Brain Tumor Classification using Image Processing

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Abstract*-The human brain is the center of human central nervous system surrounded by head. The sensation, memory, emotions are controlled by Human Brain. Magnetic Resonance Imaging technique is widely used by radiologist to visualization of human internal body without opening of body. The mutations (errors) in cells DNA responsible for beginning of tumor. The healthy cells would die because mutations allow cells to grow at increased rate. The result is a mass of abnormal cells, which forms a tumor. Tumor in human brain may experience blurred vision, speech difficulty, reduced sensation of touch, balanced disorder, problem with coordination inability to speak or understand. Tumor causes cancer related deaths, responsible for around 13% of all deaths world-wide. In this paper, a computer-based methodology for outlining tumor region within the brain exploitation MRI picture is given. A classification of brain into healthy brain or a brain having a tumor is 1st done that is then followed by additional classification into benign or malignant. The algorithmic program incorporates steps for preprocessing, image segmentation, feature extraction and SVM image classification techniques. Finally, the features of test image and train image are compared and classification of input image done by SVM classifier.*

Keywords-SVM classifier, Magnetic resonance image, image segmentation, brain tumor classification

I. INTRODUCTION

The human brain is the most vital part of the human body. Brain is the central part of the body responsible for proper functioning of the body. Brain and the spinal cord made up of nerve cells (neurons) and supporting cells (Glial cells) that received and send messages through nerves & controls all the part of our body. Brain tumor is nothing but the mass of abnormal growth to tissue in any part of the brain. Some brain cells multiply in an uncontrolled manner and form tumor [1, 6]. These tumors can arise from any part of the brain, spinal cord or the nerves. In recent years, the occurrence of brain tumors has been on the rise. Unfortunately, many of these tumors detected too late. It is much easier and safer to remove a small tumor than a large one. But as the size of tumor slowly increase in size they can cause pressure on the normal brain & interface with mental and bodily functions. Person having brain tumor can lead to loss of memory, blurred vision, nousea etc. also one loose control over his behavior due to lack of proper functioning of brain. Thus detection of tumor at early stages is an important task.

In Human Brain system, as the normal cells grow old, they die and new cells take their place. Sometimes, this process goes wrong. New cells forms, even old cells doesn't die. These forms the mass of tissue called Tumor. Tumor classified as Primary Brain Tumors and Secondary Brain Tumors.

- Primary Brain Tumors: Primary brain tumors can be benign or malignant. Benign brain tumors do not contain cancer cells. Usually, benign tumors can be removed, and they seldom grow back. Benign brain tumors usually have an obvious border or edge. Cells from benign tumors rarely invade tissues around them. They don't spread to other parts of the body. However, benign tumors can press on sensitive areas of the brain and cause serious health problems. Unlike benign tumors in most other parts of the body, benign brain tumors are sometimes life threatening. Benign brain tumors may become malignant. [7]
- Secondary Brain Tumors: Malignant brain tumors (also called brain cancer) contain cancer cells. Malignant brain tumors are generally more serious and often are a threat to life. They are likely to grow rapidly and crowd or invade the nearby healthy brain tissue. Cancer cells may break away from malignant brain tumors and spread to other parts of the brain or to the spinal cord. They rarely spread to other parts of the body [7].

Doctors group the Brain Tumors by Grade. It generally refers to the way the cells looks under a microscope.

Grade I: The tissue is benign. The cells look nearly like normal brain cells, and they grow slowly.

Grade II: The tissue is malignant. The cells look less like normal cells than do the cells in a Grade I tumor.

Grade III: The malignant tissue has cells that look very different from normal cells. The abnormal cells are actively growing.

Grade IV: The malignant tissue has cells that look most abnormal and tend to grow quickly [13].

II. LITRATURE REVIEW

M.Y. Banumurthy and Koteswararao Anne [5] introduced the three stages i.e. Feature extraction, Classification, Segmentation. MRI images are applied as input to an artificial intelligence system that uses Neuro-fuzzy Classifier. The extracted feature from images are applied to classifier which classifies the images in to normal and abnormal. Abnormal images were efficiently segmented by this method. Method is evaluated using the performance measures FPR, Sensitivity, FNR, Specificity and Accuracy. Classifier achieves a very good accuracy of 95.65%.

