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Classification of MRI Images Using Particle Swarm Optimization Based Support Vector Machine for Tumor Detection

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Abstract: This paper searches the possibility of pertaining techniques for segmenting the regions of medical image. For this we require to examine the use of different techniques which helps for detection and classification of image regions. In the paper, a new method is proposed for tumor detection using morphological operations to address brain tumor from MRI images to be used as a tool in real time during surgeries a new method using particle swarm optimization technique to recognize and remove the limit of a brain tumor. Using abnormal images of a variety of brain tumors, this study shows that the proposed algorithm provides a robust technique in expressions of accuracy and computation time, making it appropriate for real-time processing. Results also show that this algorithm is proficient of producing one-pixel-width continuous edges with accurate positioning of particular region where tumor was detected.

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

I. INTRODUCTION

Modern technology has made it feasible to generate procedure, transmit and accumulate digital images proficiently. As a result, the quantity of visual information is growing at a go faster degree in many unusual application regions. This elevated mortality time of brain tumor significantly enlarges the consequence of Brain Tumor detection. Real time analysis of tumors by using more consistent algorithms has been the most important focus of the most up-to-date improvements in medical imaging and detection of brain tumor in MR Mages and CT scan images has been an active research region. The partition of the cells and their nuclei from the have a break of the image content is one of the major difficulties features by the largest part of the medical imagery diagnosis schemes. MRI scanners use strong magnetic fields and radio waves to form images of the body. The method is extensively utilized in hospitals for medical diagnosis, performance of disease and for summarize without introduction to ionizing radiation. MRI has an extensive variety of applications in medical diagnosis and there are predictable to be over 25,000 scanners in use global [1]. MRI has an impact on diagnosis and treatment in many area of expertise even though the consequence on progressed health results is tentative [2]. Since MRI does not use any ionizing radiation it's utilize is proposed in partiality to CT when either modality could give way the similar information [3]. MRI is in common a protected method but the numbers of occurrences causing patient harm have got higher [4]. Contra suggestions to MRI comprise a large amount cochlear inserts and cardiac pacemakers, shrapnel and metallic unknown bodies in the orbit and some ferromagnetic surgical implants. The protection of MRI during the first trimester of pregnancy is undecided but it may be choose able to unusual alternatives [5]. The continued enhance in require for MRI within the healthcare industry has led to apprehensions about cost efficiency and over diagnosis [6, 7].

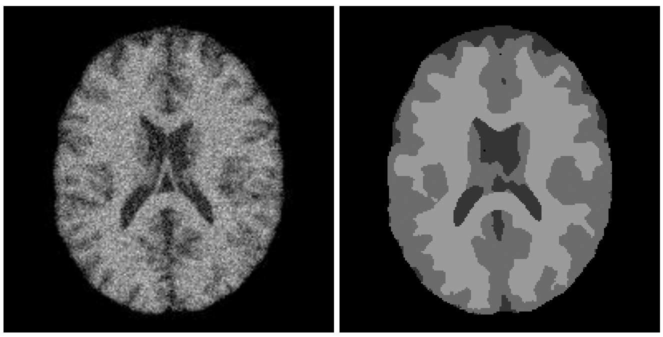


Figure 1: MRI Images [6, 7]

The brain is the forward most part of the central nervous system. Brain tumor is an intracranial solid neoplasm. Tumors are produced by an abnormal and unrestrained cell division in the brain. In this effort, they have utilized axial examination of the brain image (2D) from MRI scan because MRI scan is a smaller amount damaging than CT brain scan. A patient is area under discussion to unusual diagnostic techniques to verify the reason of the indications declared by him. Techniques like performing arts a biopsy, presenting imaging, like attractive a MRI or CT scans of the brain will be done. In biopsy, pathologists take an example of the brain tissue beneath concern for examination the presence of tumor. A pathologist looks at the tissue cells under a microscope to check for existence of defect. Though biopsy will give you an idea about the presence of tumor and its pathology, when doctors go for surgery, they must know the tumor extent and the exact location of tumor in the brain, which can be found by attractive MRI scan of the patient as MRI doesn't involve the utilize of damaging radiations when evaluated to CT scan. Conventional technique in hospitals is to segment the medical image under concern, manually and this depends on how well the physician can recognize the image under concern to get the essential region removed out, which is made easier said than done for the reason that of minute variations and similarity between the original and exaggerated biological part in the image. The deficiency of radiologists and the huge volume of MRI to be examined make these evaluations labor concentrated and also cost expensive. It also depends on the expertise of the technician examining the images [8]. Approximations also specify that between 10 and 30% of tumors are missed by the radiologists during the routine screening.

