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Research paper

Swarm based Optimization Technique for Detection of Brain Tumor in T2-Weighted MRI Images

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Abstract

Tumor detection is one of the most critical tasks from the brain MRI images. Commonly magnetic resonance scanner produces brain images with burst tissues where distinctive and combined sights of the tissues are required. The manual view of such tissues on image is impossible and leads to generate errors. Hence with the help of soft computing techniques, the detection of tumor region can be effectively done which will assist the radiologist extensively without errors. Several soft computing techniques have been proposed to improve the accuracy and reduce the false contour detection in medical images. In this work automatic brain tumor detection from MRI images using nature inspired meta-heuristic optimization technique is proposed. The proposed methodology consists of four stages such as preprocessing, segmentation, feature extraction and classification. In preprocessing, the quality of the image is enhanced with median filter by removing the noise. The particle swarm optimization (PSO) algorithm segments the pre-processed image and several textural and shape features are extracted through gray level co-occurrence matrix (GLCM) technique. Finally, the support vector machine (SVM) classifies the extracted tumor from the brain MRI images. The performance of the proposed automated detection method is evaluated on publically available dataset and real images and the obtained results are compared with existing methods. This method yields good, robust and fast segmentation results.

Keywords: *Brain tumor; Classification; Feature extraction; MRI T2-Weighted; PSO algorithm.*

1. Introduction

People throughout the world were affected with one or other forms of cancer. In all over the world brain tumor has been one of the main causes of increment in death. An uncontrollable expansion of abnormal tissues or cells is generally known as brain tumor [1]. Abnormal tissues (tumors) of brain are typically classified as malignant and benign. Malignant is cancerous brain tumor which has the characteristics like non-uniform structure, rapid growing of active cancer cells, extend to other components of the head and spinal cord, more harmful and leads to fatality. Benign is non-cancerous brain tumor which has non-active cancer cells with lesser growth rate and aggressive. As per world health organization (WHO), the tumors are categorized with grades from grade I to grade IV based on abnormalities present in brain tissue. Grade I tumors are slightest malignant tumors and are commonly associated by means of long-standing survival and approximately normal in appearance. Grade II tumors grow deliberately and appear slightly abnormal. Malignant tumors are Grade III kind of tumors, actively producing abnormal cells. Grade IV tumors are most malignant, it reproduce rapidly. These tumors create new vessels of blood and they preserve rapid growth [2].

Brain tumor may affect individual at any stage. The impact lying on every personality is not similar. As per the estimation of American Brain Tumor Association (ABTA) during the year 2017, in USA only, there are almost 80,000 new patient cases are diagnosed through primary brain cancer and a total of over 700,000 living with the brain cancer out of them 28,000 kids fighting with brain tumors. Approximately there are 32 percent (one-third) of brain tumors are malignant. The national brain tumor foundation (NBTF) estimated that the increase of brain lesions among people and people expire out with brain tumor raising every year [3]. Different screening modalities available such as Computed tomography (CT), PET, Single positron emission computed tomography (SPECT) and MRI. Compare to all other medical imaging modalities, the MRI presents excellent contrast for different brain tissues. For the applications of exposure and identification of lesion in the brain, the MRI is very efficient due to high contrast for soft tissues; its spatial resolution is high. MRI doesn't produce radiation, not harmful to brain and its tissues. It is a non-invasive technique and more comfortable than CT scan for diagnosis which produces more radiation, harmful to brain. An MRI screening modality is cable of producing different imaging pulse sequences such as T1-W (T1 weighted), T2-W (T2-weighted) and PD (proton density). Early detection along with screening of brain tumor increases the longer existence of patients as possible in terms of quality. The digital screening systems assist greatly in diagnosis of cancers. These systems also used to provide second opinion through radiologists for the confirmation of diagnostic outcomes. It is advantage in aspects of tumor area quantification, speed, accuracy, reduces the miss rate, and reduces the burden. A minor incorrect treatment or artificial miss can guide to wrong and poor treatment. So, to analyse the tumor area, digital imaging and its processing techniques can help greatly [4].

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The major life threatening diseases of mankind is the tumor, so it needs to go for best treatment by early diagnosis with maximum accuracy. Past few days, several types of research on brain tumor diagnosis has been evolved highly for different imaging modalities but not fully imperative. Many researchers investigating for advanced diagnosis systems. Segmentation is vital and fundamental process and is one of the difficult tasks in image processing. Several segmentation methods have been improved by researchers for identification, extraction and classification of the tumors from medical images. The segmentation techniques are categorized as thresholding based, watershed, edge and region based, clustering techniques (supervised and unsupervised), hybrid and soft computing based methods [5].

