

Brain Tumor Detection Modern Improved by using PSO Technique

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Abstract— Brain tumor detection and removal is one medical major issue that still remains difficult in the area of biomedicine. Early imaging methods such as pneumoencephalography and cerebral angiography had the disadvantage of being all-encompassing and hence the CT and MRI imaging procedures help the surgeons in providing a better vision. In this paper, a new method is proposed for tumor detection using morphological operations to address brain tumor from MRI images to be used new method using particle swarm optimization technique to recognize and remove the boundary condition of a brain tumor proposed algorithm make available a robust technique in expressions of accuracy and computation time, making it suitable for real-time processing. Results also show that this algorithm is skilled of producing continuous edges with accurate positioning of particular region where tumor was detected.

Keywords: Magnetic resonance imaging (MRI), computed tomography, Image Segmentation, Region of Interest (ROI)

I. INTRODUCTION

Now-a-days the concentration in digital biomedical image processing methods takes a most significant position in two principal and significant areas [1]. The most significant one is an enhancement of pictorial information for human studies and processing of biomedical image data for storage. A biomedical image every now and then is defined as a two-dimensional function, $F(x, y)$, where x and y are the value or gray level of a biomedical image at a specific point. F are all finite, discrete quantities. As we know that to say an image is a digital image is when it is created of a finite number of elements, each of which has an exacting location and assessment. Biomedical images are as different as the areas of the human body. For example, to learning soft tissue in the human body then we have to use the MRI scan for soft tissue images such as Brain liver and other soft tissue in the human body. On the other hand, those concerned in learning hard tissue such as bone or cartilage should use X-ray for a hard tissue image rather than the MRI. The difference in the biomedical image is not just in the region but also unusual in the way of processing.

Recent MRI imaging technique can provide complete information about human body internal view. It is completely secured and free from any kind of injury due to radiation, since there is no drug injecting into the human body. Likewise Positron Emission Tomography (PET) [1], [6], Computer Tomography (CT) is the other techniques available for medical imaging applications. In traditional methods even experienced doctors also taking more time to identify the diseases. So for this reason inevitability of clear-cut and fully automatic process that can make available detailed evidence to the doctor is imperative [2], [6]. Similar works previously undertaken by authors mainly rely on the manual and automatic natured segmentation on MRI brain tumors, that are broadly categorized into two types non-

intelligent and intelligent based. In [3] the author presented image denoising using Haar and Daubechies Transforms. It is found to be Daubechies3 (db3) wavelet seems to be more efficient than Haar wavelet for reducing a certain level of speckle noise in the medical images and also it enhances the visual quality of the medical image a lot.

In [4] the author states that there are numerous noise reduction techniques had been developed for removing noise and conserving edge details in images. Each technique has its own suppositions, benefits and restrictions. Finally the idea behind these techniques is to acquire better results in terms of quality and in removal of different type of noises.

In [5] the author presented a technique to improve the image quality with the help of denoising and resolution enhancement. Here the paper concentrates on the average, median type of filter and Wiener type filtering for image denoising purpose and an interpolation based Discrete Wavelet Transform (DWT) method for resolution enhancement. The continued enhance in require for MRI within the healthcare industry has led to apprehensions about cost efficiency and over diagnosis [7, 8].

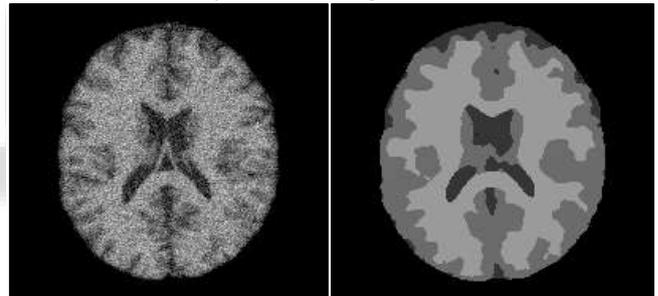


Fig. 1: MRI Images [7, 8]

II. LITERATURE SURVEY

In this paper author presents a comparative study of three segmentation methods implemented for tumor detection. Here author has following are the outcomes of the work [10]: using methods include k-means clustering with watershed segmentation algorithm, optimized k-means clustering with genetic algorithm and optimized c-means clustering with genetic algorithm. Segmentation was achieved for all the proposed techniques tumor detection was done.

