

Brain Tumor Classification from MRI Imaging using Polynomial SVM

Rishab Moza

Dept. of Computer Science &
EngineeringA.D. Patel Institute of Technology,
Vithhal Udyog Nagar, Anand, Gujarat,
India

sanjaymoza66@gmail.com

Mangrolia Jayandratih

Dept. of Computer Science &
EngineeringA.D. Patel Institute of Technology,
Vithhal Udyog Nagar, Anand, Gujarat,
India

jay.mangrolia@gmail.com

Nikesh Patel

Dept. of Computer Science &
EngineeringA.D. Patel Institute of Technology,
Vithhal Udyog Nagar, Anand, Gujarat,
India

it.nikeshapatel@adit.ac.in

Abstract— Brain tumor is an uncontrollable growth of cells that may spread in different tissues. It can be recognized through Magnetic Resonance Imaging (MRI) which is a non-surgical investigation of organ for diagnosing any disease related to the symptoms. Tumors may be cancerous or non-cancerous or it can be considered as life threatening or less dangerous. A tumor belongs to two distinct categories such as benign or malignant. Benign tumor is considered as non-cancerous or less dangerous and it does not spread to the other part of the brain. It has solid boundaries or contouring that indicates the particular shade of the tumor but malignant is the cancerous tumor which is highly dangerous and it can be spread to the other part of the brain by itself. The boundaries of the malignant tumor are not solid in appearance, instead of that it appears as faded in nature. Here the proposed system is able to classify the tumor type along with brain tumor diagnosis. Here the proposed system uses polynomial Support Vector Machine (SVM) for dealing with the impairments and diagnose the disease accordingly. System perceived high level of accuracy as compare to the previous model.

Keywords—Polynomial Support Vector Machine, Brain Tumor, Segmentation, Cell Classification, Malignant, Benign, MRI, Brain Cells.

I. INTRODUCTION

Magnetic Resonance Imaging is a standard harmless philosophy utilized in clinical field for the examination, finding and treatment of brain tissues. The early finding of brain tumor helps in saving the patients' life by giving appropriate treatment. The exact identification of tumors in the MRI images turns into a critical errand to perform consequently, by this proposed framework, the classification and division the tumor locale should be possible precisely. Division and 3D reproduction additionally utilizes the recognition of tumor from a MR image. The manual and visual investigation by specialists is limited to keep away

from time utilization. The brain tumor recognition permits limiting a mass of unusual cells in a slice of Magnetic Resonance (MR) utilizing SVM Classifier and division of the tumor cells to be familiar with the size of the tumor present in that sectioned region. The separated elements of the sectioned part will be prepared utilizing counterfeit brain organization to show the sort of the tumor. These highlights will likewise be utilized for contrasting the precision of various classifiers in Classification student application [1]. The brain is conceivably the most specific and delicate organs in the human body. The high death rate is due to brain tumors unimaginably fabricate. As demonstrated by the National Brain Tumor Society, brain tumors are the incredibly disastrous contamination to individuals. It is the grouping or mass of impaired cells in the brain. The cerebral cortex around the brain is very close. Brain tumors can be carcinogenic (compromising) or non-destructive (innocuous). As compromising or perilous tumors foster they increase the squeezing factor inside your brain. Undermining tumors are disconnected into two sorts; Primary and auxiliary tumors are more risky than innocuous tumors. As the undermining tumor spreads rapidly to various tissues in the brain, the patient's condition declines. An innocuous (sans malignant growth) brain tumor is a mass of steadily creating cells in the brain. It doesn't normally stand and spread. The signs of a brain tumor depend upon how gigantic it is and where it is arranged in the brain. A couple of tumors that grow continuously make no signs every step of the way. Typical secondary effects are not kidding, persevering cerebral agony, seizures (adequate), constant squeamishness, spewing and sluggishness. Earlier condition or fundamental condition, sometimes called likely condition or fundamental condition, is a condition wherein the phones suggested in the peril of disease are surprisingly formed. At the point when left untreated, these circumstances can provoke disease [2].