Threshold based method is one of the classical segmentation techniques and helpful to image linearization (binarization), which is a necessary task for any type of lesion segmentation [6]. G.E.Sujji et al. [7] proposed Otsu's thresholding along with combination of thresholding and clustering to partition the brain images. Thresholding approach is much sensitive to unwanted noise along with intensity homogeneities. Alyaa H. Ali et al. [8] proposed Otsu's global thresholding as well as enhanced Otsu's techniques to segment the brain tumor from MRI images and determined tumor size and area only.

Ashima proposed watershed segmentation method and SOM classification [9]. This is the finest technique to cluster pixels of the images on their intensities basis. But their sensitivity to intensity dissimilarity results over-segmentation. Suman Rani [10] proposed edge detection approach with mathematical morphology (EDMM). The mathematical morphological operations such as erosion to shrinks the foreground, dilation to expands, closing to remove holes, and opening to drift foreground pixels. Proposed EDMM is very sensible to noise. C.L.Devasena et.al. [11] proposed an efficient system for identification of abnormal tissues within MRI images by hybrid abnormality detection algorithm (HADA). In this system the noise has removed and smoothed by hybrid filter. DWT method has proposed to feature reduction and extraction, hence identify the abnormality and finally classified the lesion type but classification technique has not proposed.

Fuzzy C-means is a fuzzy clustering technique; it allows a portion of data belongs to two or more clusters. Zhu and Yan [12] designed a method based on FCM and a linear sequence of knowledge based rules. A. Rajendran et al. [13] proposed enhanced probabilistic FCM (EPFCM) clustering technique for recognizing the tissues within normal and also pathological human brain MRI images. Proposed approach can segment the images automatically and effectively, but time consumption is more hence it is a disadvantage. The system is sensitive to noise and computationally more expensive.

El-Sayed A. El-Dashan et al. [14] reviewed on different latest techniques of brain MRI image segmentation, attribute extraction and categorization of tumor including advantages and disadvantages. Also designed an automatic system to diagnose the tumor from T2-weighted human brain MRI images and the system consists of median filter to pre-process, feedback-pulse-coded convolution neural networks (FPCNN) for ROI segmentation, DWT for attribute extraction, dimensionality resizing with PCA and finally ANN used for classification of healthy and pathological brain. By extracting some more features the classification accuracy may increase. G.Vishnuvarthanan proposed fuzzy logic based brain MRI segmentation and tumor extraction, determined the peak-signal-to-noise-ratio (PSNR) and mean square error (MSE) for extracted image [15]. Udaya Suriya et al. proposed DWT based brain lesion image fusion [16]. B.Shobhan Babu et.al., projected DWT and clustering based segmentation and SVM classifier to classify the tumor type. This system had limitation to detect some types of abnormalities of in brain, PSNR and accuracy of the proposed method is not much good because poor directionality, phase information absented and shift sensitivity [17].

N.B.Bahadure et al. [18] proposed a brain tumor detection system with different techniques of segmentation such as watershed, FCM, DWT and BWT and by comparing these four BWT selected as prominent one and best technique. Morphological operations, GLCM and genetic algorithm (GA) has been used as feature extraction and classification. Genetic algorithm used to segment the brain image by initializing proper levels of thresholding, population, fitness function, crossover and mutation [19]. G.Yang et al. [20] proposed bio-geography based optimization for automatic recognition and classification of brain images with wavelet energy and KSVM. R.Agarwal et al [21] proposed k-means clustering for brain lesion segmentation from MRI and CT imagery. The accuracy obtained using this technique in MRI images is very less. N.V.Shree et al proposed region growing method of segmentation to identify the tumor in MRI images, the obtained accuracy and PSNR is less and MSE is more [22]. To increase the accuracy and PSNR and to reduce the error, the optimization techniques are very much suitable because the optimization performs fine thresholding on medical images. Several problems inside medical images have been cracked by considering bio-inspired meta-heuristic optimization algorithms such as Genetic Algorithm (GA), Ant Colony Optimization (ACO) and Artificial Bee Colony Optimization (ABCO). These nature-inspired techniques have been applied in condition where conventional methods cannot discover a satisfactory result or they take more time to estimate the result.