- The k-means clustering with watershed segmentation algorithm, optimized k-means clustering with genetic algorithm and optimized c-means clustering with genetic algorithm were the main techniques.
- A comparison was also made in terms of tumor region and search time.
- The c-means clustering after optimization was found improved than other techniques.
- The difficulty of over segmentation was also concentrated on.

As conventional k-means algorithm is responsive to the initial cluster centers. Genetic c-means and k-means

clustering methods are used to detect tumor in MRI of brain images. At the end of development the tumor is removed from the MR image and its precise position and the shape are found out. An experimental result shows that genetic c-means not only remove the over-segmentation difficulty but also make available rapid and well-organized clustering effects.

In this type of segmentation, the user outlines the Region of Interest (ROI) with the mouse and the algorithms are applied so that the path best fits the edge of the image is implemented. This is how the segmentation procedure is accomplished using semi – automatic algorithm and one such algorithm is used in this work and it is called the seed based region growing algorithm. Initial level ROI is selected using a mouse click and that region or voxel act as the seed point based on which the segmentation is performed.

Tumor-Cut: segmentation of brain tumors on contrast enhanced MR images for radio surgery applications [11] is capable of segmenting only contrast enhanced T1 weighted images. The usage of the tumor cut algorithm is limited towards T1 contrast enhanced images and not upon other modalities of brain images. Tumor detection is done using the basic principle of Region of Interest (ROI) and requires manual assistance for segmentation procedures.

One particular challenge in imaging features is the similarity between tumors located inside the brain white matter and those that overlap intensity distributions with the gray matter. This pattern is particularly evident at the boundary between a tumor and the surrounding tissue. Partial volumes (PVs) are considered as boundary features containing a mixture of different tissue types [12]. The thicknesses of the image slices (5–7 mm) produce significant PV effects, in which individual image pixels describe more than one tissue type. As a result, peripheral tumor regions are mis-classified. This occurrence is common in T2-w images. A similar problem occurs toward the outer brain edge, where the CSF and gray matter overlap with the image sample. This circumstance may generate image intensities that erroneously indicate tumor presence.

Hemang J. Shah et al. studied various methods for detecting a tumor on MRI Images. In their research, they compared different image segmentation methods for evaluating their performance in the segmentation of a tumor. Those were Level Set Segmentation, K-means clustering, Difference in Strength Technique, and Watershed method. From their results, they concluded that all these methods have their own advantages and disadvantages. Level Set Segmentation requires the prior choice of the critical parameters such as the initial location of seed point, the appropriate propagation speed function and the degree of smoothness. The output image from K-means clustering has different intensity regions. An incorrect choice of threshold results in very weak accuracy in the segmented image when using Difference in Strength technique. Finally, Watershed suffers from the problem of over segmentation (a large number of segmented regions around each local minimum in the image) [15].

Recently, Aysha Bava M et al. (2014) studied segmentation of a brain tumor in MRI using Multi-structural Element morphological edge detection. In their research, a morphological edge has been found using the opening and closing operations. Their results showed that their algorithm

is more efficient for medical image analysis and edge detection than the usual edge detection methods such as Sobel, Prewitt, Robert and Canny edge detector. However, its computation is more complex compared to these conventional edge detection techniques [16].

Ali S.M. et al. (2013) studied brain tumor extraction in MRI images using clustering and morphological operations techniques. In their research, MRI T2 weighted modality has been preprocessed by a bilateral filter to reduce the noise and maintain edges among the different tissues. They used the morphological operation (erosion and dilation) to smooth four different techniques: Gray level stretching and Sobel edge detection, the K-means clustering technique based on location and intensity, the Fuzzy C-means clustering, and an Adapted K- means technique. Their results showed that the four implemented techniques can successfully detect and extract the brain tumor. However, more work is required to improve the segmentation results, and this may be achieved by implementing certain supervised classification methods [14].