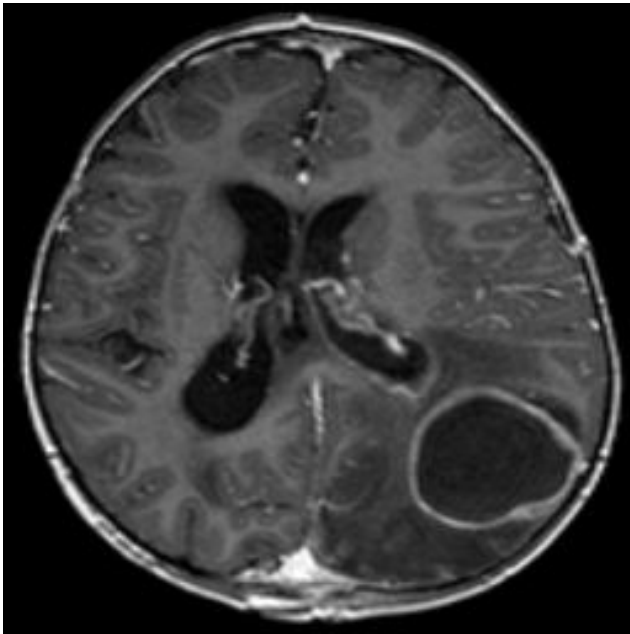


Fig. 1. Benign Tumor MRI Image

Risky tumors are destructive tumors that continuously decline and lead to death. As opposed to cleanse tumors, destructive ones grow rapidly, they are covetous, they search for another area and they spread (metastasize). Impaired cells that structures a perilous tumor grows rapidly. The magnetic field fragment used to conclude radio recurrence to make unequivocal pictures of organs, sensitive tissues, bone and other internal developments in the human body. The MRI-strategy is particularly reasonable in recognizing brain tumors. Brain tumor acknowledgment ought to be conceivable with MRI pictures. In image processing, image updates clusters that are used for clinical image diagnosis to additionally foster picture quality. EDGE detection, histogram and division limits expect a critical part in recognizing and gathering brain tumors. The objective of this work is to find different channels, detachment methods and estimations to perceive brain tumors [2].