Therefore, this paper provides a powerful optimization technique in terms of speed, PSNR, MSE, segmentation accuracy and computational time. This paper presents an automatic brain tumor detection approach based on soft computing and swarm based optimization algorithm. The steps in this system are: 1) initially read the input MR images, 2) to increase the contrast of brain MRI T2-W images, the median filter technique is used to adjust intensity levels and eliminate high frequencies and develop the visual appearance and quality of input image, 3) PSO algorithm to segment or cluster and optimize the segmented results in less time consumption and with high accuracy, 4) the GLCM and LBP (local binary pattern) approach extracts the features, 5) SVM classifier decides the tumor is cancerous or not.

The structure of this article has arranged as follows. In section 2, the methods and resources are presented. The PSO technique used for segmentation of brain image is explained with full details in section 3. In section 4 the results are presented and discussed. Finally, the conclusions and extent for future are presented in the section 5.

2. Methods and Materials

The block diagram for proposed methodology is as exposed in fig.1. The more details about the methodology and process flow is explained in below subsections.

2.1. Image Acquisition

The T2-weighted brain MR images has acquired from websites which having publically available datasets such as BrainWeb, Harvard Medical School and real patient images also used.

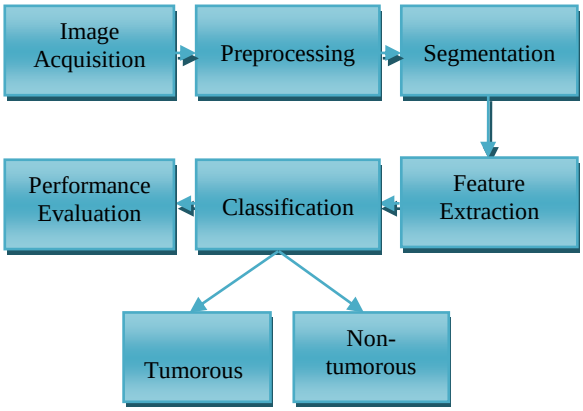


Fig. 1: Block diagram for automatic exposure of tumor from human brain MRI

2.2. Preprocessing

Noise can mask and blur the significant features in T2-W MR images and it makes difficult in processing of further steps in image analysis. The mean of the preprocessing is the improvement in the image quality by removing the noise and clearout the undesired parts in background and makes more reliable. Generally the noise fading filters blur the boundaries. Hence median filter has been utilized to eliminate the noise and also preserves the image edges. Median filter is a non-linear filtering technique that removes high frequency elements in MR images without concerning the edges. The median filter employs when proper arrangement of the required pixel values in the increment order and considered the most mid pixel value as the result of the median filter.

2.3. Segmentation

The technique which is employed to isolate the specific suspicious region from an image is called segmentation, it plays a very significant role in biomedical imaging and computer assisted diagnosis of tumor identification from the brain T2-weighted MR images. Here, PSO algorithm is applied to partition the image based on the global best intensity which employed as thresholding level. The details about this technique are provided in section 3.

2.4. Feature Extraction using GLCM

Gray level co-occurrence matrix (GLCM) is most classical texture based attribute extraction technique. It establishes the textural relationship among pixels by executing a function according to second order statics in the segmented image. The second ordered gray intensity probability distribution for the texture image can be determined by considering the gray intensities of pixels in pairs at a time. So it is referred as co-occurrence distribution. The texture feature computations use contents of GLCM to present a calculation of the dissimilarity in the intensity in significant pixel. This co-variance matrix is estimated with help of two important parameters. The relative space between its pixel pair *d* determined the pixel number and the relative orientation such as 0° which horizontal, 45° which in one of the diagonal, 90° which is in vertical direction and 135° which is in another diagonal. The local texture features from the neighbouring of every pixel are extracted by LBP.

2.5 Classification

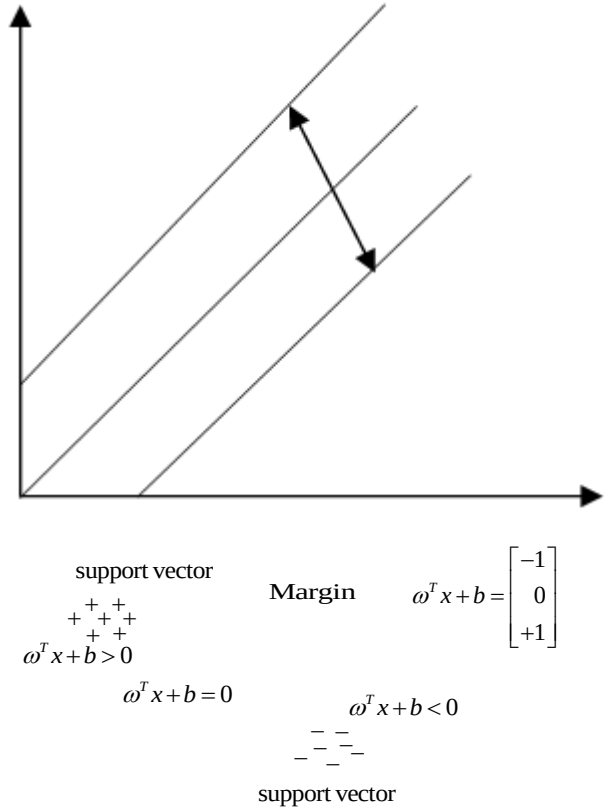


Fig. 2: Representation of SVM.