III. PROPOSED METHODOLOGY

This section presents three significant techniques of image segmentation for removal of tumor in the MRI images. They have used these essential circumstances to detect tumor in our code and the code goes all the way through the following steps:

- Take an input dataset of disease images.
- Find the filtered image of the input image.
- Now apply PSO-SVM classification approach.
- Apply Single iteration based and multi-level based segmentation classified image.
- Classify the defected portion in the image

A. Algorithm Procedure:

- 1) The basic steps in pre-processing are the following:- Image is converted to gray scale image in first step. Noise is removed if any. The acquired image is then exceeded through a high pass filter to detect edges. Then they acquired image is added to original image to improve it.
- 2) In processing step of segmentation is done on basis of a threshold, due to which entire image is transformed into binary image. Basic matlab commands for threshold are used for this segmentation.

B. Algorithm Step:

Input: MRI Gray Scale Image

Output: Separation of Tumor Detected on that image.

- 1) Step1:- Convert MRI scan image into grayscale image.
- 2) Step2:- Next the image passed through a high pass filter for removing noise and other spike in the image and that filtered image is added to the grayscale image.
- 3) Step3:-Convert the enhanced image (image of step2) in to binary image with a threshold value
- 4) Step4:- Separate the tumor from segmented image by Watershed – Method up to the 10 iteration and using used for the optimization technique of SVM.
- 5) Step5:- Select only that part of the image from step4 which has the tumor with the part of the image having more intensity and more area.

- 6) Step6:- Now apply PSO-SVM classification approach.
- 7) Step7:-Obtained image from step6 are further to the original gray scale image from step1 and the resultant image is output.

The following algorithm is used for the optimization of SVM.

Initialize max-iterations and number of particle and dimensions.

```

for i= 1:no_of_particles
for j= 1:dimensions
particle_position(i,j) = rand*10;
particle_velocity(i,j) = rand*1000;
p_best(i,j) = particle_position(i,j);
end
end
for count = 1:no_of_particles
p_best_fitness(count) = -1000;
end
for count = 1:max_iterations
for count_x = 1:no_of_particles
x = particle_position(count_x,1);
y = particle_position(count_x,2);
ker = '@linearKernel';
global p1 ;
p1 = x;
C = y;
trnX=X;
trnY=Y;
tstX=X';
tstY=Y';
[nsv,alpha,bias] = svmTrain(trnX,trnY,C);
actfunc = 0;
predictedY
svcoutput(trnX,trnY,tstX,ker,alpha,bias,actfunc);
Result = ~abs(predictedY)
Percent = sum(Result)/length(Result)
soln = 1-Percent
if soln~=0
current_fitness(count_x) = 1/abs(soln)+0.0001;
else
current_fitness(count_x) =1000;
End
End

```

Support Vector Machine (SVM) is we train a Support Vector Machine (SVM) categorizer [9] supervised learning approach which operates on the finding of hyperplane which uses an interclass distance or margin width for the separation of positive and negative samples. For the unequal misclassification cost a coefficient factor of C_+ & C_- denoted as 'J' is used for the generation of errors can be outweighs both positive and negative examples. Hence the optimization problem of SVM becomes:

$$\text{minimize } \frac{1}{2} \|w\|^2 + C_+ + \sum_{i,y_i=1} N_i + C_- \sum_{j,y_j=-1} N_j \quad (1)$$

This satisfies the condition,

$$y_k (w x_k + b) \geq 1 - N_k, \quad N_k \geq 0$$

Parameters	Explanation
y_i	Class labels used in the training dataset
w	Normal to the hyperplane

$ b /\ w\ $	Perpendicular distance from origin to the hyperplane
$\ w\ $	Euclidean norm of w
C	Regularization parameter used to find the tradeoff between training error and margin width d
N_i	Slack variable that allows error in classification [9].

SVM is implemented in linear and non-linear way, the non-linear form or Radial bias kernel are used for the non-linearly separable data with lagrange multiplier Hence optimization problem becomes:

$$\text{minimize } w(\alpha) = \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i,j=1}^l \alpha_i y_i \alpha_j y_j K(x_i, y_j) \quad (3)$$

Where,

$$C \geq \alpha_i \geq 0 \quad \forall_i, \sum_{i=1}^l \alpha_i y_i = 0 \quad (4)$$

Due to the chance of non-linearity and error SVM is based on black box models. For the classification of medical diabetes mellitus a final decision is crucial requirement by the end users. Hence Feature Extraction is implemented for the exact working of the SVM.