Detecting the accurate boundary of the area containing a known brain tumor is a complex problem and must be concentrating on since it applies to many medical modalities and tumor categories. The objective of this proposal is to give an efficient algorithm for detecting edges of brain tumors to help neurosurgeons recognize the area of the critical region of tumor and discriminate the exact margin of the tumor from the rest of the brain tissue during the surgery. In this paper, we work on MRI brain tumor images as a tool to aid surgeons. MRI image segmentation is a fundamental step as a beginning procedure to concentrate the region of interest, which is the brain tumor region. This work proposes a new method using particle swarm optimization technique to recognize and remove the edge of a brain tumor. Using abnormal images of a variety of brain tumors, this study shows that the proposed algorithm provides a robust technique in expressions of accuracy and computation time, making it appropriate for real-time processing. Results also show that this algorithm is proficient of producing one-pixel-width continuous edges with accurate positioning of particular region where tumor was detected.

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 [9]: 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.

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) [10].

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 [11].

Pratibha Sharma et al. (2012) studied an application of edge detection for brain tumor detection. Their algorithm involved various steps. They used a Median filter to remove noise and a Laplacian filter. Then, they converted the image to binary and applied morphological operations (erosion and dilation) to smooth results. Finally, for edge detection, they used the 2D cellular automata rule 255. Also, they used Watershed segmentation as a method for verifying output. Their algorithm was applied on numerous images, and the results were good. However, accuracy obtained in the final result depends on processing of each stage. For each stage, there are various techniques presented. Therefore, it is hard to choose the suitable methods that provide best results [12].

C.C. Leung et al. (2003) proposed a new approach to detect the boundary of a brain tumor based on the generalized Fuzzy operator (GFO). One typical example is used for evaluating this method with the contour deformable model (CDM). Their result showed that the boundary detection using their method is better than the method of CDM. However, there is a 2% error in their method because there is a small region of normal tissue located within the tumor. As a result, their method remains inefficient to detect the boundary for the brain tumor [13].

Riries Rulaningtyas et al. (2009) studied edge detection for brain tumor pattern recognition. In their research, they enhanced the image using a histogram. Then, they used an edge detection process to take the edge pattern of a brain tumor. They used three methods of edge detection (Robert, Prewitt, and Sobel). The obtained results showed that Sobel is more suitable for edge detection of a brain tumor than the Robert and Prewitt operators [14].

Manoj Diwaker et al. (2013) proposed a new method for edge detection using cellular automata. They used Cellular Automata rules to help determine the exact location and size of a brain tumor. They adopted Cellular Automata rule 124 in their research. Also, they presented comparison results between their method and Sobel, Robert, Prewitt, Canny and Marr-Hildreth methods. Their results showed that the output obtained by Cellular automata is better than conventional methods [15].

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 [16].

III. Proposed Methodology

This section presents three significant techniques of image segmentation for removal of tumor in the MRI images. The measurement of the image containing the tumor usually has more intensity then the other part of image and they can imagine the region, shape and radius of the tumor in the image. 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:

In pre-processing some essential image enhancement and noise reduction methods are executed. Apart from that unusual techniques to differentiate edges and doing segmentations have also been utilized. The reason of these steps is essentially to progress the image and the image quality to get more security and effortlessness in detecting the tumor.

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: Isolation of Tumor Detected on that image

Step1:- Convert MRI scan image into grayscale image.

Step2:- Next the image passed through a high pass filter for removing noise and other spike in the image.

Step3:- Now filtered image is added to the grayscale image.

Step4:-Convert the enhanced image (image of step3) in to binary image with a threshold value

Step5:- Separate the tumor from segmented image by Watershed – Method up to the 10 iteration and using used for the optimization technique of SVM.

Step6:- 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.

Step7:- Now apply PSO-SVM classification approach.

Step8:-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 [20] 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:

$$minimize\frac{1}{2}||w||^2 + C_+ + \sum_{i.y_i=1} \aleph_i + C_- \sum_{j.y_j=-1} \aleph_j \quad (1)$$

This satisfies the condition,

$$y_k(wx_k + b) \geq 1 - \aleph_k, \quad \aleph_k \geq 0 \quad (2)$$

Table 1: Various Annotation Used

Parameters	Explanation
y_i	Class labels used in the training dataset
W	Normal to the hyperplane
|b|l||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
$\aleph_i$	Slack variable that allows error in classification [8].