Support vector machine is a most effective supervised learning and pattern classification technique, determined by Vapnik & Cortes. In this research work, the SVM classifier used to specify the extracted brain image is cancerous (tumor present) or noncancerous (tumor absent). SVM is a binary classifier, takes group of input information and categorizes the data into one of the two dissimilar classes. The power of this classifier lies on its capability to convert data to a high dimensional space where the data can be divided using hyper plane and distinct two classes by maximizing the distance or margin between them. As illustrated in above fig.2, hyper plane is mathematically represented as $\omega^T x+b=0$, where ω^T is normal towards hyper plane and *b* is the bias of the hyper plane from the origin. The two classes are represented as $\omega^T x+b>0$ and $\omega^T x+b<0$.

3. Particle Swarm Optimization Technique

Particle swarm optimization is an evolutionary computational technique initiated by Kennedy and Eberhart in 1995. PSO is population supported stochastic optimization approach. It has been motivated by social conduct and movement dynamics of insects, birds and discipline of fish.

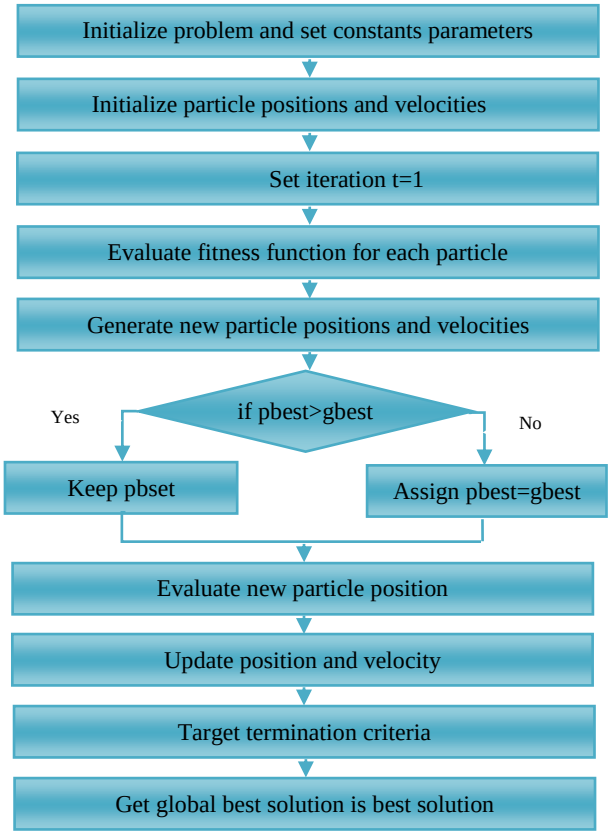


Fig. 3: Flow diagram of proposed PSO algorithm

In PSO, the algorithm preserves a population size of particles, where every particle signifies a potential result of optimization. The particles modify their positions by soaring around in a multi-dimensional search space until a relatively unchanged position has been encountered, or until computational limitations are exceeded. Each particle maintains track of their co-ordinates of problem space. This associated with the best solution, fitness, it has achieved so far. The personal experienced fitness value called *pbest*. When a particle takes the whole population as its topological neighbours, the best value is a global best and is called *gbest*. It has been experienced that PSO acquires better outcomes in a faster and cheaper way compared with other methods. PSO is attractive when the few parameters can adjust. The process flow of the segmentation and optimizing steps using PSO are shown in fig.3.