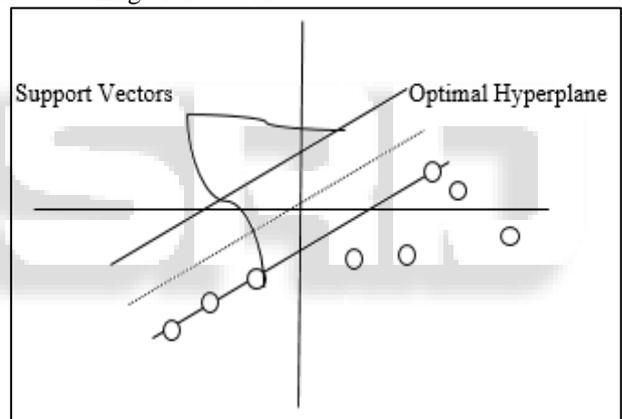


Fig. 2: Basic Architecture of Linear SVM

Particle Swarm Optimization (PSO) The PSO algorithm has become an evolutionary computation technique and an important heuristic algorithm in recent years. Particle swarm optimization (PSO) is a population based method, where a population is called a swarm. The PSO algorithm simulates the behaviors of bird flocking [13]. Particle Swarm Optimization (PSO) is easier to implement and it is easy the parameters of PSO.

The Basic form of Particle Swarm Optimization (PSO) consists of the moving velocity of the form:

$$V_i(k+1) = V_i(k) + \gamma_{1i}(P_i - X_i(k)) + \gamma_{2i}(G - X_i(k))$$

And accordingly its position is given as:

$$X_i(k+1) = X_i(k) + V_i(k+1)$$

Where,

Parameter	Summary
I	Particle Index
K	Discrete time index
V	Velocity of the ith particle
X	Position of ith particle
P	Best position found by ith particle

G	Best position found by swarm
$\gamma_{1,2}$	Random numbers on the interval [0, 1] applied to i th particle.