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 α_i,
Hence optimization problem becomes:

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

Where,

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

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.

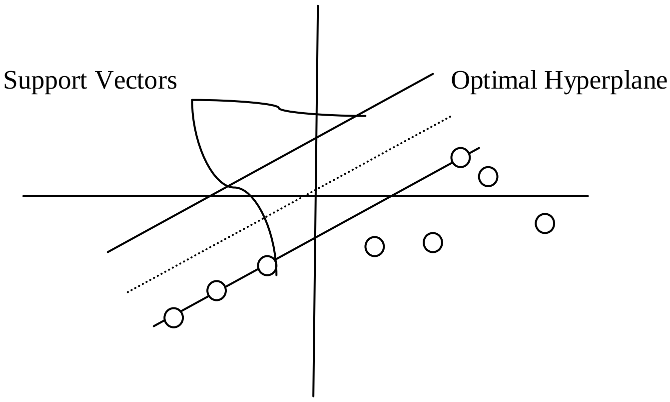


Figure- 2: Basic Architecture of Linear SVM

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 [19]. 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:

$$V_i(k+1) = V_i(k) + \gamma_{1i}\big(P_i - X_i(k)\big) + \gamma_{2i}\big(G - X_i(k)\big) \quad (5)$$

And accordingly its position is given as:

$$X_i(k+1) = X_i(k) + V_i(k+1) \tag{6}$$

Where,

Table 2: Basic Parameter or Notations of PSO

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 ith particle.

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 [9].

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. Towards proposing new performance measures for comparing the outcomes of IR experiments (two such recent attempts can be found in ([17, 18]). Here, we take a different standpoint. We focus on widely used measures (precision, recall, and F-score), and infer distributions for them that allow us to evaluate the variability of each measure, and assess the significance of an observed difference. Although this framework may not be applicable to arbitrary performance measures.