During the swarm evaluation, each particle has a velocity vector $V_i = (v_{i1}, v_{i2}, ..., v_{iD})$ and a particle position vector $X_i = (x_{i1}, x_{i2}, ..., x_{iD})$ to guide itself to a potential optimal solution, where i is a positive integer indexing the particle in the swarm. The personal or individual best position of particle i is denoted as $pbest_i = (pbest_{i1}, pbest_{i2}...., pbest_{iD})$, the global best position of the particle is $gbest = (gbest_{i1}, gbest_{i2}....., gbest_{iD})$. The velocity V_i and the position x_i are randomly initialized in the search space and they are updated with the following formulas at the $(t+1)$ generations:

$$V_{i,j}(t+1) = \omega V_{i,j}(t) + c_1 r_{1,j}[pbest_{i,j}(t) - X_{i,j}(t)] + c_2 r_{2,j}[gbest_{i,j}(t) - X_{i,j}(t)] \quad (1)$$

$$X_{i,j}(t+1) = X_{i,j}(t) + V_{i,j}(t+1) \quad (2)$$

where $i \in [1, 2, ..., NP]$ means the i^{th} particle in the population and $j \in [1, 2, ..., D]$ is the j^{th} dimension of this particle, NP is the population size and D is the dimension of the searching space. The c_1 and c_2 are acceleration constants. $r_{1,j}$ and $r_{2,j}$ are three random numbers uniformly distributed in [0,1] and ω is the inertia weight and inertial feature is varying between $[\omega_{min}, \omega_{max}]$, that is used to balance global and personal search ability. The best position has been acquired from the time [0 to t]. The velocity is in the ranges $V_{i,j} \in [-V_{max}, V_{max}]$. The velocity $V_{i,j}$ is limited by predefined maximum velocity V_{max}.

4. Results and Discussion

The proposed research work is performed and trained on MATLAB R2016a using the image processing toolboxes and running under Windows 8.1 on Intel Core i3-5005U processor with speed of 2.00 GHz and installed memory (RAM) is 4GB. The proposed approach has applied to the dataset which contains more than 155 brain T2-W MR images. The performance of the proposed system is evaluated by various performance metrics and the results obtained at each step are discussed in the following subsections.

4.1. Database

The T2-weighted brain MR images are acquired from the Harvard Medical School website [23] and BrainWeb [24] publically available databases and real images. The samples of axial T2-weighted brain MR images are shown in fig.4.

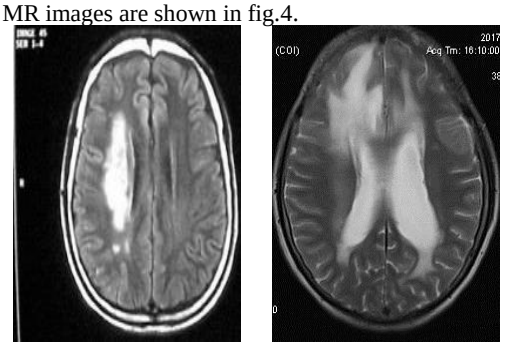


Fig. 4: Samples of T2-weighted MR images

4.2. Preprocessing

A preprocessing stage should be considered to improve the quality of the MR brain image before segmentation to make easy of further processing. This stage is used designed for shrinking the image noise, emphasizing edges, or exhibiting digital images. In this work, median filter method applied to boost the quality of the image and protect the borders of brain MR images. The output images of pre-processing using median filter are shown in fig 5. These are outcomes by applying the images shown in figure 1 to median filter. By comparing fig 4 and 5, the images illustrated in fig 5 are clearer in visual.

4.3. Segmentation

In this proposed system PSO algorithm is employed to part the tumor of the brain MRI images. The success of the application of PSO to image segmentation depends on proper consideration of various parameters such as personal and individual weights such as c_1 and c_2 respectively, population size N, quantity of iterations I, inertial factor ω, particle velocities and number of intensities to segment and decide the quantity of threshold levels and so on.

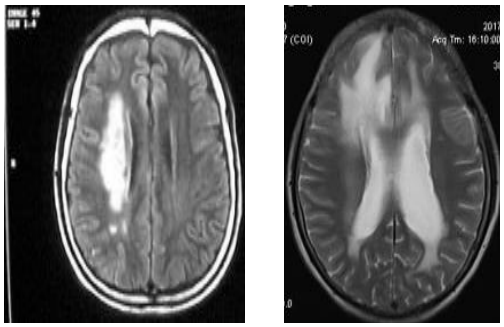


Fig. 5: Preprocessing results of T2-weighted brain MR image samples using median filter.