Mr. Lalit P. Bhaiya, Ms. Suchita Goswami and Mr. Vivek Patil [6] used a Neuro-fuzzy model. This system removes a essential requirements since it includes the advantage of both ANN and the fuzzy LoGic systems. Classification of different brain images using Adaptive Neuro-fuzzy inference system is done. The proposed hybrid system have wider scope and present dual advantages of type-2 fuzzy LoGic based decision support system using ANN technique. This technique increases accuracy.

R.J.Deshmukh and R.S.Khule [8] proposed the sophisticated framework for multi object classification using Neuro-fuzzy system. This proposed technique is fast in execution, efficient in classification and easy in implementation. This paper presents a automated recognition system for the MRI image using the neuro fuzzy LoGic. Result in better classification during the recognition process. Time and accuracy level is 50-60% improved compared to the existing neuro classifier.

J.selvakumar and A.Lakshmi T. [9] provides implementation of simple algorithm for detection of range and shape of tumor in brain MR images using K-clustering and Fuzzy C-mean algorithm. The noise free image is given as a input to the k-means and tumor is extracted from the MRI images. And then segmentation using Fuzzy C means for accurate tumor shape extraction of malignant tumor and thresholding of output in feature extraction.

M.Murugesan, Syed Ammal, Dr.(Mrs)R.Sukanesh [10] presents an automated system for efficient detection of brain tumors in EEG signal using Artificial Neural Networks (ANN). The ANN employed in the proposed system is feed forward back propagation neural network. The proposed system has taken an EEG signal as input. Then feature of interest are extracted from EEG signal. Subsequently, the ANN is employed. Finally neural network has detected the presence of brain tumor in the test signal.

Anand Bhardwaj and Kapil Kumar Siddhu [11] deals with the extraction of features using PCA and after that training using ANFIS tool. The performance of the ANFIS classifier was evaluated in terms of training performance and classification accuracy. This paper presents an automated recognition system for MRI image using the neuro fuzzy LoGic. Experimental result indicates that the technique is workable with accuracy greater than 90%. This technique is fast in execution, efficient in classification and easy in implementation.

Ruchi D. Deshmukh and Prof. Chaya Jadhav [12] introduced a new method which is Fuzzy Local Gaussian Mixer Model segmentation method by assuming local data within pixel neighborhood satisfy Gaussian Mixer Model and grey level co-occurrence is used for feature extraction. Gray level co-occurrence matrix characteristics feature are used with the MR images for training of neural network then tumor is detected using neuro fuzzy classifier. It is the efficient method for Brain MR Image segmentation and brain tumor detection.

III. PRAPOSED METHODOLOGY

The projected system is recommended to be used as a second decision to the specialist. It detects tumors in MRI brain images and it defines the growth. The system consists of six stages, that are image pre-processing, image segmentation, feature extraction, svm classifier and finally tumor classification. Fig.3 shows a flow chart of the steps for the proposed system.

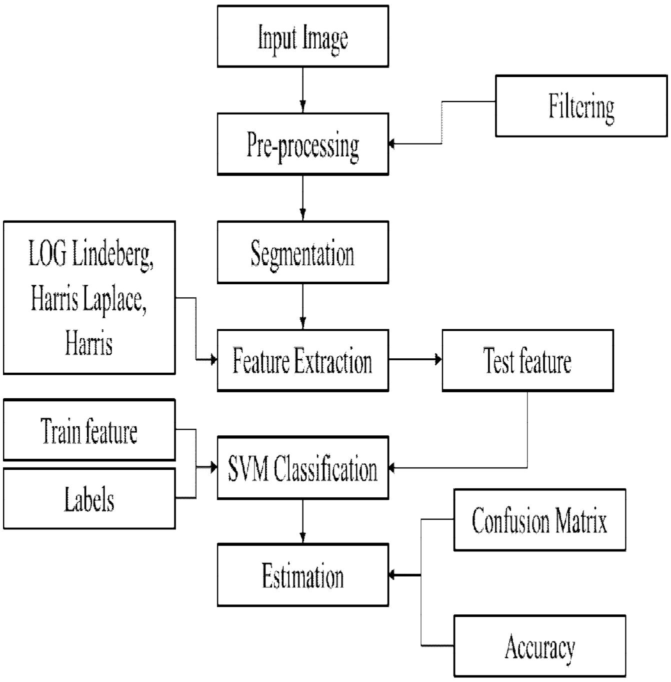

Figure 3: Flow Diagram

A. PRE-PROCESSING

The first step in the algorithm is a pre-processing for the brain image. In this step, the brain boundary is expanded to fill the input image size and the image size is changed to be 256x256, also the gray level is expanded to be from 0 to 255 if it occupies less than that. Fitering is done for removing the noise and also it smoothes the image.