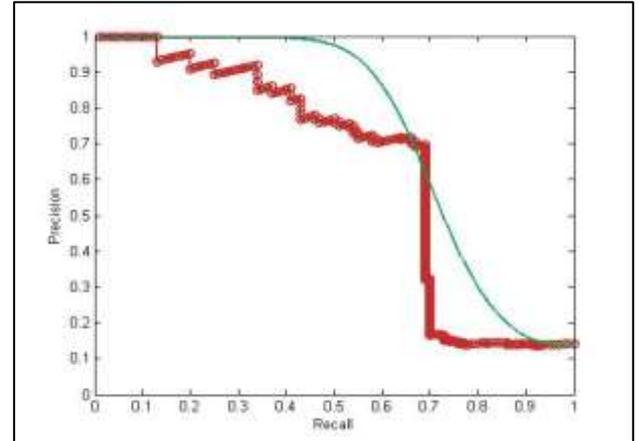
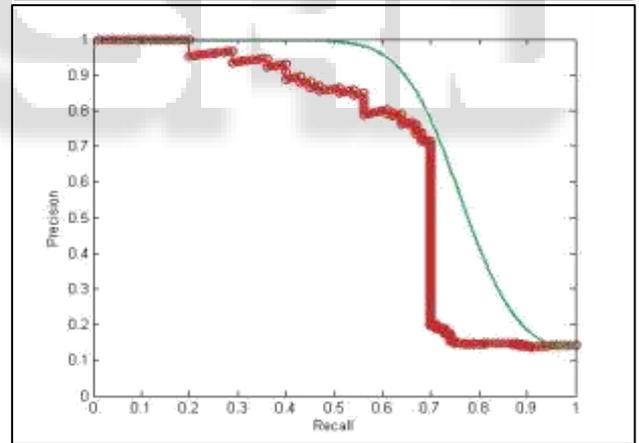
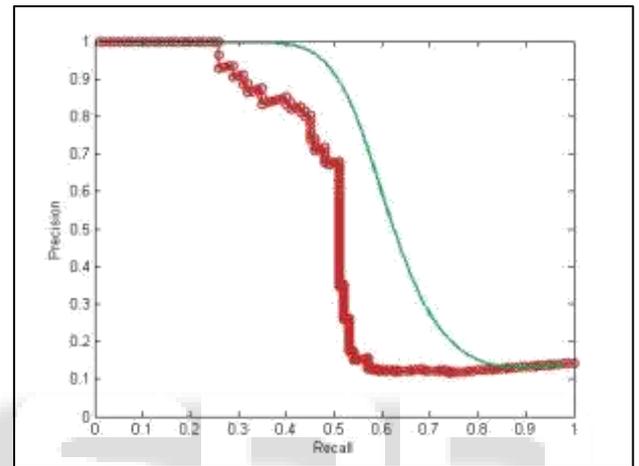
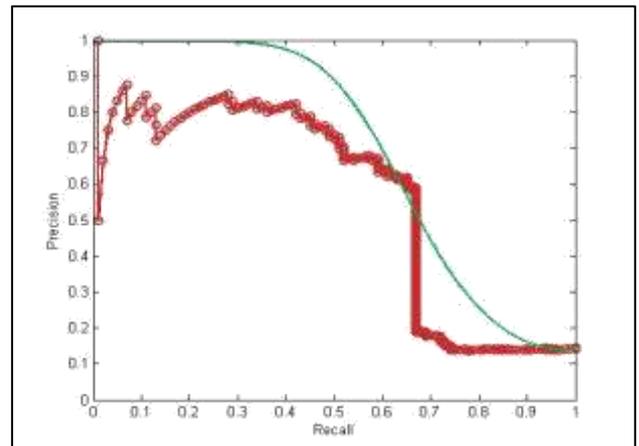
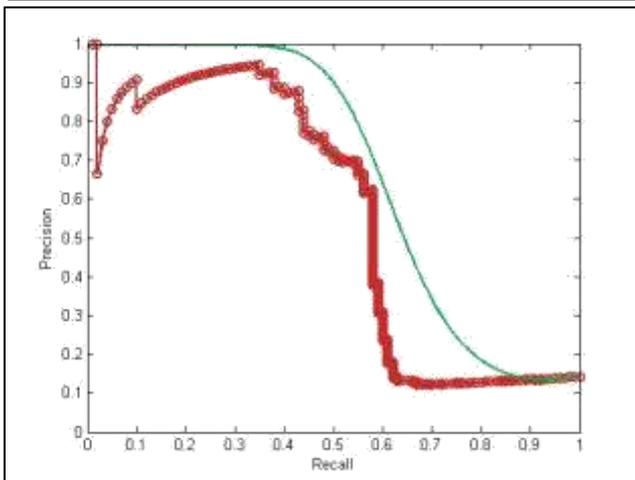
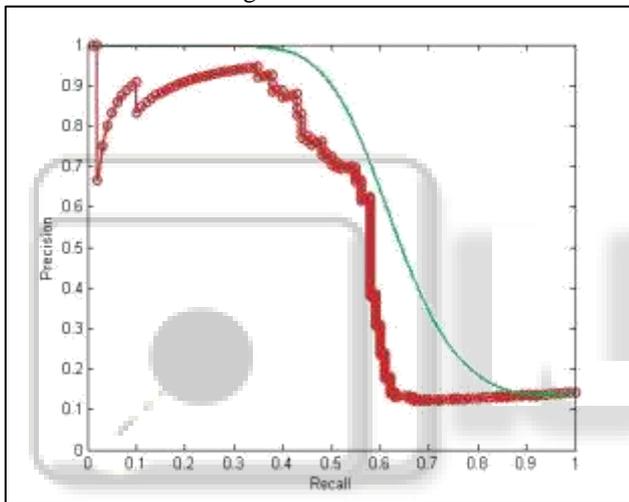
Table 2: Basic Parameter or Notations of PSO

IV. EXPERIMENTAL RESULTS

We exhaustively compared our approach to analysis of the medical images provides a way of detecting and predicting diseases in the images. In view of the fact, that different methods are executed for the analysis of images containing diseases. The existing technique implemented for the disease classification using manifold learning provides efficient detection and classification of diseases in MRI images on a publicly available two images with binary ground truth. The methods used for comparison included paper [10].

A. Experiment 1:

We evaluated the performance of disease classification is based support vector machine based classifier which is a smaller amount well-organized and holds more error rate.