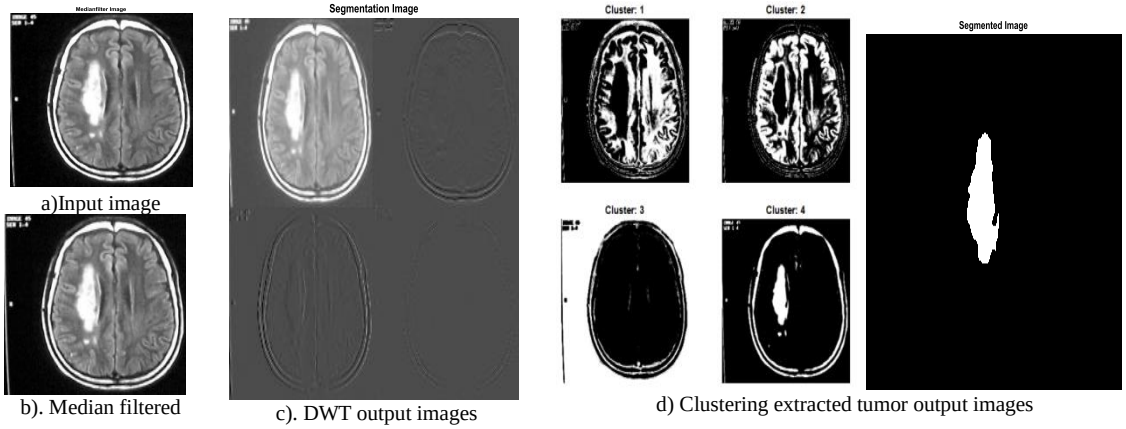
All these constraints and their initial values for our work are described in table. Tumor situated in the images has been detected using global best values, which can be employed as thresholding values for PSO.

Table 1: Parameter setting and description for brain tumor detection using PSO algorithm

Parameters	PSO	Description
L_{max}	255	Maximum intensity of pixel value
I	150	Iterations size in PSO algorithm
N	150	Population size for multiple segmentation
c_1	0.8	Cognitive/ personal weight of particle
c_2	0.8	Social weight of particle
r_1, r_2	[0,1]	Random variables lies between [0,1]
ω	1.2	Inertial factor
V_{max}	5	Max. velocity value of particle position
V_{min}	-5	Min. velocity value of particle position
L	6	Number levels of PSO algorithm
$L-1$	5	Number of thresholding levels

4.3. Feature Extraction and Classification

By using GLCM and SVM classifier techniques, the tumor situated with the test image has been classified as benign (non-cancerous) or malignant (cancerous). If the tumor size is larger than 8 mm^2 it is assumed as malignant otherwise it is benign [18]. The results of preprocessing, segmentation, tumor extraction using proposed median filter, DWT based fuzzy clustering and GLCM respectively for sample images are shown in fig.6 and fig.7. This clustering results shows that the WM, GM, CSF and tumor sub images. And at final the extracted tumor is shown extreme right in above figures 6 and 7. Similarly PSO based segmentation results along with preprocessing, and extraction are exposed in fig.8 and fig.9. Here also the WM, GM, CSF and tumor are represented separately in sub images. All these tissues are generated by



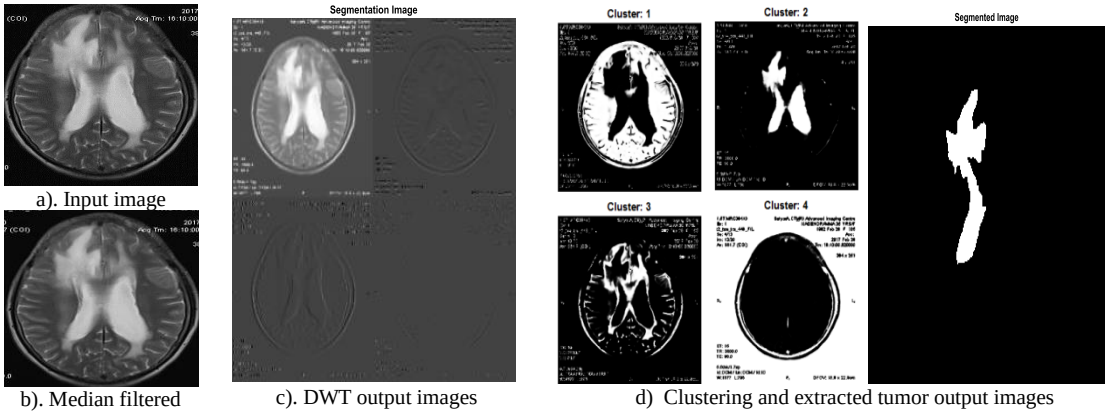
a)Input image

b). Median filtered image

c). DWT output images

d) Clustering extracted tumor output images

Fig.6: Preprocessing, segmentation and extraction results of brain image1 by DWT and Clustering technique