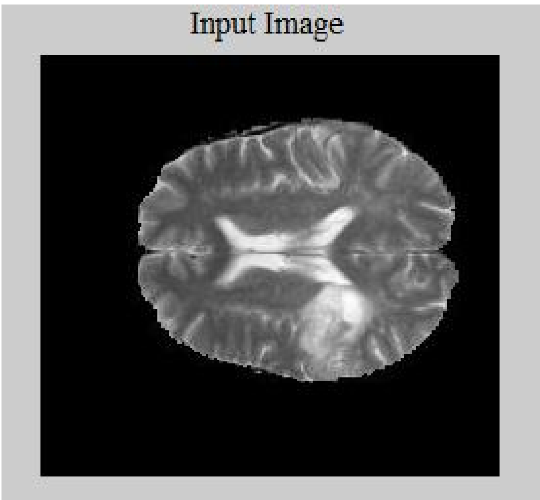

Figure 4: Input Image

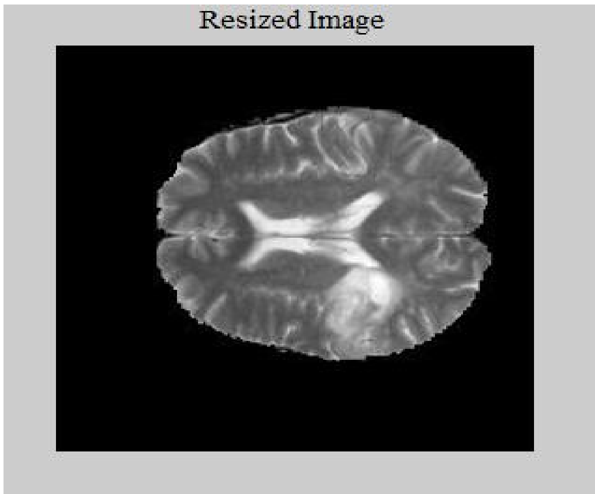

Figure 5. Resized Image

a. Gaussian Filter

Gaussian filter is smoothing filter. It is a type of image-blurring filter that uses a Gaussian function (which also expresses the normal distribution in statistics) for calculating the transformation to apply to each pixel in the image. Filtering is done for removing the noise and also it smoothes the image.Gaussian smoothing operatoris 2D convolution operator that isused to blur the image and remove detail and noise. It is similar to mean filter but it uses a different kernel.

The Gaussian distribution has the following form:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where, x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and σ is the standard deviation of the Gaussian distribution. When applied in two dimensions, this formula produces a surface whose contours are concentric circles with a Gaussian distribution from the center point. Values from this distribution are used to build a convolution matrix which is applied to the original image.

B. SEGMENTATION

Segmentation is important step in Image Analysis. There are different segmentation techniques like thresholding approaches, region growing approaches, artificial neural networks, deformable models, clustering approaches, Markov random field models and atlas-guided approaches. From previous work and from analysis of nature of Brain Images we find thresholding and canny edge detection approach provide more accurate result. So for better result we use both the techniques.

a. Adaptive Thresholding

Image tresholding is simple and effective way to partitioning an image into foreground and background. Adaptive thresholding basically takes gray-scaled or color image as input and provide segmented binary image as output. For each pixel in the image threshold has to be calculated. If the pixel value is below the threshold it is set to the background value, otherwise it assumes the foreground value. In adaptive thresholding the threshold value at each pixel location depends on the neighboring pixel intensities