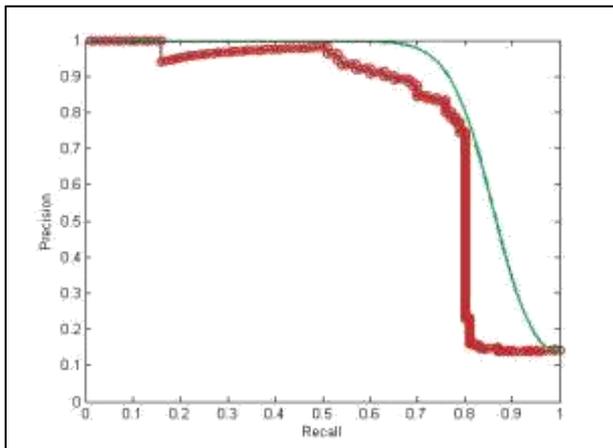


Fig. 3: Average Precision-Recall curve is generated given saliency map with different range

For a given saliency map with values in the range [0, 255], the easiest technique to get a binary segmentation of the salient object is to threshold the saliency map at a threshold $T_f \in [0, 255]$. When T_f varies from 0 to 255, different precision-recall pairs are obtained, and a precision-recall curve can be drawn. The average precision-recall curve is generated by averaging the results from all the 1000 test images. The resulting curves are shown in the following figure. The figure shown below is the analysis and overall comparison the proposed methodology. The analysis is done on seven iterations in which the precision, recall, F-measure have calculated in proposed methodology

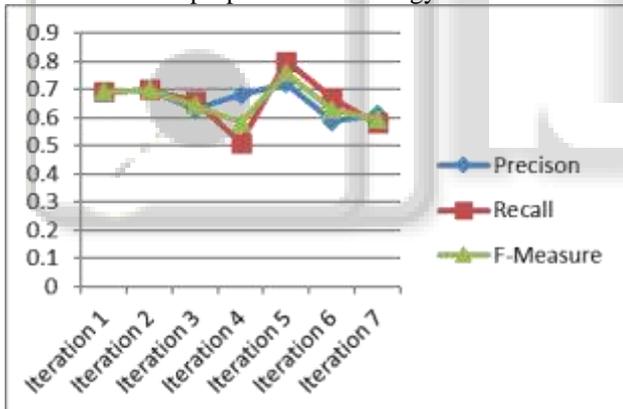


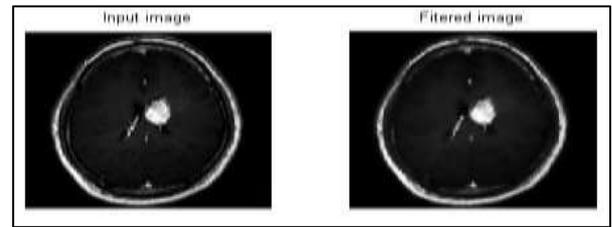
Fig. 4: Overall Comparisons of Precision, Recall and F-Measure of Proposed Methodology.

B. Experiment 2:

In this experiment, we used an image dependent adaptive threshold to segment objects in the image. Towards proposing new performance measures for comparing the outcomes of IR experiments. we can compute the F-measure, which is defined as:

$$F = (1 + \beta^2) * \text{Precision} * \text{Recall} / (\beta^2 * \text{Precision} + \text{Recall})$$

we set $\beta^2 = 0.3$ in our experiments. F-measure can reflect the overall prediction accuracy of an algorithm. Averaged F-measure over different images achieved by each tumor detection algorithm is listed in the following table:



Pre-Processing Step of Input image get filtered Image

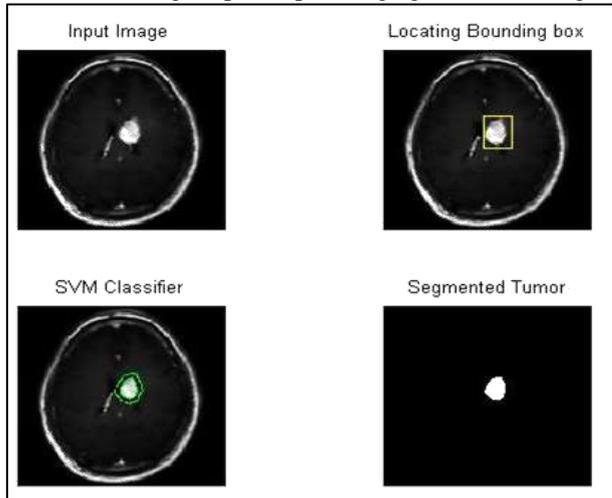


Fig. 5: Overall Comparison of finding tumor from SVM classifier

The table shown below is the analysis and comparison of the existing methodology and the proposed methodology. The analysis is done on three images in which the accuracy of the proposed methodology is better as compared to the existing methodology.