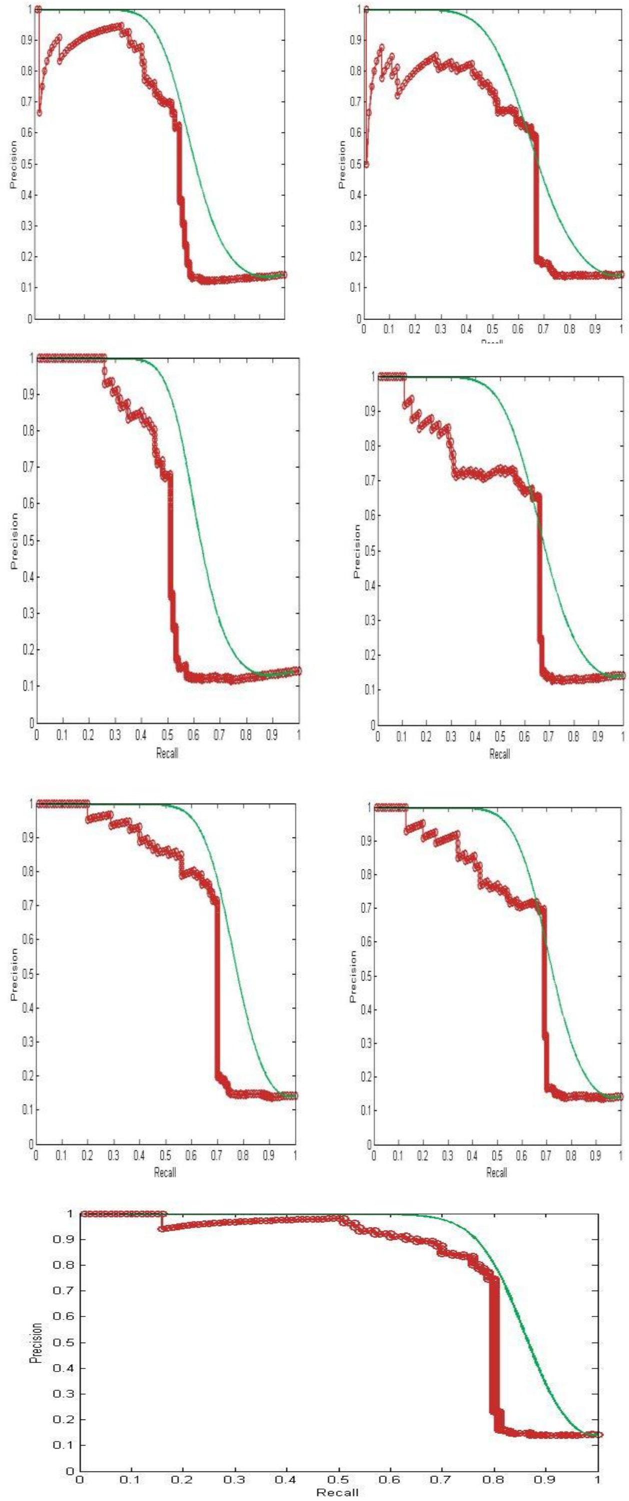


Figure-3: Average Precision-Recall curve is generated given saliency map with different range

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

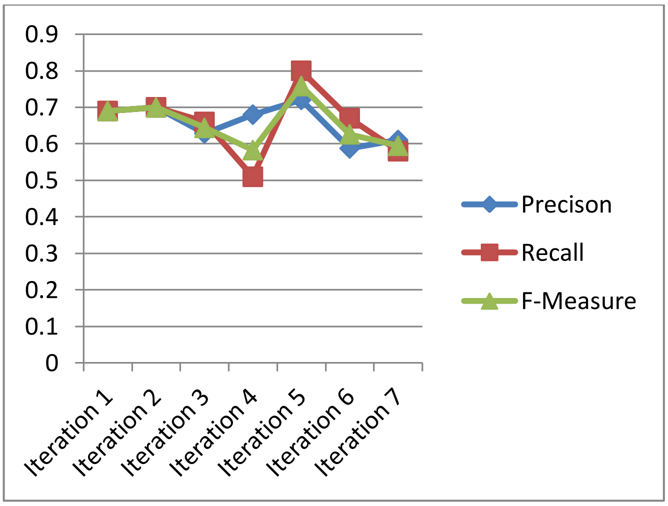


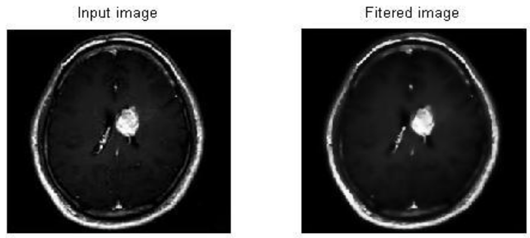
Figure 4: Overall Comparisons of Precision, Recall and F-Measure of Proposed Methodology.

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 (two such recent attempts can be found in ([17, 18]). Specifically, such an adaptive threshold T_a is determined as twice the mean saliency of the image. Using the adaptive threshold, we could obtain binarized maps of salient objects extracted by each of the tumor detection algorithm. The figure shown below is the original input image in which disease part is to be detected. The input image taken here is an MRI Image of heart. Then, for each algorithm, for each image, we can compute the *F*-measure, which is defined as

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

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

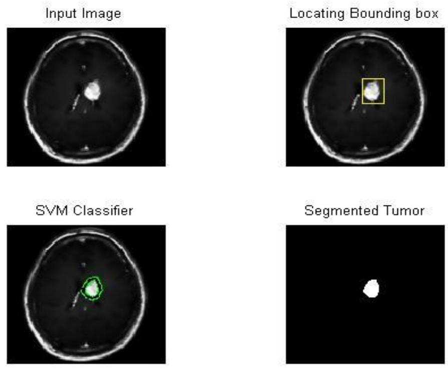


Figure-5: Overall Comparison of finding tumor from SVM classifier

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.

Test Images	**Original Image value**	**Existing Work algorithm (Pixel value)**$\times 10^{-3}$	**Proposed Work algorithm (Pixel value)**$\times 10^{-3}$
Image 1	50372	629	659
Image 2	42405	583	644
Image 3	46260	700	780

Table 3.1 Comparison of Accuracy

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.