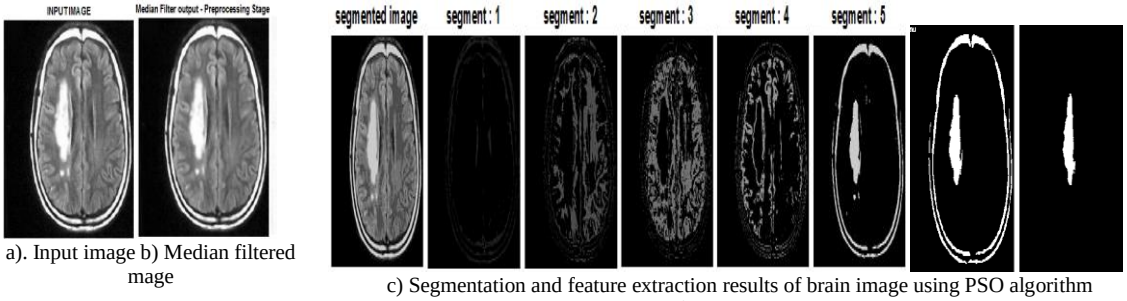
a). Input image

b). Median filtered image

c). DWT output images

d) Clustering and extracted tumor output images

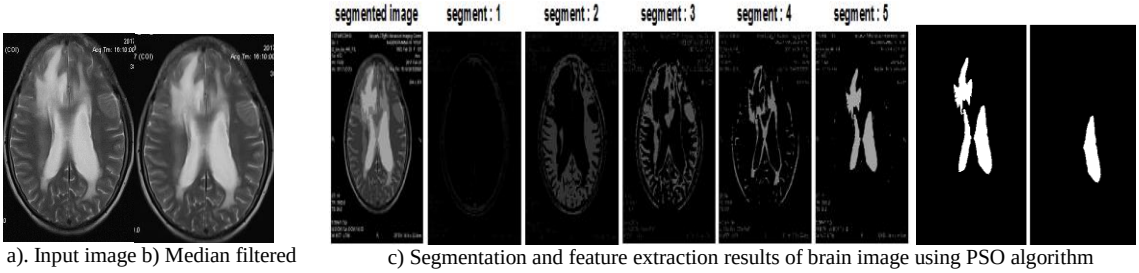
Fig.7: Preprocessing, segmentation and extraction results of brain image2 by DWT and Clustering technique.



a). Input image b) Median filtered mage

c) Segmentation and feature extraction results of brain image using PSO algorithm

Fig. 8: Preprocessing, segmentation and extraction results of brain image1 using PSO technique



a). Input image b) Median filtered image

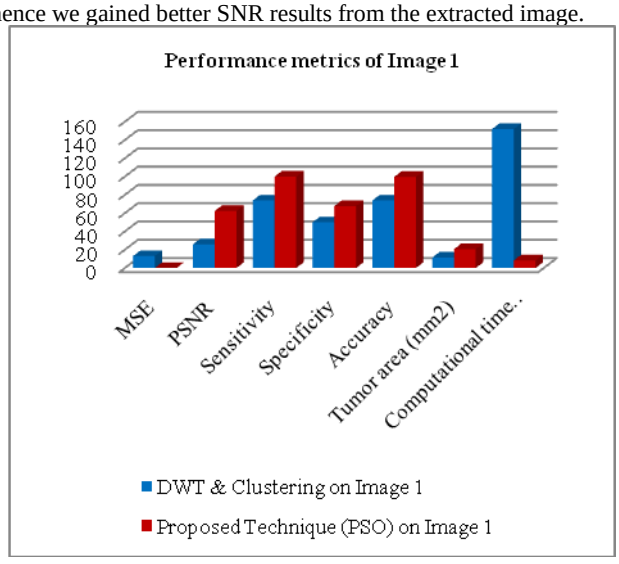
c) Segmentation and feature extraction results of brain image using PSO algorithm

Fig. 9: Preprocessing, segmentation and extraction results of brain image2 using PSO technique

Table 2: Performance metrics evaluated by two algorithms

Technique	**Existing Method (DWT&Clustering)**		**Proposed Method (PSO)**	
Parameter	**Image 1**	**Image 2**	**Image 1**	**Image 2**
MSE	12.9975	11.0271	0.0380	0.0506
PSNR	25.8536	27.2816	62.3329	61.0892
Sensitivity	73.8554	75.3664	99.9498	97.5357
Specificity	50.0000	50.0000	67.6791	60.0000
Accuracy	73.8467	75.3310	99.6231	95.9432
No defected cells	1864	2346	6081	4509
Tumor area (mm^2)	11.3980	12.7870	20.5869	17.7274
Computational Time (sec)	152	160	8.3571	8.9054

considering the thresholding levels. The MSE values obtained by DWT and fuzzy clustering technique for images 1 and 2 are 12.9975 and 11.0271 respectively. Similarly using PSO algorithm the MSE for those two images are 0.0380 and 0.0506 respectively. PSNR values determined using DWT and fuzzy clustering for two images are 25.8536 and 27.2816. Similarly using PSO the PSNR has been calculated as 62.3329 and 61.08929 respectively for two images. A lower magnitude of MSE and higher magnitude of PSNR indicates good amount of noise elimination from the image, hence we gained better SNR results from the extracted image.



