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DETECTION AND CLASSIFICATION OF BRAIN TUMOUR IN MRI IMAGES USING PARTICLE SWARM OPTIMIZATION AND MACHINE LEARNING ALGORITHM

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ABSTRACT

Today, people of all ages suffer from headaches and pain in the internal areas of the brain caused by a tumour. Radiologists face a difficult problem when it comes to the detection and categorization of tumours from magnetic resonance image modalities because this organ is critical to the decision-making process regarding the operation of the entire human body system, and any incorrect identification could seriously harm someone's health. Therefore, a multilevel thresholding-based particle swarm optimization and support vector machine classifier are presented here to decrease the false-finding rate by accurately detecting and separating brain tissues. The proposed method comprises of four phases: image enhancement, image segmentation, feature extraction, and classification. The resulting image is updated by a median filter using Otsu's entropy-based multilevel thresholding particle swarm optimization to improve visual quality and make it easier to detect the presence of tumours. A grey-level co-occurrence matrix and a linear binary pattern are utilized to extract and choose the segmented feature, and a support vector machine is employed to categorize it. When textural aspects, statistical characteristics, and performance metrics from the brain dataset are seen at various thresholding levels and compared to other optimization strategies and single thresholding approaches, multilayer thresholding is found to be more accurate.

KEYWORDS: *Brain Tumour, Classification, Multi-level Thresholding, Particle Swarm Optimization, Segmentation*

1. INTRODUCTION

The brain is the body's most vital and important component, and it is responsible for planning, directing, and forecasting the actions of all other body parts. The main factor shortening human life expectancy and causing mortality is brain tumours. It also has an impact on potential influencers of all ages. In 2005, roughly 12760 persons out of a total of 18,500 instances, one person died from a brain tumour. diagnosed, according to the American Cancer Society. Given the rising rate of mortality, it is predicted

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that the total amount of illnesses is expected to have grown to more than 26 million by 2030, with 1.8 million individuals suffering of cancers of the brain [1]. An accumulation of aberrant cells forms a tumour. Brain tumours (BTs) are often divided into benign (B) and malignant (M) categories. A malignant brain tumour is one that is cancerous and exhibits traits like significant swelling as well as an unusually quick proliferation of cancer cells that form a heterogeneous shape and non-uniform structure inside the brain. Even the spinal cord and other areas of the brain are affected by it. It is more dangerous and ultimately fatal. A benign brain tumour is one that is not cancerous, has inactive cancer cells, grows more slowly, is less aggressive, and retains its homogeneous structure. Risk from benign conditions is largely avoided by taking the appropriate precautions and consulting with specialists frequently [2].

Accessible eminence imaging technologies can be used to obtain correlated information about numerous aspects of life. The brain is a highly sensitive organ within the human body. On demand, a variety of imaging modalities can be utilized to screen such a sensitive area. Standard screening techniques include MRI - “Magnetic Resonance Imaging”, CT- “Computed Tomography”, PET – “Positron Emission Tomography”, often known as PET-CT, and SPECT (Single Photon Emission Computed Tomography). The CT scan accurately and precisely detects bone, and it is used to assess the effectiveness of subsequent therapies like rehabilitation. Typically, patients must be exposed to the imaging device in order to receive the images from it. Once they have diverged due to boosting elements or signs, an image of the part's composition can then be obtained [3].

