentation method is difficult task because of the great verities of the lesion shapes, sizes, and colors along with different skin types and textures. The drawback of FCM clustering for image segmentation is that its objective function does not take into consideration any spatial dependence among pixels of image but deals with images the same as separate points. Second drawback of FCM clustering method is that the membership function is mostly decided by (xk, Vi), which measures the similarity between the pixel intensity and the cluster center. Higher membership depends on closer intensity values to the cluster center. Hence membership function is highly sensitive to noise [16].

K-means, as the most famous clustering algorithm, was used for further processing of the binary image and it is an unsupervised iterative clustering technique and it separate the given data into K predefined distinct clusters. The cluster is defined as a collection of data points exhibiting certain similarities Clustering the image means grouping out the pixels depends on some characteristics. In K-means clustering the number of clusters k has to be defining first. The cluster centers k has to be chosen randomly. Then distance between these cluster centers and pixels are calculated. Every pixel is individually compared with all cluster centers with the help of distance formula. The pixel is moved to particular cluster which has shortest distance among all. This process is continuous until the clustering criterion converges. The objective function describing k-means clustering can be written as:

$$S= \sum_{b=1}^{k}\sum_{a=1}^{x} ||x_a^{(b)} - c_b||^2$$

Where $|x_a^{(b)} - c_b||^2$is the predefined distance from data point $x_a^{(b)}$and cluster center c_b. S is the indicator of the distance of the N points from their respective cluster centers. Partition the data set by using these following points:

1) Each data point belongs to a cluster with the nearest mean.
2) Data points belonging to one cluster have high degree of similarity.
3) Data points belonging to different clusters have high degree of dissimilarity.

The algorithm steps of k-means clustering can be expressed as:
Step 1:
1) Choose the number of clusters 'K'
2) Randomly select any 'K' data

Step 2:
1) Select cluster centers in such a way that they are as farther as possible from each other.

Step 3:
1) Calculate the distance between each data point and each cluster center.
2) The distance is calculated either given distance function or by using Euclidean distance formula.

Step 4:
1) Assign each data point to some cluster.
2) A data point is assigned to the cluster where center is nearest to that data point.

Step 5:
1) Recomputed the center of newly formed clusters.
2) The center of a cluster is computed by taking mean of all the data points contained in that cluster.

Step 6:
1) Keep repeating the procedure from Step 3 to Step 5 until any of the following stoping criteria is met.
2) Center of newly formed clusters do not change
3) Data points remain present same cluster.
4) Maximum numbers of iterations are reached.

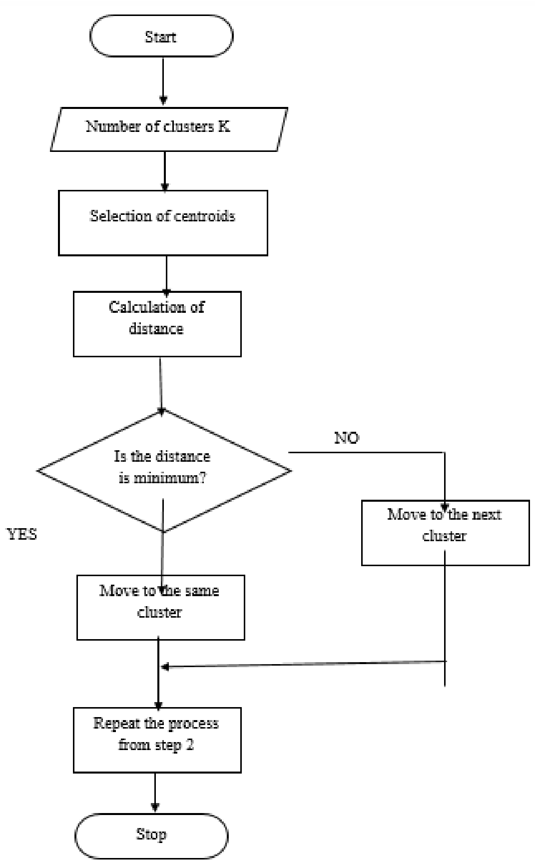

Figure 2: Flow chart of K means clustering

4) Post Processing
Post processing employs to main parts: Feature Extraction and Feature Reduction.