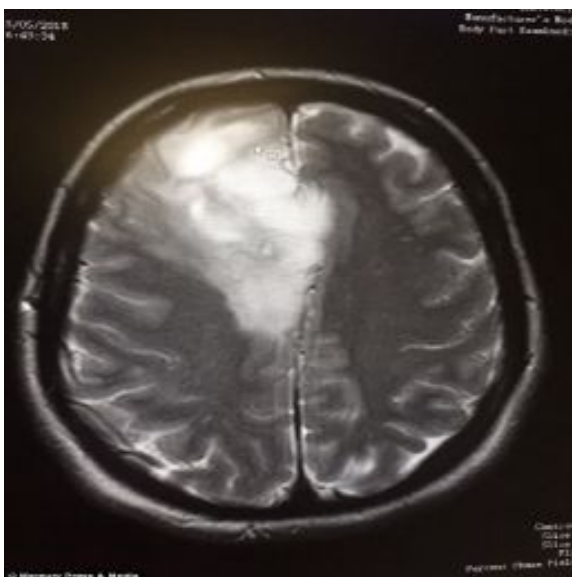


Fig. 2. Malignant Tumor MRI Image

II. RELATED WORKS

A. Related Works

Mircea Gurbin et al. [3] proposed the brain tumor recognition and classification framework is carried out utilizing CWT, DWT and SVMs. The proposed strategy involves various levels for wavelets, the high precision part is gotten utilizing CWT. The CWT forestalls the deficiency of edges in division. The outcome shows that SVMs having the legitimate arrangements of preparing information can recognize unusual and typical tumor locales and characterize them accurately as a harmless tumor, malignant tumor or normal brain. SVMs have critical computational benefits. This classification is vital for the doctor in laying out an exact symptomatic and suggesting a right further treatment. The acquired outcomes show that CWT gives higher calculation contrasting DWT. Regardless of whether the calculation time is longer, on the off chance that we are principally keen on perception, coordinating and include recognition, utilizing CWT is better. In the event that we are keen on de-noising, pressure, rebuilding, DWT is much of the time more fitting. A half and half methodology is suggested in settling appropriately the location and classification issues in brain tumors. T. A. Jemimma et al. [4] proposed brain tumor division and classification is executed through the Water Shed Algorithm (WSA), Dynamic Angle Projection Pattern highlights and these elements are ordered by utilizing CNN. The significance of the watershed division calculation removes the tumor areas in a powerful way for capable DAPP highlight extraction. The DAPP removes the surface elements from the fragmented tumor districts and histogram highlights are acquired. These component vectors are elevated to the contribution for CNN classifier which plays out the classification. The division and classification of MRI brain image are vital for the capable conclusion of brain tumor. The trial results are executed through the BRATS data set which accomplishes better dice score proficiency 93.5% and awareness 94.2%. Later on work, for classification and division of brain tumor, a few other various elements can measure up to get more exactness. It can likewise be stretched out to distinguish different kinds of tumors like a pancreatic tumor, adenomas, fibromas.

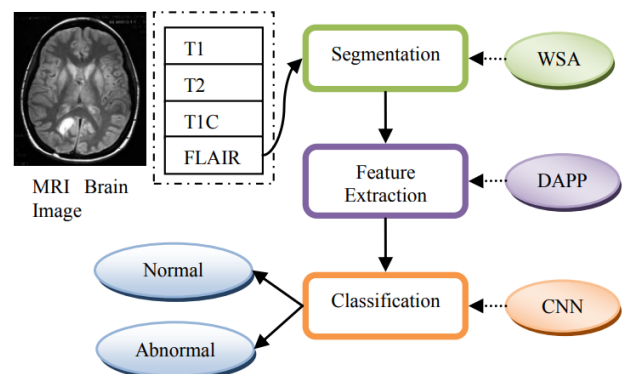


Fig. 3. Overview of the System [3]

R.Lavanyadevi et al. [5] proposed strategy includes precisely perceiving the semantically significance full regions in an image. As result, by connection of each and every pixel in the image alongside which signify a

semantically importance and the doctor or radiologist can identify threat and conclude it. The elements of adjoining twofold models and dark level co-events are eliminated from brain images with harmless or dangerous or typical images. In preparing mode the eliminated highlights alongside semantic elements are prepared utilizing PNN classifier. In classification mode similar highlights are removed from test brain image and mystery with prepared models utilizing PNN classifier. At the point when the test image isn't like any preparation image then the image can be remembered for preparing set information. On correlation among PNN and CNN, PNN is considered to enjoy significant benefits. It is because of reality that PNN gains from preparing information momentarily. As PNN has speed of learning capacity, it can adjust its learning progressively. Hein Tun Zaw et al. [6] proposed technique can help the clinical staffs, for example, specialists and radiologists to analyze the brain malignant growth from MRI images particularly for GBM which requires the discovery of all conceivable spreading destructive regions. In this strategy, brain tumors have been identified utilizing Naïve Bayes classification with the assistance of most extreme entropy edge. The REMBRANDT data set is utilized in this review. The created calculation can precisely distinguish the tumor in all potential areas of the brain that the tumor can exist, including the worldly projection. The calculation yields 81.25% recognition rate on tumor images and 100 percent discovery rate on non-tumor images with the general precision 94%. Ragib Shahariar Ayon et al. [7] proposed a procedure for simple division of the brain tumor and ID of the tumor type. Brain tumor discovery is finished by preprocessing the image with denoising and inclination remedy which was then taken care of to the handling stage as information image. We applied the spatial FCM for sectioning the brain MR image and took the likely tumor cut. After that the tumor cut was taken care of to the post-handling stage where it goes through an area channel. The result image is a separated image of anticipated tumor area. We utilized similar highlights to prepare various kinds of classifiers and pick the one with most precision which predicts the tumor type. Subsequent to contrasting and various kinds of bunching and classification calculations we can express that the proposed strategy is better for tumor division and classification than ordinary techniques.