The figure shown below is the analysis and comparison of the existing methodology and the proposed methodology. The analysis is done on three images in which the accuracy of the proposed methodology is better as compared to the existing methodology. The two methodologies implemented here for the classification of Disease in MRI Images using Support vector machine and the optimization of Support vector machine using Particle Swarm Optimization is done here and the experimental results are performed on various MRI images on the existing and the proposed methodology. The proposed methodology implemented here provides better classification of disease in MRI images.

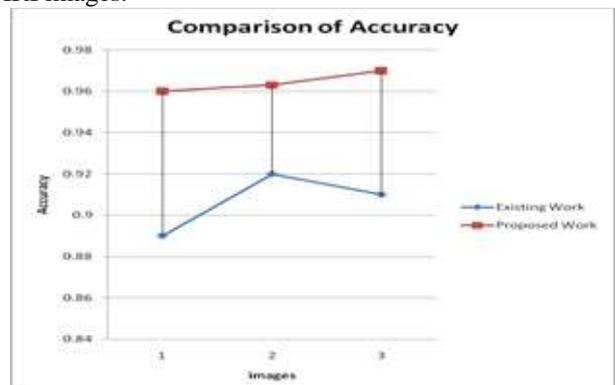


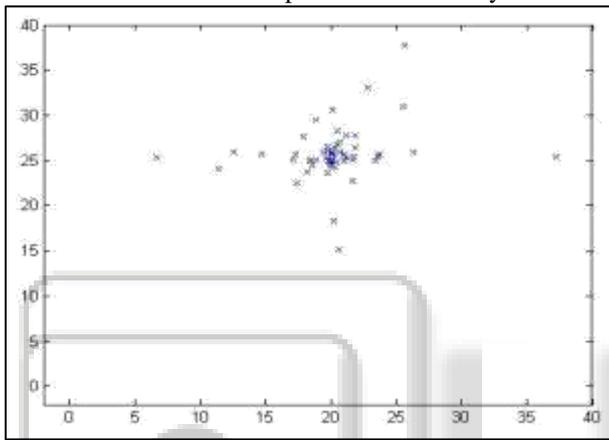
Fig. 6: Comparison of Accuracy of the existing and proposed methodology

C. Experiment 3:

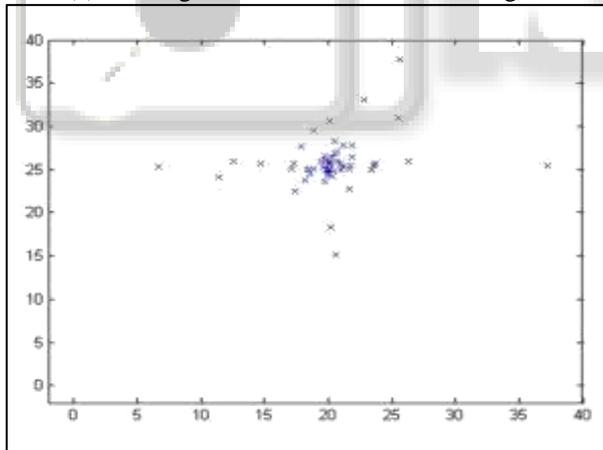
In addition to the disease classification using manifold learning provides efficient detection and classification of diseases in MRI images accuracy, the computational costs of various methods were also evaluated. The time cost consumed by each evaluated saliency detection method for processing one 400×300 color image is listed in the following table.

Test Images	Original Image value	Existing Work algorithm (Pixel value)×10 ⁻³	Proposed Work algorithm (Pixel value)×10 ⁻³
Image 1	50372	659	629
Image 2	42405	644	583
Image 3	46260	780	700

Table 3.1: Comparison of Accuracy



(a) Existing classifier Result of MRI images.



(b) Proposed Result of SVM Classification using PSO method PSO from SVM classifier.

Fig. 7: Overall Processing Comparison of PSO from SVM classifier.