4.1Feature extraction
Feature extraction is process of extracting quantitative information from an image such as color features, texture, shape and contrast. Here we used DWT (discrete wavelet transform) for transform feature extraction and GLCM (gray-level co-0ccurrence matrix) for Spatial feature extraction.

4.1.1) Spatial feature extraction using GLCM
GLCM is a statistical method to obtain the relative pixel position of an image. This texture-based feature extraction technique was first introduced by R.M. Haralick. It measures the occurrence of a pixel i of intensity I in relation to other pixel j at a distance d and angle ϴ.The total number of occurrences of a pixel i becomes an element of the GLCM. After calculating GLCM, features are determined from the resultant matrix. In this study, we measured contrast, correlation, energy and homogeneity.
There are two types of features is there
1) The Intensity Based Feature
2) Texture Based Feature

1) The Intensity Based Feature
The intensity-based feature is most commonly used features compared to texture-based features in image processing algorithm. Mean, standard deviation, variance, median, skewness and kurtosis are considered as the intensity-based features. The two dimensional function of the image is denoted by f(a,b), intensity level is denoted by h(i), N is denoted by the total number of gray levels in the entire image and p(i) denotes the probability density

➢ **Mean**
Mean is defined as the average level of intensity of image and It clearly shows that the mean is a function probability density.

$$\mu = \sum_{i=0}^{N-1} i, p(i)$$

➢ **Standard Deviation**
The mean value of the pixels and their probability densities are used to measure the standard deviation

$$\sigma = \sqrt{\sum_{i=0}^{N-1} (i-\mu)^2 \ .p(i)}$$

➢ **Entropy**
The uncertainty in the random variable is measured by the entropy. It depends on the probability density p(i).

$$En = -\sum_{i=0}^{N-1} p(i)\log_2[p(i)]$$

➢ **Variance**
The variation in the intensity is measured with the help of variance. It is also calculated by squaring the standard deviation.

$$\sigma^2 = \sum_{i=0}^{N-1}(i-\mu)^2 .p(i)$$

➢ **Kurtosis**
The histogram flatness is measured by kurtosis and it depends on the standard deviation, mean and probability density.

$$\mu^4 = \sigma^4 \sum_{i=0}^{N-1}((i-\mu)^4 .p(i)) - 3$$

- **Skewness**

Symmetry of an image is defined by the skewness and It is denoted by μ3.

$$\mu^3 = \sigma^{-3} \sum_{i=0}^{N-1}((i-\mu)^3 \cdot p(i))$$

2) Texture Based Feature

The higher order description of an image is offered by the texture features. It provides the details about spatial distribution of tonal variations or gray tones. The texture -based feature extraction includes the homogeneity and similar regions of an image. The gray matter, white matter, cerebrospinal fluid and tumor region are classified from the MRI by this feature.

- **Inverse Difference Moment (IDM)**

The local homogeneity of an image is calculated by IDM. It takes two images and parameters that specify the viewing condition. IDM is local homogeneity and it is high when local gray level is uniform and inverse GLCM is high.

$$\text{IDM} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{1}{1+(i-j)^2}, p(i,j)$$

- **Contrast**

The intensity variation of threshold and its nearest pixel is determined by contrast.

$$\text{Contrast} = \sum_{n=0}^{N-1} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j)^2$$

- **Correlation**

It is used to measure the relationship between the threshold and nearest pixel.

$$\text{Correlation} = \frac{1}{\sigma_a \sigma_b} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i,j)p(i,j)^2 - \mu_a \mu_b$$

- **Energy**

Sum squared of GLCM elements.It is also called as angular second moment or uniformity

$$\text{Energy} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j)^2$$

- **Homogeneity**

Homogeneity is calculated by the energy. It measures the variation in image intensity.