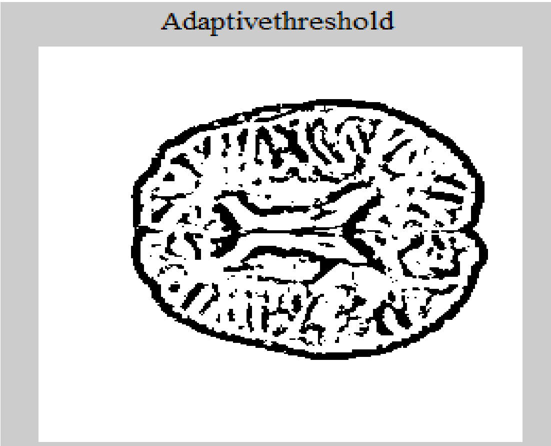

Figure 6: Segmented Image using Adaptive Threshold method

b. Canny Edge Detection

Canny edge detector is an operator is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images. It was developed by John F. Canny in 1986. Canny also produced a computational theory of edge detection. Canny edge detection has widely applied in various computer vision systems. The general criteria for edge detection: -

i. Detection of edge with low error rate, which means that the detection should accurately catch as many edges shown in the image as possible
ii. The edge point detected from the operator should accurately localize on the center of the edge.
iii. A given edge in the image should only be marked once, and where possible, image noise should not create false edges.

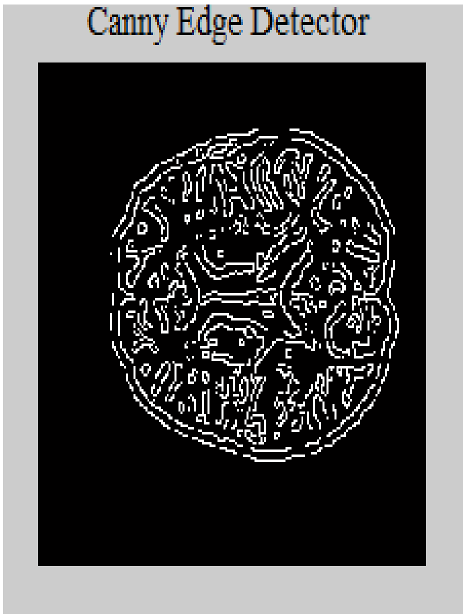

Figure 7: Brain Image after Applying Canny Edge Detector

C. FEATURE EXTRACTION

Feature extraction is an important step in image classification. The aim of feature extraction is that to extract the relevant information that characterizes the class. The relevant features are extracted to form feature vector. These feature vector are used by classifier to classify image. There are different classification techniques as Histogram of Oriented Gradients (HOG), LoG-lindeberg algorithm, Harris algorithm, Speeded Up Robust Features (SURF), Harris-Laplace algorithm, Local Binary Patterns (LBP), Haar wavelets, and color histograms. From above techniques we are using LoG-lindeberg algorithm, Harris algorithm and Harris-laplace algorithm for accurate feature extraction.

a. LoG-lindeberg Algorithm

LoG-lindeberg is a common blob detector. It is used to reduce processing time and complexity in the image analysis. The scale space representation of theimagedefinedby*L(x,y,σ)*isobtainedbyconvolvingtheimag ebyavariable scale Gaussian kernel *G(x,y,σ)*where

$$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y)$$

And

$$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2}\, e^{\frac{-(x^2+y^2)}{2\sigma^2}}$$

For computing the Laplacian operator, the following formula is used

$$\nabla^2 L(x,y,\sigma) = L_{xx}(x,y,\sigma) + L_{yy}(x,y,\sigma)$$

The standard deviation of the Gaussian is used to control the scale by changing the amount of blurring. In order to automatically capture blobs of different size in the image domain, a multi-scale approach with automatic scale selection is proposed in 21 through searching for scale space extreme a of the scale-normalized Laplacian operator.

$$\nabla^2_{norm} L(x, y, \sigma) = \sigma^2 (L_{xx}(x, y, \sigma) + L_{yy}(x, y, \sigma))$$

Applying LoG-Lindeberg algorithm to the segmented MRI Brain:-

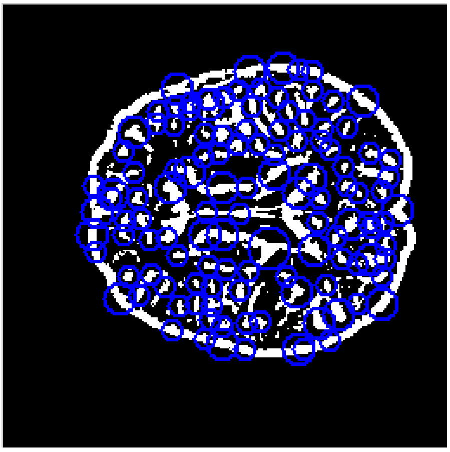

Figure 8: LoG-lindeberg algorithm applied to Input Image

b. Harris Algorithm

The 2×2 symmetric auto-correlation matrix used for detecting image feature sand describing their local structures can be represented as

$$M(x, y) = \sum_{u,v} w(u, v) * \begin{bmatrix} I_x^2(x, y) & I_x I_y(x, y) \\ I_x I_y(x, y) & I_y^2(x, y) \end{bmatrix}$$