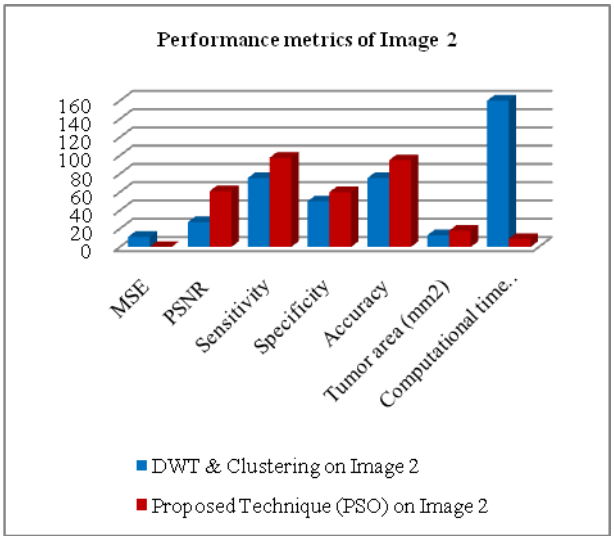


Fig.10: Comparison of performance parametrs of Image 1 and Image2

The accuracies of the presented technique on both images are 99.6231 and 95.9432, which are higher values compare with accuracies obtained by DWT fuzzy segmentation technique which are 73.8467 and 75.3310 for image 1 and 2 respectively. There is a variation in determined number of tumor affected pixels from both images for both clustering and optimization techniques. The PSO technique gives the accurate pixels of tissues because it works pixel to pixel basis so misclassification very less and segmentation accuracy is more compare with the DWT fuzzy segmentation techniques, which directly works directly on image by separating some sub-regions, hence misclassification of pixels is more and accuracy is less. The performance of the proposed system can evaluate with some important performance metrics which are indicated with equations from (3) to (7).

$$MSE = \frac{1}{P \times Q} \sum\sum \left[f(i,j) - f^{R}(i,j) \right]^2 \quad (3)$$

$$PSNR = 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \quad (4)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (5)$$

$$Specificity = \frac{TN}{TN + FP} \quad (6)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

- TP is true positive, specifies perfect classification of tissue area and detection of tumor part.
- FP is false positive, indicates normal tissue part as tumor part.
- FN is false negative, specifies the tumor part as normal region.
- TN is true negative, specifies perfect classification of normal tissue area.

Table 3: Comparison of proposed and existing techniques.

Technique	MSE	PSNR	Accuracy
K-Means [21]	-	-	82%
Region Growing [22]	6.1210	14.0110	95%
Otsu's [17]	-	52.5159	80%
Proposed	0.0506	61.0892	96%

From the table 3, it can be seen that our proposed method give highest segmentation accuracy and PSNR and also lower MSE from the processed brain MRI images.

5. Conclusion and Future scope

In the presented study, the brain MRI images are segmented into normal and abnormal tissues such as white matter, gray matter, CSF and tumor-infected tissues. Here, we use preprocessing to decrease the consequence of useless noise imprisoned during the acquirement of MRI and develop the quality in raw MRI. The best possible segmentation outcomes obtained based on various numbers of levels and various numbers of iterations. The global best solution while searching is considered like threshold level. Multilevel thresholding based PSO reduces the complexity when processing the data. GLCM features are determined and converted the image into integer labels illustrating small-scale textures inside the image. Finally SVM classifier classifies the feature extracted image. The outcomes of this experiment achieved average segmentation accuracy of 97.78%, 98.74% of average sensitivity and specificity of 63.84%. Our experimental outcomes illustrated that the PSO based system can assist in the accurate and timely classification of brain tumor. Thus, the proposed approach is significant, reliable and robust in brain tumor detection from human brain MR T2-W images. The future research work will reduce the MSE, improve the PSNR, accuracy and specificity using advanced search based meta-heuristics algorithms.

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