The MRI is an advanced therapeutic imaging system that provides living structures to human tissue. It provides highly qualified two-dimensional or third-dimensional learning amid the delicate tissues. A variety of brain MRI image modalities, including T1 - weighted (T1-W), T2 - weighted (T2-W), PD - weighted (PD-W), and FLAIR images, are accessible for MRI screening. An individual may experience a brain tumour at any stage. The effect of lying varies depending on the person's personality. The best potential quality of life for patients is increased by both early identification and accurate screening for brain tumour diagnosis. A small error in assessment or false alarm can result in incorrect or subpar therapy. The imaging processing techniques can be quite helpful for analyzing the tumour area [4]. Over the past few days, a variety of studies on the diagnosis of brain tumours have advanced significantly for various imaging modalities, however they are still not entirely necessary. Many scientists are looking at cutting-edge diagnostic methods. A T1-W (T1 weighted), T2-W (T2-weighted), and PD (proton density) imaging pulse sequence can be produced by an MRI screening modality. These imaging modalities and their plus sequences are frequently employed in clinics. These pulsation categorizations largely offer information on different types of contrast levels and intensities. The MRI may provide multispectral pictures that have different intensities and are produced using different excitation sequences [5]. Normal brain constituents comprise the cerebrospinal fluid (CSF), the grey matter (GM), along with white matter (WM). Here, substance is simply matter. Brain tumour detection & extraction (BTDE) differentiates various tumour tissues such as solid tumour (ST), edema, and necrosis. Because MRI can provide numerous excitation image sequences (EIS) and precise data about intelligence materials. It is a very effective instrument in the field of medicine for enhancing diagnosis.

2. LITERATURE SURVEY

Many researchers are looking on enhanced diagnosis methods. Segmentation is a key and essential procedure that divides an image into similar classes of qualities. Researchers have enhanced a number of segmentation approaches for identifying, extracting, and classifying tumours from medical illustrations includes threshold-based, watershed-based, region-based, cluster-based, hybrid models with soft computing techniques [6]. To isolated tumour tissues, brain tumour segmentation (BTS) is often employed in medical imaging, such as magnetic resonance (MR) scans or other contemporary techniques for imaging. The early diagnosis of a brain tumour is critical for providing the patient with better treatment. Whenever an internal brain malignancy is empirically considered suspects, medication commences such that it must be radiologically evaluated to assess its position and placement (PP), shape and size (SS), and influence and impact (II) on the neighboring region [7].

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E.A. Maksoud et al. [8] suggested an image segmentation-based early detection system for brain tumours. For MRI brain segmentation, it combines K-means clustering (KMC) and the Fuzzy C means (FCM) approach. Two further segmentation techniques, namely thresholding and level set procedures for medical picture segmentation, were utilized, which accurately recognized brain tumours for diverse data sets and provided higher performance. F. Hoseinii et al. [9] proposed a deep convolutional neural network (DCNN) technique for detecting brain tumours on MRI data. A patch-based approach to segmentation is used to classify all of the brain MRI pixels. M. P. Arakeri et al. [10] described a method for grouping brain pictures using the FCM clustering approach to find tumours in brain MRI data. T.L Narayana et al. [11] proposed genetic algorithm-based brain tumour detection and classification without multilevel thresholding. In that study, obtained more MSE and less accuracy. Premananda Sahu et al. [12] suggested an LLRBFNN model based on ACO-SA for downgrading and detection of encephalon tumour images. Fuzzy clustering is employed to automatically establish control settings. Rabab Hamed M. Aly et al. [13] presented three major feature extraction techniques: binary particle swarm optimization (BPSO), ant colony optimization based on travel salesman (ACO-TSP), and artificial bee colony optimization (ABCO). When using GMDH for prediction and classification, the three approaches obtained the better accuracy. When the methods were compared, it was discovered that ACO-TSP is the superlative technique for extracting features from brain tumour images (BTI).

The current study's goal is to reduce the false finding by segmenting the all tissues at different threshold levels using multi-level threshold-based optimization method for brain lump (anomaly) exposure and cataloguing to enhance the accuracy of the tumour findings. Therefore, accurate tumour identification is achievable.

The proposed research article is structured in the following manner: the first section (i.e., Section 1) provides an introduction about brain tumour, its types, screening modalities and presents statistics; the second section (i.e., Section 2) provides the literature on recent studies; the third section (i.e., Section 3) describes the methods and materials; the fourth section (i.e., Section IV) provides the outcomes & conversation and the last section (i.e., Section V) explains the conclusion and imminent work.

3. METHODS AND MATERIALS

The proposed methodology is explained with the illustration shown in Fig. 1. as a block diagram. The subsections following explain the approach and process flow in more detail.