The table shown below is the analysis and comparison of the existing methodology and the proposed methodology. The analysis is done on three images in which the Elapsed Time of the proposed methodology is better as compared to the existing methodology.

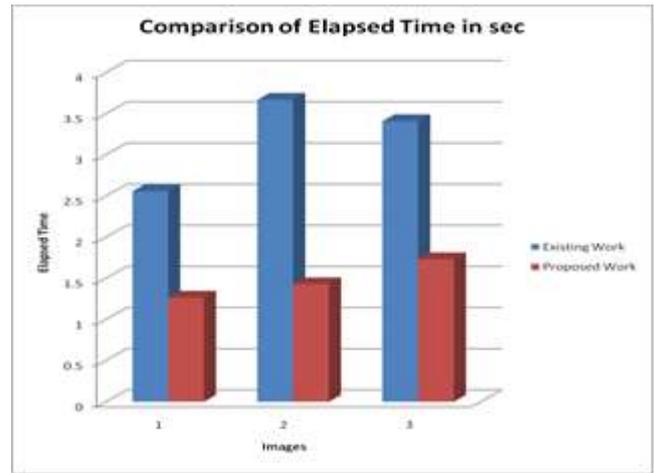
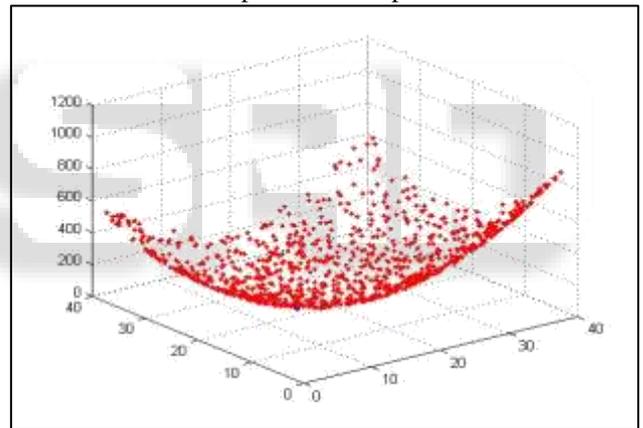


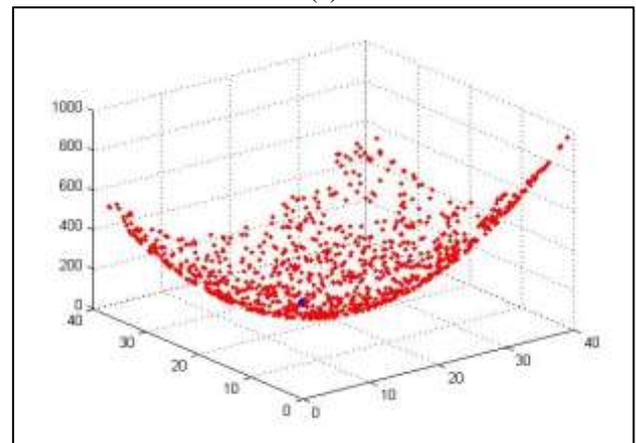
Fig. 8: Comparison of Elapsed Time of the existing and proposed methodology

Test Images	Existing Work for Search time with number of iterations (sec.)	Proposed Work for Search time with number of iterations (sec.)
Image 1	1.232730 sec. (7)	1.181853 sec.(7)
Image 2	1.2421470 sec.(7)	1.1928764 sec.(7)
Image 3	1.241682 sec.(7)	1.191258 sec.(7)

Table 3.2: Comparison of Elapsed Time in sec



(a)



(b)

Fig. 9: (a) Existing Classification Result of Segmented Image. (b) Proposed Result of SVM Classification using PSO method of Segmented Image.

V. CONCLUSION

As all the expansion of biomedical image processing has increased consideration from the scientists, there are still some problems with biomedical image processing that have become visible, mainly with MRI imaging. This paper presents an analysis of various proposed methods for segmenting an MRI image which relatively take lesser time for searching than manual process to detect and extract the brain tumor and detecting the particular boundary of the region containing a distinguished brain tumor that is a complex difficulty and must be addressed since it applies to many medical modalities and tumor categories. Experimental results show that PSO-SVM classification approach can we obtain far superior results than the traditional techniques for tumor detection.

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