III. PROBLEM IDENTIFICATION

L.Jagjeevan Rao et al. [8] proposed an implementation model which is based on FCM (Fuzzy C-Means Clustering) and CNN (Convolutional Neural Network) approaches. Here system uses FCM for extracting the features of the brain as well as impairments and CNN is used as classifier. But C-means clustering is generally used for classification and CNN is used for feature extraction. CNN has not been designed for classification process, CNN is a convolutional neural network that has the potential to obtain the input features and enhances the features by using distinct filter and train the layers accordingly and generate a model that can able to diagnose or recognize the target object. SVM is considered as the best classifier in the field of disease diagnosing. The disadvantage of the FCM is that; it requires large amount of time to converge the data and it is more sensitive to the noise and hard to handle the non-linear data.

Conventional CNN model is poor in training and building heavy network that directly affects the execution time. System pertained 91% of accuracy which is bit lesser that can be enhanced by using distinct methods.

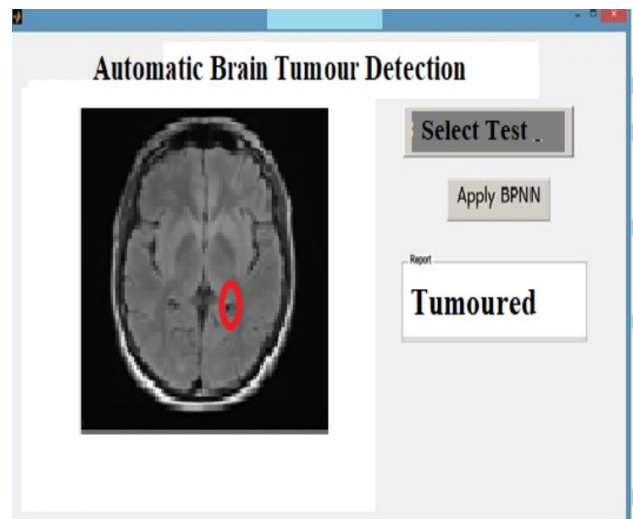


Fig. 4. Graphical Representation of Result [8]

IV. PROPOSED WORK & IMPLEMENTATION

The proposed work is able to diagnose the brain tumor with high level of accuracy. System is also able to classify the tumor whether it is benign or malignant. The implementation of the system has been divided into three categories such as- benign, malignant and normal. In the benign case; the boundaries of the tumor appears as solid in structure or fixed in size and not able to grow itself and it is less dangerous while in the other hand malignant is dangerous and can spread over distinct part of the brain. The boundaries of the malignant tumor become hazy or faded and it can classify from the benign image. Normal image of brain does not contain any tumor and it considered as the healthy brain image. Here the proposed system uses polynomial SVM which is a kernel based classifier that can handle the non-linear data and obtain the result with better preciseness.

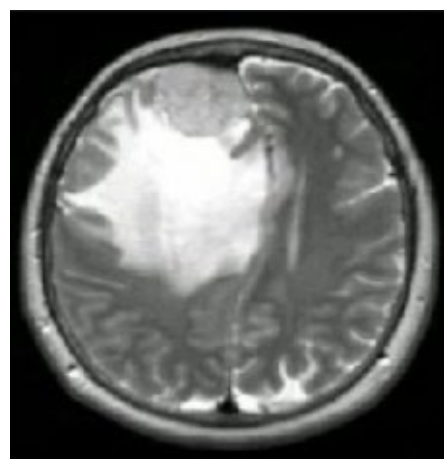


Fig. 5. Original Brain Tumor MRI Image

Fig. 5 shows the original MRI image of the brain tumor where whiten part appears in the image is considered as the tumor part of the image and as per the groundtruth and the actual concept; it belongs to the malignant class.