Where, I_X and I_Y are local image derivatives in the *x* and *y* directions respectively, and *w(u,v)* denotes a weighting window over the area*(u,v)*. For finding interest points, the eigen values of the matrix *M*are computed for each pixel. If both eigen values are large, this indicates existence of the corne rat that location. The response map can be done by calculating the cornerness measure *C(x,y)* for each pixel *(x,y)* using

$$C(x, y) = det(M) - K(trace(M))^2$$

Where

$$det(M) = \lambda_1 * \lambda_2 \quad and \quad trace(M) = \lambda_1 + \lambda_2$$

The *K*isan adjusting parameter and λ_1,$\lambda_2$are the eigen values of the auto-correlation matrix. The non- maximum suppression should be done to find local maxima and all non-zero points remaining in the cornerness map are the searched corners.

Fig. shows the result of applying Harris algorithm to the segmented image:-

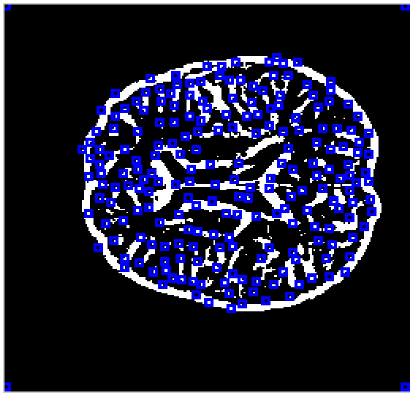

Figure 9: Harris algorithm applied to Segmented Image

c. Harris Laplace Algorithm

It relies heavily on both the Harris measure and a Gaussian scale-space representation. The second-moment matrix utilized in that detector is modified to make it independent of the image resolution. The scale adapted second-moment matrix used in the Harris-Laplace detector is represented as

$$M(x, y, \sigma_I, \sigma_D) = \sigma_D^2 \, g(\sigma_1) \begin{bmatrix} I_x^2(x, y, \sigma_D) & I_x I_y(x, y, \sigma_D) \\ I_x I_y(x, y, \sigma_D) & I_y^2(x, y, \sigma_D) \end{bmatrix}$$

Where I_X and I_Y are the image derivatives calculated in the irrespective direction using a Gaussian kernel of scale σD. The parameter σI determines the current scale at which the Harriscorner points are detected in the Gaussian scale-space. The derivative scale σD decides the size of Gaussian kernels used to compute derivatives. The integration scale σI is used to performed a weighted average of derivatives in a neighborhood. The multi-scale Harris cornerness measure is computed using the determinant and the trace of the adapted second moment matrix as

$$C(x, y, \sigma_I, \sigma_D) = del[M(x, y, \sigma_I, \sigma_D)] - \alpha . trace^2[M(x, y, \sigma_I, \sigma_D)]$$

The value of the constant α is between 0.04 and 0.06. At each level of the representation, the interest points are extracted by detecting the local maxima in the 8-neighborhood of a point*(x,y)*.Then, a threshold is used to reject the maxima of small cornerness, as they are less stable under arbitrary viewing conditions

$$C(x, y, \sigma_I, \sigma_D) > Threshold_{Harris}$$

Inaddition, the Laplacian- of-Gaussian is used to find the maxima over the scale. Where, only the points for which the Laplacian attains maxima or its response is above a threshold are accepted.

$$\sigma_I^2 \left| L_{xx}(x,y,\sigma) \;+\; L_{yy}(x,y,\sigma) \right| > Threshold_{Laplacian}$$

The Harris-Laplace approach provides are presentative set of points which are characteristic in the image and in the scale dimension.