$$\text{Homogeneity} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{p_{i,j}}{1+(i-j)^2}$$

4.1.2) Transform feature extraction using DWT

In this stage, discrete wavelet transform (DWT) technique was applied to the segmented image to extract the features. Here first converting images from the spatial domain to frequency domain. Then actual DWT is performed by filtering the image using two filters those are low pass filter and a high pass filter, in both the vertical and horizontal direction. Here the image is divided into four coefficients: LL,LH, HL and HH in every DWT level. The LL sub-bands come from using the lowpass filter in the horizontal direction and the lowpass filter in vertical direction, and these sub-bands are known as the approximation coefficient. The other sub-bands are known as detailed coefficients and more detailed information is extracted from the tumor using DWT.

4.2). Feature Reduction Using PCA

Extra unnecessary features will increase the classification complexity, require more storage memory and prolong the computational time. Thus, feature reduction is considered as a part of our proposed system. Principal Component Analysis (PCA) is one of the popular methods to reduce the dimensionality of wavelet transform. PCA is used to reduce the dimension of data according to their importance and variance. The PCA method makes the components of the input feature set perpendicular, and then it rearranges them in terms of the highest variation. The component with a low variation in the feature set are removed. PCA allows the identification of standards in data and their expression in such a way that their similarities and differences are emphasized. Once patterns are found, they can be compressed, i.e. their dimensions can be reduced without much loss of information. Such a reduction is advantageous for image compression, data representation, calculation reduction necessary in subsequent processing, etc.

5) Classification

The original support vector was developed by Vapnik which is a binary classification method to minimize structural risk. SVM is based on supervised techniques which can be used to one-class classification problem to multiple-class classification problem [13]. SVM can be used as a kernel machine. The main impact of kernel trick is that in a transformed feature space kernel allows to fit the maximum-margin hyperplane. A kernel support vector machine (KSVM) was finally applied for MRI classification. There are several families of SVM such as auto scale, box constraint, and kernel. The kernel support vector machine was selected due to its wide range of kernel functions, such as linear, polynomial, and gaussian radial basis function (GRB). In this study, SVM with linear kernel is used to separate the images into two classes. The form of linear function is shown by using the following equations:

$$\alpha(\mathrm{m})=w^{T}\,\varphi(m)+c$$

Where w, T is the hyper plane parameter and φ(m)function maps the vector m into higher plane. Training samples are separated by hyper plane using,

$$\alpha(\mathrm{m})=w^{T}\,\varphi(m)+c=0$$

So, based on the high plane two classes are separated.

Performance analysis:

Arrangement, understanding, accuracy of the present system and sensitivity of the model are finding out by using these relations.

1. True positive is at the abnormal condition, it's identified correctly. x True negative is said like normal brain condition, it's identified properly.
2. False negative is at the abnormal brain condition, it's identified properly.
3. False positive is at the normal brain condition, it's identified properly.

These parameters are mainly helped to check the classifier status in the model.

1) Sensitivity= True positive/100 %*(True positive +FN).

2) Specificity = True negative /100 %*(True negative +FN).

3) Accuracy= $\left(\frac{(TP+TN)}{(TP+TN+FP+FN)}\right)$ *100%

6) GRAPHICAL USER INTERFACE (GUI) WINDOW

New technologies and the available computing tools are becoming more important every day in the teaching evolution. The use of Graphical User Interfaces (GUI) with MATLAB enables the implementation of practical teaching methodologies to make easier the comprehension of a given subject. GUI has simple tool for a better understanding on how to design GRIN elements for optical systems. Another GUI's advantage is that they can be converted to an executable file, so any one could use the interface in their own computer without having a MATLAB license. The GUI developed performs the basic operations on the medical images. It gives the user a better view about each operation at the click of the button. This GUI can be used for any general image [44]. A GUI (graphical user interface) is a system of interactive visual components for computer software. A GUI displays objects that convey information, and represent actions that can be taken by the user. The objects change color, size, or visibility when the user interacts with them. The GUI was first developed at Xerox PARC by Alan Kay, Douglas Engelbart, and a group of other researchers in 1981. Later, Apple introduced the Lisa computer with a GUI on January 19, 1983.A graphical user interface (GUI) is a pictorial interface to a program. A good GUI can make programs easier to use by providing them with a consistent appearance and with intuitive controls like push buttons, list boxes, sliders, menus, and so forth. The GUI should behave in an understandable and predictable manner, so that a user knows what to expect when he or she performs an action.