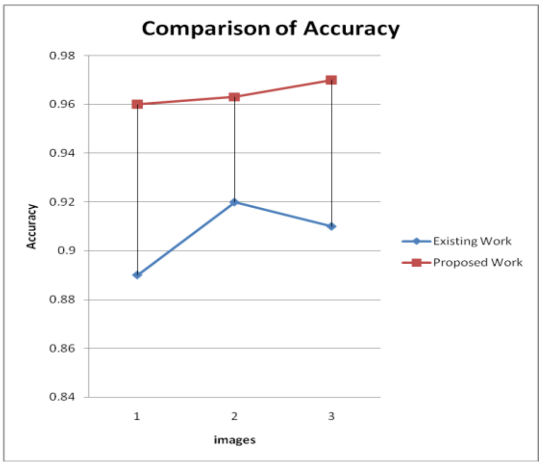
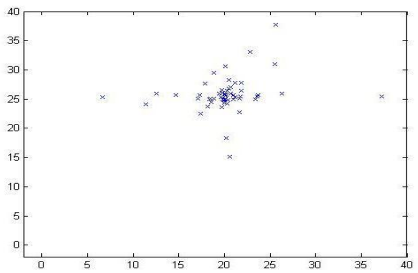


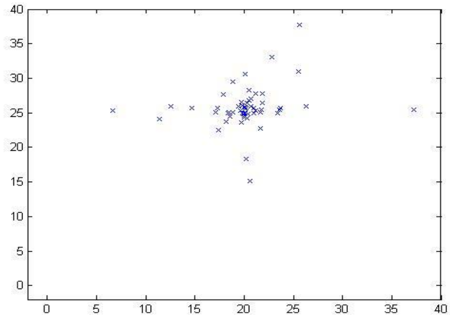
Figure 6: Comparison of Accuracy of the existing and proposed methodology

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 figure shown below is the iterative process of applying PSO-SVM on the input image for the detection of disease in the MRI Image. Particle swarm optimization is a supervised learning approach used for the optimization of features that are not extracted using other methodology. Here Particle Swarm Optimization is used for the optimization of Support vector machine so that more number of features can be extracted from the images. Experiments were performed on a standard HP Z620 system with a 3.2GHZ Intel Core i-3 CPU and a 4G RAM. The software platform was Matlab R2009b. The time cost consumed by each evaluated saliency detection method for processing one 400×300 color image is listed in the following table.



(a) Existing classifier Result of MRI images.



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

Figure-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.

Table 3.2 Comparison of Elapsed Time in sec

Test Images	**Existing Work for Search time with number of iterations (sec.)**	**Proposed Work for Search time with number of iterations (sec.)**
Image 1	1.232830 sec. **(7)**	1.181893 sec.**(7)**
Image 2	1.2421370 sec.**(7)**	1.1928364 sec.**(7)**
Image 3	1.241382 sec.**(7)**	1.191458 sec.**(7)**

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 Elapsed Time 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.

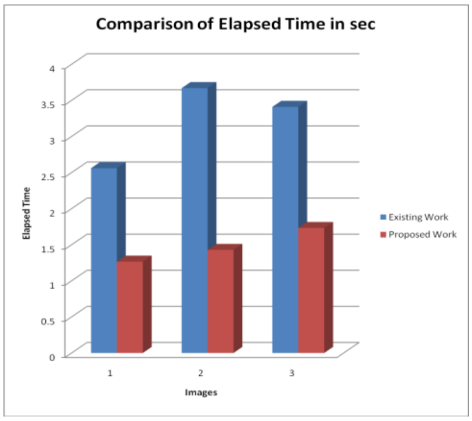
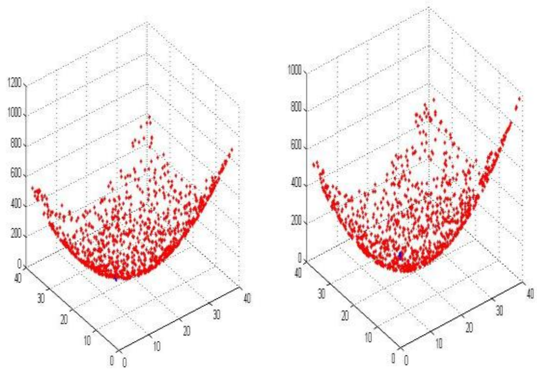


Figure 8: Comparison of Elapsed Time of the existing and proposed methodology



(a) (b)

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

V. CONCLUSION

This paper presents an analysis of various proposed methods for segmenting an MRI image which relatively take lesser time 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 successfully segment a tumor gived the parameters are set appropriately in MATLAB environment. This paper explores a method to identify tumor in brain disorder diagnosis in MRI images.

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