3.1 Methodology of the Proposed System

Image Acquisition: Specifies the collection of the data such as MRI images from private and public available databases [14]. *Image Preprocessing:* Enhances the dissimilarity of attained brain MRI imageries by using median filtering process (MFP), make resize and colour conversion which helps to smooth and easier the processing of further stages of execution and helps to get better visual characteristics than the original. *Thresholding and Segmentation:* Segments the preprocessed image by using Otsu's thresholding and PSO methods and provides a good way to find various feature of the segmented image. *Feature Selection and Extraction:* Selects the region of interest and determine the statistical, texture, colour and other features of the segmented image by LBP and GLCM techniques. *Image Classification:* Classifies the category of the brain MRI metaphors as whether it is anomalous or ordinary. Also classifies whether it is benign or malignant. *Training and Testing:* It is must to train the dataset to learn the process and used to fit the parameters for a classifier. Then validate and test the sample images collected from databases. Note that the test dataset follows the same probability distribution of training dataset but independent from it. *Performance Analysis:* Determine various performance metrics and analyze the precision and effectiveness of the proposed methodology by contrasting the existed methods.

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3.1. Multi-level Thresholding

Thresholding techniques are commonly used to segment pictures. The thresholds determine the intensity numerical value to classify the segregated images into various groups from the grayscale images. Two basic groups of threshold approaches are used for image segmentation. There are two types of thresholding: (a) bi-level and (b) multi-level.