IV. RESULT AND DISCUSSION

The proposed methodology for brain tumor detection and classification using GUI (graphical user interface) window. Each and every response from the computer is visually communicated through GUI. Experimental results of tumor area calculation and Step by step result also shown in this chapter using GUI window. The comparative analysis of proposed system has been carried out in terms of performance parameters such as sensitivity, specificity and accuracy. The proposed system gives better result compare to few existing systems.

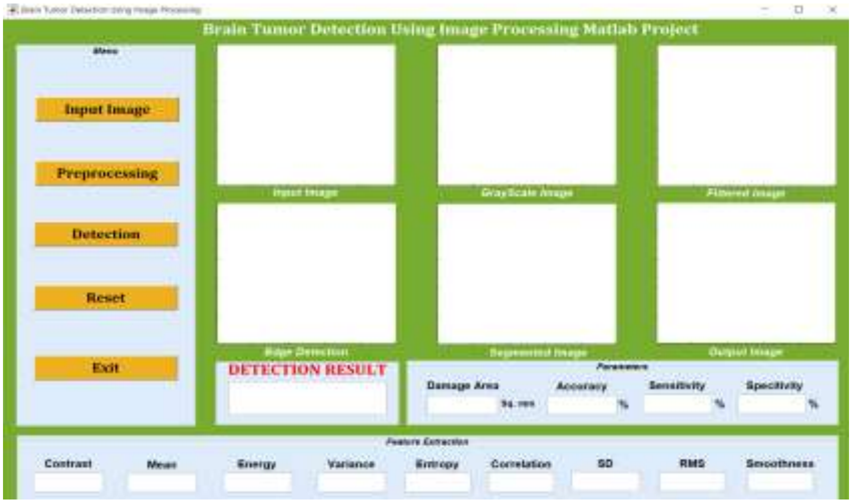

Figure 3: The first step of a GUI operating system. In this section we present initial process

Below is a picture of the Windows 10 desktop and an example of a GUI operating system. In this example, We use a mouse to move a pointer and click a program icon to start a program.

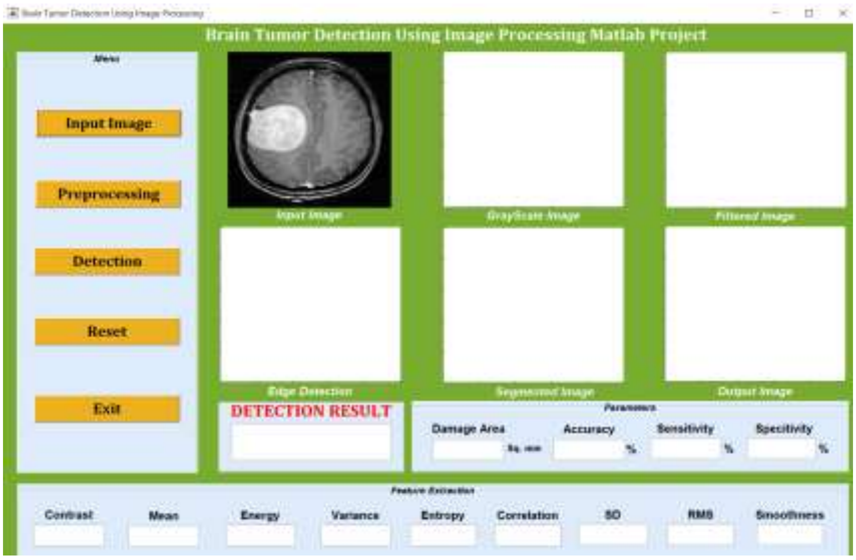

Figure 4: The second step of a GUI operating system. In this section we present the result input MRI image