A. Smoothing

Fig. 6 shows the smoothen image of the original one where regions have been smoothen and clusters can be formed easily for segmentation. Segmentation is the process where certain clusters have been divided into different groups as per the threshold value or color pixels of the image that later classifies through the classifier and obtain the result accordingly.

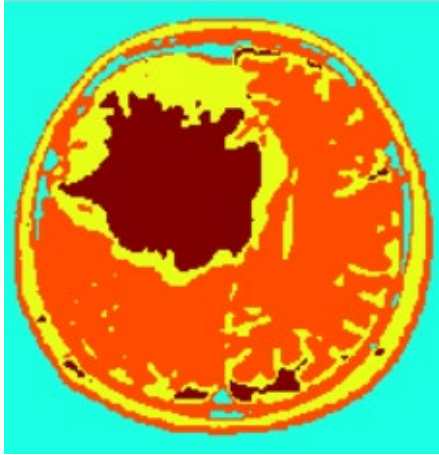


Fig. 6. Region Smoothing the Brain Tumor MRI Image

B. Segmentation

Image segmentation is a technique wherein a digital image is separated into different subgroups called Image segments which helps in decreasing the intricacy of the image to make further handling or examination of the image less difficult. Segmentation in simple words is allotting names to pixels. All image components or pixels having a place with a similar class have a typical name relegated to them. For instance: Let's take an issue where the image must be given as contribution to protest discovery. Instead of handling the entire image, the identifier can be inputted with a locale chosen by a segmentation calculation. This will keep the identifier from handling the entire image consequently decreasing surmising time.

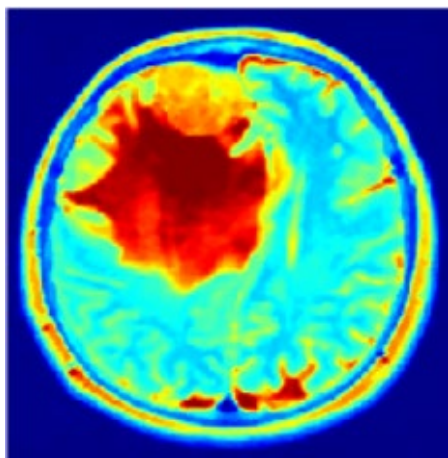


Fig. 7. Brain Tumor Segmentation

Fig. 7 shows the segmentation of brain tumor image where red part shows the cluster of imaired cells and rest all are

considered as the background of the image which needs to erode later for better classification.