3.2. Multilevel (n-level) Thresholding Formulation using Otsu's Method

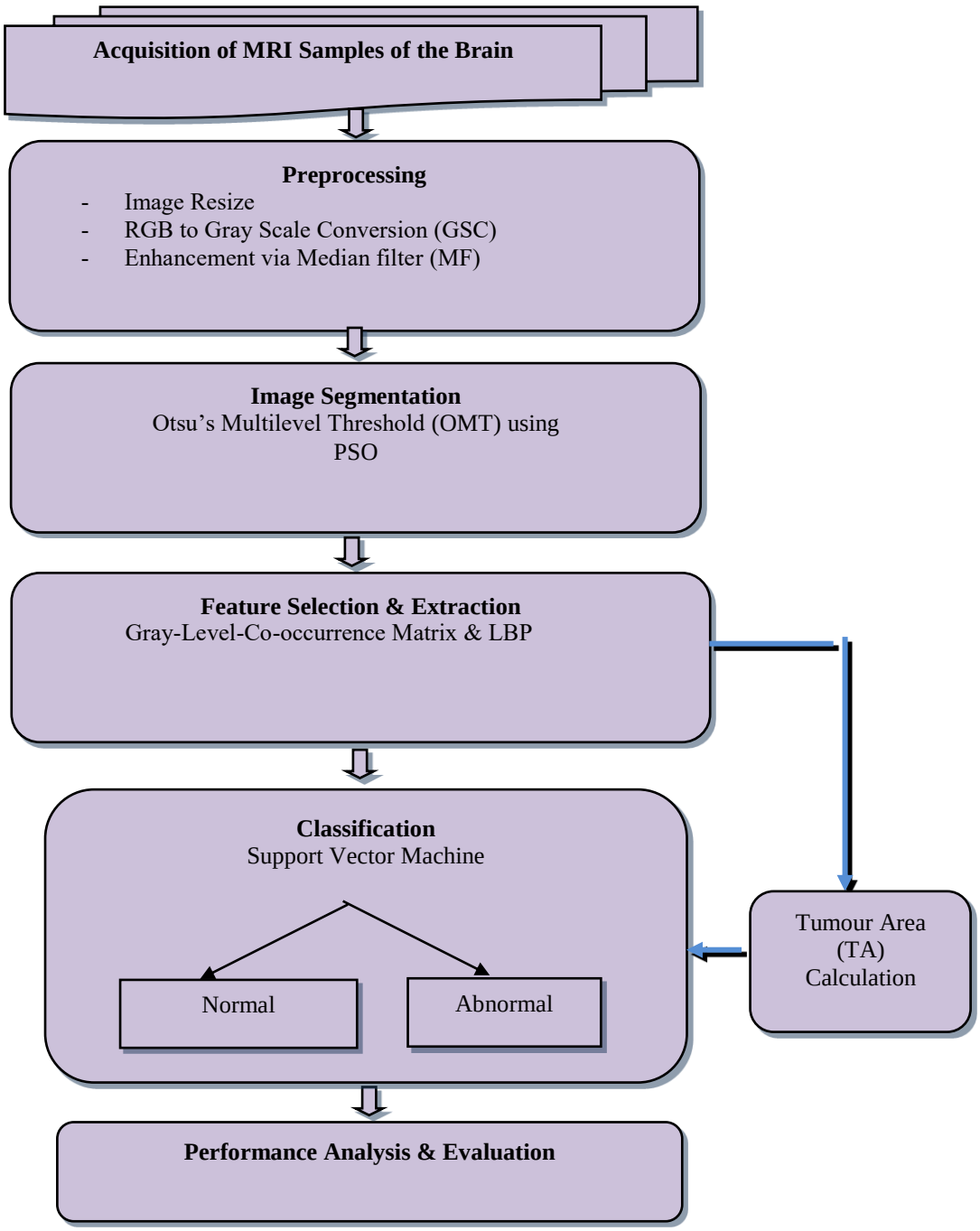

Fig. 1. Schematic diagram to demonstrate the proposed techniques

Using multilevel thresholding or n-level thresholding (here in our research work we considered n=L-1) the brain MRI scans are segmented into several unique regions, comprising dark matter, white matter, brain fluid, edema, and tumour. Generally, the brain MRI images are in gray level and are partition into

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more than one threshold level with certain brightness regions, among the corresponding regions one represents background and other represents several objects (e.g., tissues in brain which mentioned above). Let the total pixel count in a gray level image is N and are distributed as objects and background. The problem can be identified from the gray level image by selecting the multilevel thresholds values from the set Th(l), l=1,2,3…..,L-1 where L is mentioned as the intensity level of the selected image. The original brain image will be converted to an image with L-1 levels as results of Otsu's thresholding. If Th(l), l= 1,2, …, L-1 are the value of thresholding levels with T(1)<T(2)<T(3),…,<T(L-1) and f(x,y) is the image function which. The ensuing image F(x,y) as explain before, is defined as:

$$F(x,y)\begin{cases}0, & if \quad f(x,y) \le Th(1)\\ 1 & if \quad Th(1) \le f(x,y) \le Th(2)\\ . & \\ . & \\ L-1 & if \quad f(x,y) \ge Th(L-1)\end{cases} \tag{1}$$

As a result, the problem of multilevel thresholding can be reduced to an optimization problem. The goal is to research (search) for and implement threshold values that maximize the fitness function / gray-level element. In order to be untainted by the number of pixels in the image, this means that this method requires essentially a normalization of the histogram h. Taking N = P Q as the total number of pixels in the image, and assuming ni as the number of pixels to a gray-level i in the range [0, 255]. With h representing the image's histogram and P and Q representing the image's width and height. So, using the following equation, h(i) is determined:

$$h(i) = \frac{n_i}{N} \tag{2}$$

And the fitness ϕ is defined as

$$\phi = \max \sigma^2(Th) \tag{3}$$

$$Th(1) < Th(2) < Th(3), ..., < Th(L-1) \tag{4}$$

Where σ^2 is variance

$$\sigma^2 = R_1\sigma_1^2 + R_2\sigma_2^2 \tag{5}$$

and

$$\sigma_1^2 = \frac{1}{Th}\sum_{i=0}^{Th-1}\left(h(i)-\mu_1\right)^2 \;\&\; \sigma_2^2 = \frac{1}{256-Th}\sum_{i=T}^{255}\left(h(i)-\mu_2\right)^2 \tag{6}$$

$$\mu_1 = \frac{1}{Th}\sum_{i=0}^{Th-1}\left(h(i)\right) \;\&\; \mu_2 = \frac{1}{256-Th}\sum_{i=0}^{255}\left(h(i)\right) \tag{7}$$

$$R_1 = \frac{1}{P\times Q}\sum_{i=0}^{Th-1}\left(h(i)\right) \;\&\; R_2 = \frac{1}{P\times Q}\sum_{i=Th}^{255}\left(h(i)\right) \tag{8}$$