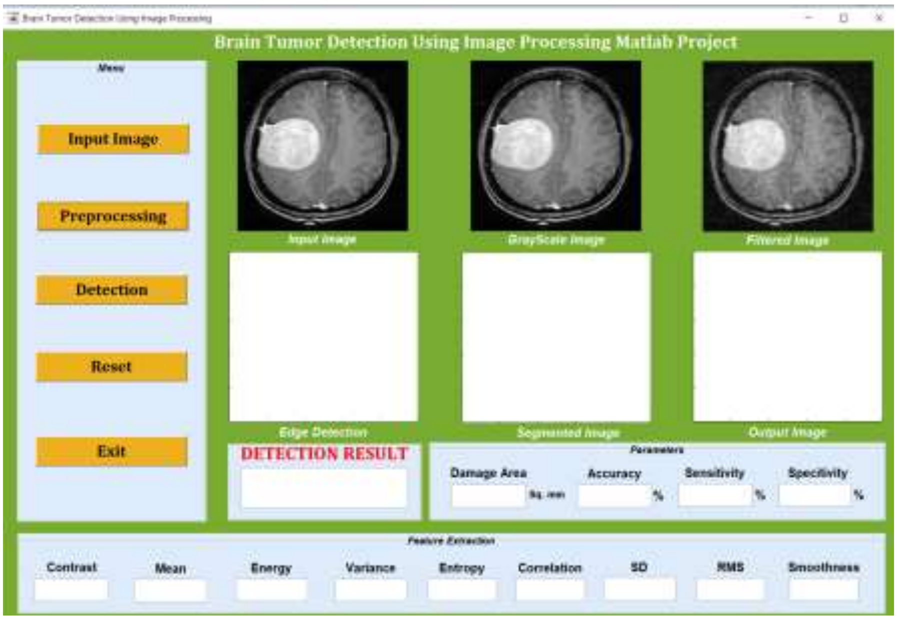

Figure 5: The third step of a GUI operating system. In this section we present the result of pre-processing

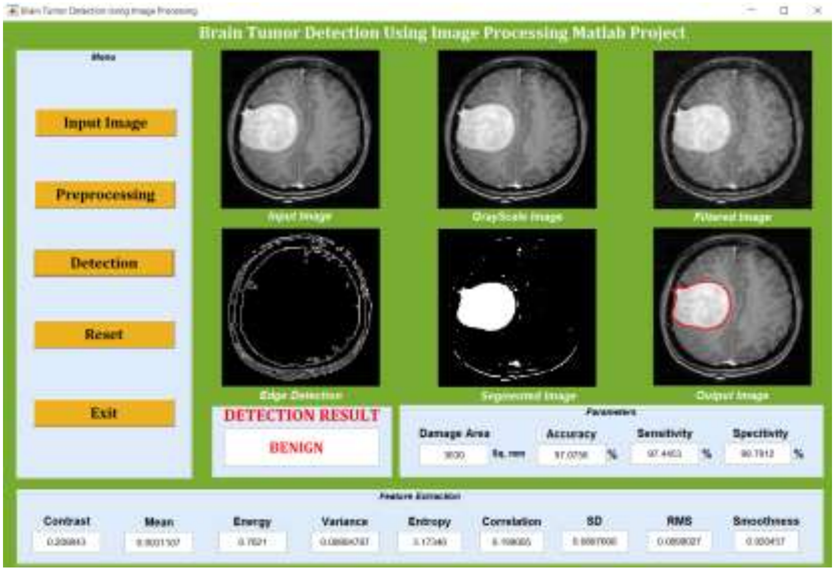

Figure 6: The fourth step of a GUI operating system. In this section we present the result of detection