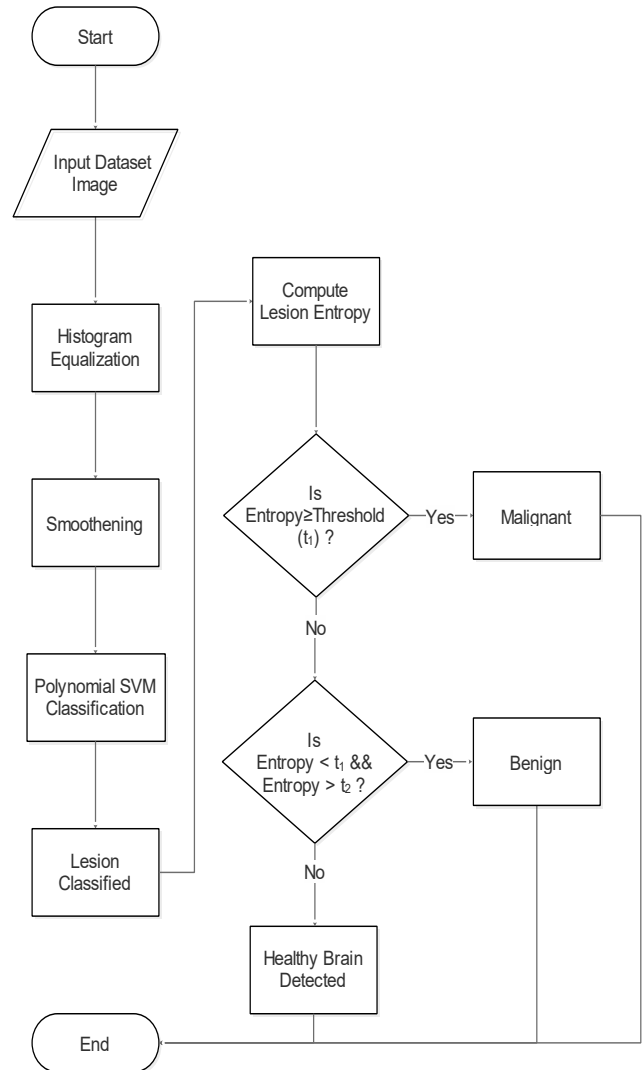


Fig. 8. Flow Chart of Proposed System

Fig 8 shows the flowchart of proposed system where system firstly loaded the dataset image as an input data. Then pre-processing module has been initiated for enhancing the visibility of the images. Histogram is one of them, it is responsible to balance the brightness and contrast of the system, once the visibility increase then smoothen the image for better visibility of lesion then features get extracted and after feature selection SVM classification can be initiated to classify the data points. Then system calculates the entropy of the extracted lesion. It decides the density of the lesion that later compare with the threshold value. Threshold value is the comparative value where decision can be made over there. There are three grades of the brain tumor; first one is malignant; so, if entropy is greater than and equal to the higher threshold value then it will be considered as malignant cancer. Second one is benign, if entropy is less than the higher threshold value but greater than the lower threshold value then it would be consider as benign otherwise healthy brain image can be considered. So, system also classifies the grade of the brain tumor as per the density of the lesion.

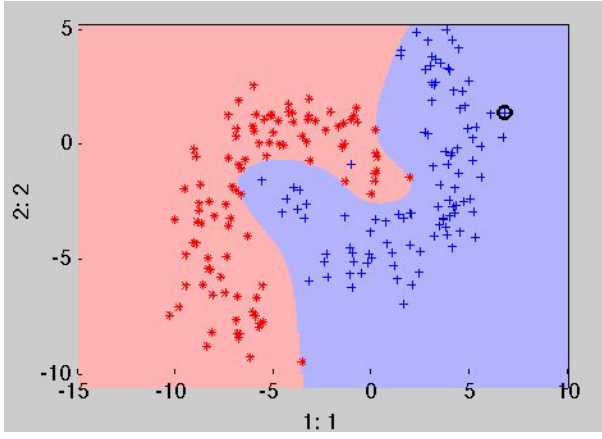


Fig. 9. Polynomial SVM Classification [9]

Polynomial-SVM Algorithm

Input: 2-D Image Matrix

Output: Entropy

Step 1: Input 2-D Image Matrix

Step 2: Convert Matrix to Gray Levels

Step 3: Apply Histogram Equalization

$$P_n = \frac{\text{number of Pixel Intensity } n}{\text{Total number of pixels}} \quad n = 0, 1 \dots L - 1$$

Where P_n is the affected pixel value after histogram equalization.

Step 4: Apply Gaussian Filter for Smoothing

$$G(x, y) = -\frac{1}{\pi\sigma^4} \left[1 - \frac{x^2 + y^2}{2\sigma^2} \right] e^{-\frac{x^2 + y^2}{2\sigma^2}}$$

The value of σ is 1 for 3x3 matrix and 2 for 5x5 matrix, (x, y) are native pixels.