Fig. shows the result of applying Harris-laplace algorithm to the segmented image:-

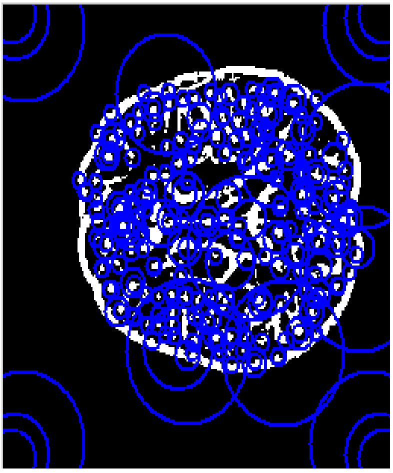

Figure 10: Harris-Laplace algorithm applied to Segmented Image

IV. CLASSIFIER

Support vectors are the data points that lie closest to the decision surface (or hyperplane). In SVM input X is mapped to output Y, where x ϵ X is some object and yϵY is a class label. Training set (*x*1,*y*1),……(*xm*,*ym*) is formed by features of all the Normal Brain Images and Benign Brain Images and Malignant Brain Images used for training, with their respective class labels. Testing set is formed by features of candidates spotted on an input image. All the candidates are classified using SVM classifier as healthy brain or benign tumor or malignant tumor. Algorithm for SVM classifier is given as,

- Label all the extracted objects in the image and measure properties of all the objects.
- Extract the features for each and every object.
- Form a set of all the objects with their respective properties and collect this to the excel file.
- Read the SVM training data sheet.
- Apply SVM training to create SVM structure to map input features to output class labels.
- Apply SVM Classifier.
- Input image are classified as Normal image, Benign Tumor image, Malignant Tumor image.

V. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

System classifies the image into three different classes depending upon training and test features comparisons such as Normal Brain Image, Benign Tumor, Malignant Tumor. We have database of total 120 MRI images. Classifier is train with 70 images and 50 images are used for testing purpose. In training, the classifier defines three classes. Class 1 contains 30 Benign Tumor MRI images whereas Class 2 contains 20 Malignant MRI images and Class 3 contains 20 Normal Brain MRI images. Table 5.1 gives confusion matrix for all three classes. True Positive(TP), True Negative(TN), False Positive(FP) and False Negative(FN) are calculated from testing data samples for each class.

Table 5.1: Confusion Matrix for three different classes

	Predicted Class			
		Benign Tumor	Malignant Tumor	No Tumor
Actual Class	Benign Tumor	29	0	0
	Malignant Tumor	1	20	1
	No Tumor	0	0	20

The accuracy, sensitivity and specificity are calculated as given in equations respectively.

1. Accuracy

The accuracy can be defined as the percentage of correctly classified instances.

$$\text{Accuracy} = \frac{\Sigma\text{TP} + \Sigma\text{TN}}{\Sigma\text{Total Population}}$$

2. Sensitivity

The sensitivity tells us how likely the test is come back positive in someone who has the characteristic.

$$\text{Sensitivity} = \frac{\Sigma TP}{\Sigma TP + \Sigma FN}$$

3. Specificity

The specificity tells us how likely the test is to come back negative in someone who does not have the characteristic.

$$\text{Specificity} = \frac{\Sigma TN}{\Sigma TN + \Sigma FP}$$

Hence for the proposed system evaluation result gives accuracy, sensitivity and specificity up to 97.14%, 97% and specificity up to 96% respectively. Fig 5.1 represents the performance analysis of the system graphically. It gives comparative results obtained for accuracy, sensitivity and specificity of three different classes.

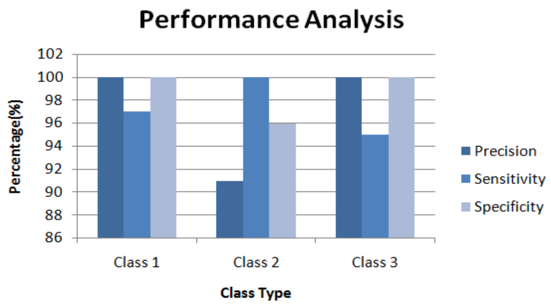

Figure 11: Performance Analysis of System

VI. CONCLUSION

Our proposed new system can be used as a second decision for the Radiologist. It determines whether the MRI Brain Input image represents a Healthy-Normal Brain or tumor brain. Further, it classifies the tumor brain as Malignant or Benign tumor. It consists of seven stages; image acquisition, preprocessing, image segmentation, feature extraction, SVM classifier, decision. Satisfactory correct recognition rate is obtained in view of the available limited data base.

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