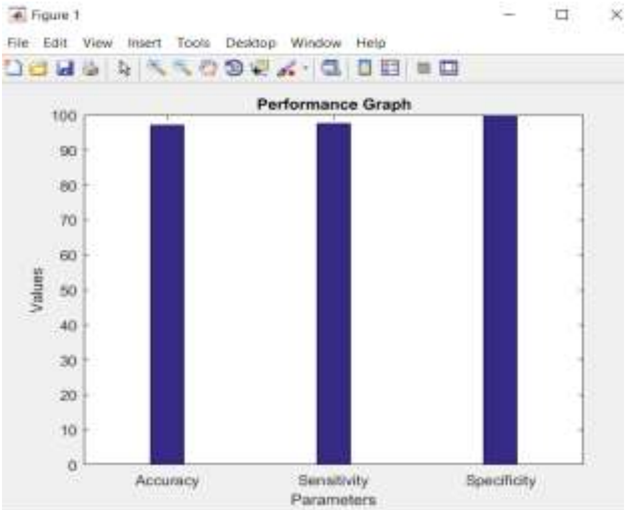

Figure7: The fifth step of a GUI operating system. In this section we present the result of performance analysis

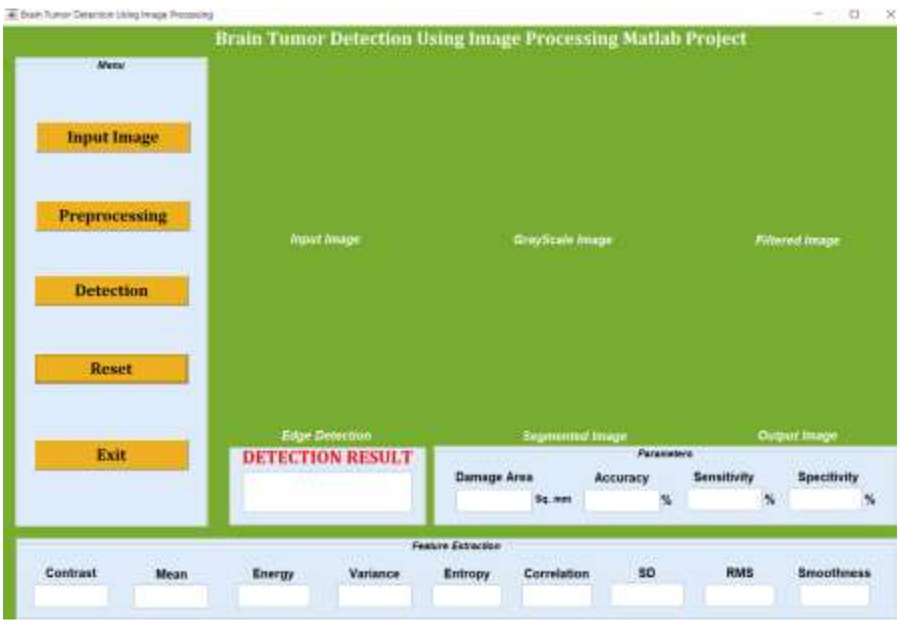

Figure 8: The final step of a GUI system. In this section we present the result for various button press events.

The text box displays the current operation performed.

IV. CONCLUSION

Due to various factors Automatic brain tumor detection and classification is still a challenging task. The brain MRI based tumor identification and grade classification method has been proposed in this paper. The initial pre-processing has been done with the help of gaussian filter. Now the pre-processed input MRI is gives to the canny edge detector to detect the edge of the tumor and area calculation. The segmentation of brain tumor is done by using K-means clustering algorithm. The key features extracted from segmented MRI using GLCM and DWT. The features are reduced with the help of PCA. Now the PCA output has been given as input to the SVM classifier. The classification of tumor into benign or malignant has performed using kernel based SVM classification. The proposed system was implemented using MATLAB 2016b. The use of SVM along with the appropriate kernel techniques can help in achieving high accuracy, sensitivity and specificity and proposed method was implemented step by step using GUI window. The proposed system reduces processing time and achieved 99% classification accuracy,98% of sensitivity and 100% of specificity.

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