Step 5: Collect data points

$$y = w_0 + w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 \dots \dots \dots$$

$$= w_0 + \sum_{i=1}^m w_i x_i$$

$$w_i = w_0, w_1, w_2 \dots \dots \dots w_m$$

Where w_i is the vector, b is the bias and x is the variable

Step 6: Separate the data points by hyperplane

$$\vec{w} \cdot \vec{x} - b = 1$$

$$\vec{w} \cdot \vec{x} - b = 0$$

$$\vec{w} \cdot \vec{x} - b = -1$$

where $\vec{w}$ is the normal vector of the hyperplane

Step 7: Classify Datapoints

Step 8: Compute Entropy

$$E = -\sum_{i=0}^{n-1} p_i \log_b p_i$$

Where n is the number of gray-levels, p is the probability of pixel having gray-levels i and b is the base of function

Step 9: if $E \geq T_1$ then

Malignant;

elseif $E < T_1$ && $E > T_2$ then

Benign;

else

Normal;

end else

end if

Step 10: End

V. RESULT ANALYSIS

A. Result Simulation

Experimental results are based on four metrics; that are True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN). True positive means if an image belongs to either malignant or benign class and system diagnosed it positively, True Negative means if an image does not belong to either malignant or benign and system diagnosed it as healthy. False Positive means if an image belongs to the normal class and system diagnosed it as either malignant or benign, False Negative means if an image belongs to the malignant or benign group but system diagnosed it as normal. There are total 76 testing images belong to benign class, 89 images from malignant class and 98 images from normal class in Kegg benchmark.

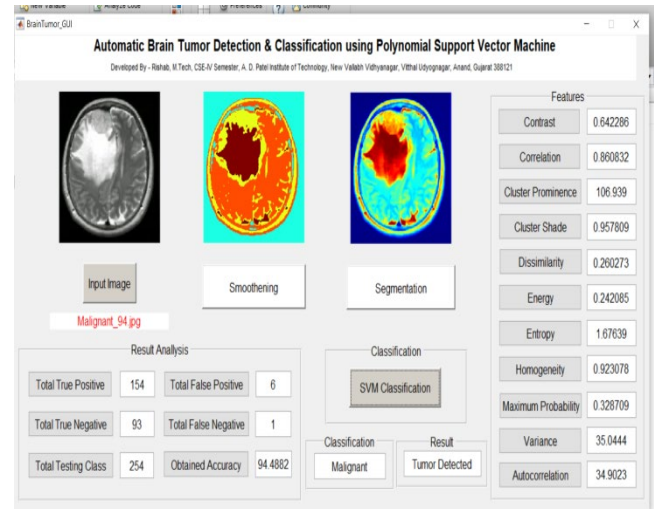


Fig. 10. Proposed API

$$\text{Sensitivity} = \frac{TP}{TP + FN} * 100 \%$$

$$\text{Specificity} = \frac{TN}{FP + TN} * 100 \%$$

$$\text{Precision} = \frac{TP}{TP + FP} * 100 \%$$

$$\text{Negative Prediction Rate} = \frac{TN}{FN + TN} * 100 \%$$

$$\text{False Positive Rate} = \frac{FP}{FP + TN} * 100 \%$$

$$\text{False Negative Rate} = \frac{FN}{FN + TP} * 100 \%$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} * 100 \%$$

$$F1 = \frac{2TP}{2TP + FP + FN} * 100 \%$$

$$\text{Recall} = \frac{TP}{FN + TP} * 100 \%$$

Table No. I Result Outcomes (Confusion Matrix)

Terms & Parameters	Proposed
Total Testing Class	254
True Positive	154
True Negative	93
False Positive	6
False Negative	1
Sensitivity in %	99.35
Specificity in %	93.94
Precision in %	96.25
Negative Predictive Value in %	98.94
False Positive Rate in %	6.06
False Negative Rate in %	0.65
Accuracy in %	97.24
F1 Score in %	97.78
Recall in %	99.35

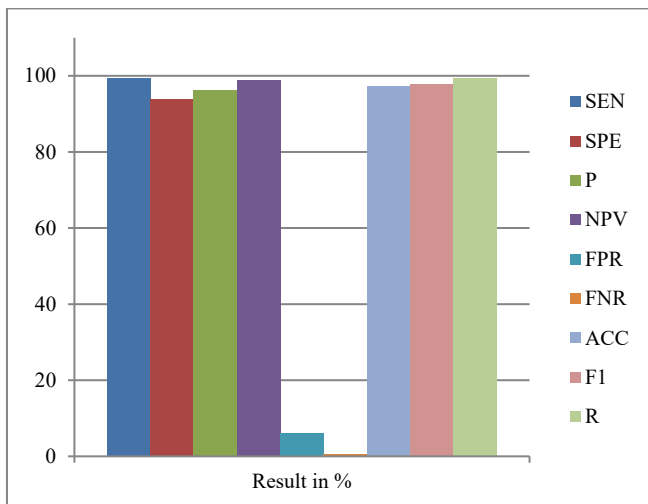


Fig. 11. Result Analysis

SEN: Sensitivity, SPE: Specificity, P: Precision, NPV: Negative Predictive Value, FPR: False Positive Rate, FNR: False Negative Rate, ACC: Accuracy, F1: F1 Score and R: Recall.

Table No. II Result Comparison

Methods	Specificity in %	Sensitivity in %	Accuracy in %
CNN [8]	92.00	91.00	91.00
BPNN [8]	89.50	91.00	89.00
KNN [8]	86.00	88.00	87.00
P-SVM (Proposed)	93.94*	99.35*	97.24*

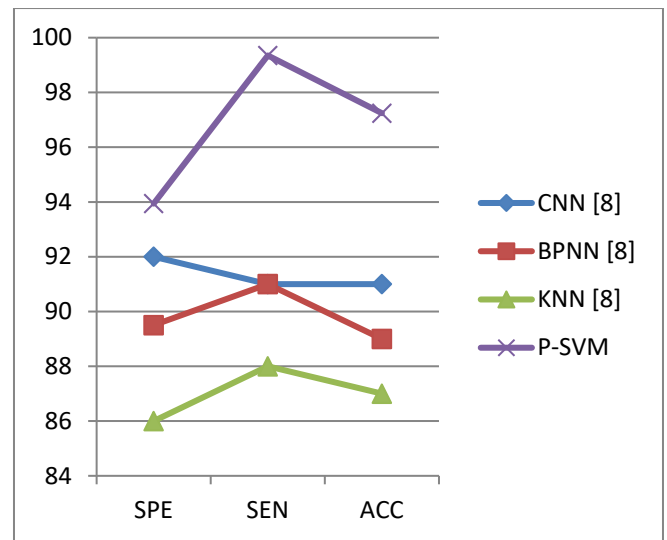


Fig. 12. Result Comparison

VI. CONCLUSION & FUTURE SCOPE

The Brain Tumor Classification from MRI Imaging using Polynomial SVM is able to diagnose the brain tumor and classify the disease whether it is malignant, benign or normal. System uses histogram equalization to adjust the contrast of the image for better visibility of the image. System also uses smoothing filter for enhancing the visibility of impairments to form a clear cluster that can help in segmentation and classification. System uses Polynomial SVM for final classification and it forms two distinct clusters; one is from abnormal or lesion cells and other is from normal cells that may be considered as the background or noise of the image. System pertained better level of accuracy as compare to the previous existing systems i.e. CNN, BPNN and KNN classifiers. In future, the accuracy, precision, specificity and sensitivity can be enhanced by using hybrid classifiers or models because accuracy plays a very important role in the field of medical science. Brain tumor is a life threatening disease, so that is why it is required to obtain the better level of accuracy with very fewer false error rates.

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