As the number of threshold levels increases the processing effort is substantially more which the major disadvantage of this approach. In recent application it can be solved by considering as computationally efficient alternatives, biologically influenced techniques were recently used in diagnostic procedures to crack optimization complications

3.3. Particle Swarm Optimization

Particle swarm optimization is abbreviated as PSO. It is a method of evolutionary computation that draws inspiration from social or aggregative behavior in fish learning and bird migration. It exhibits

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typical evolutionary computational properties such as initializing particles with a population of random solutions, inertia, and different scaling factors, and so starts the hunt for identifying the optimum by updating generations. Figure 2 illustrates the idea of shifting a particle's position within the PSO. This is related to the finest outcome that fitness has so far produced. The term "pbest" refers to the value of personal fitness experience. A particle's best significance is a global best and is referred to as "gbest" when it considers the entire population since the topological moment.

The velocity Vi,j as well as the position Xi,j are initialized at random in the process of searching domain. They are updated with the following expressions at the (t+1) generations:

$$V_{i,j}(t+1) = \omega V_{i,j}(t) + \left\{c_1 r_{1,j}[pbest_{i,j}(t) - X_{i,j}(t)]\right\} + \left\{c_2 r_{2,j}[gbest_{i,j}(t) - X_{i,j}(t)]\right\} \quad (9)$$

$$X_{i,j}(t+1) = \left\{V_{i,j}(t) + V_{i,j}(t+1)\right\} \quad (10)$$

The required values of the parameters used to initialize the PSO algorithm are represented in table 1.

3.4. Feature Extraction

GLCM: The most traditional texture-based attribute extraction technique is GLCM. It establishes the textural link between pixels by performing a function in the segmented image based on second order statics. The grey intensities of pixels in pairs can be used to determine the second ordered grey intensity probability distribution for the texture image. As a result, it's known as co-occurrence distribution. The texture feature computations make use of the GLCM contents to offer a calculation of the intensity dissimilarity in significant pixels. This covariance matrix is estimated using two key factors. The relative spacing between its pixel pairs d defined the pixel number and relative orientation, such as 0° horizontal; 45° diagonal; 90° vertical; and 135° diagonal.

3.5. Classification

According to Vapnik and Cortes [15], the most adept supervised algorithm for learning and structure categorization is the support vector machine, which is simply termed SVM.

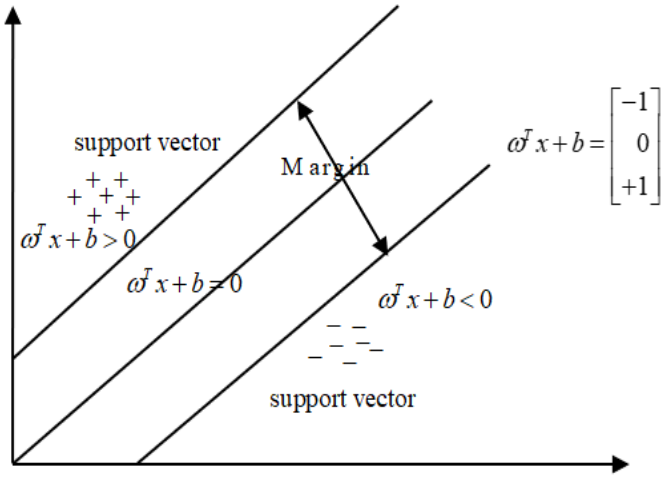

Fig. 2: Representation of SVM

In the current investigation, the classification procedure using SVM has been employed for determining whether the retrieved brain picture is malignant (tumour prominent) or noncancerous (tumour missing). SVM is a kind of binary classification algorithm that takes a set of input knowledge and categorises it into one of two different groups. This classifier's strength rests in its capacity to transfer data to a space with high dimensions, in which it may be partitioned employing a hyperplane and distinguished

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between two distinct groups by maximizing the distance or margin amongst them as illustrated in Figure 2.

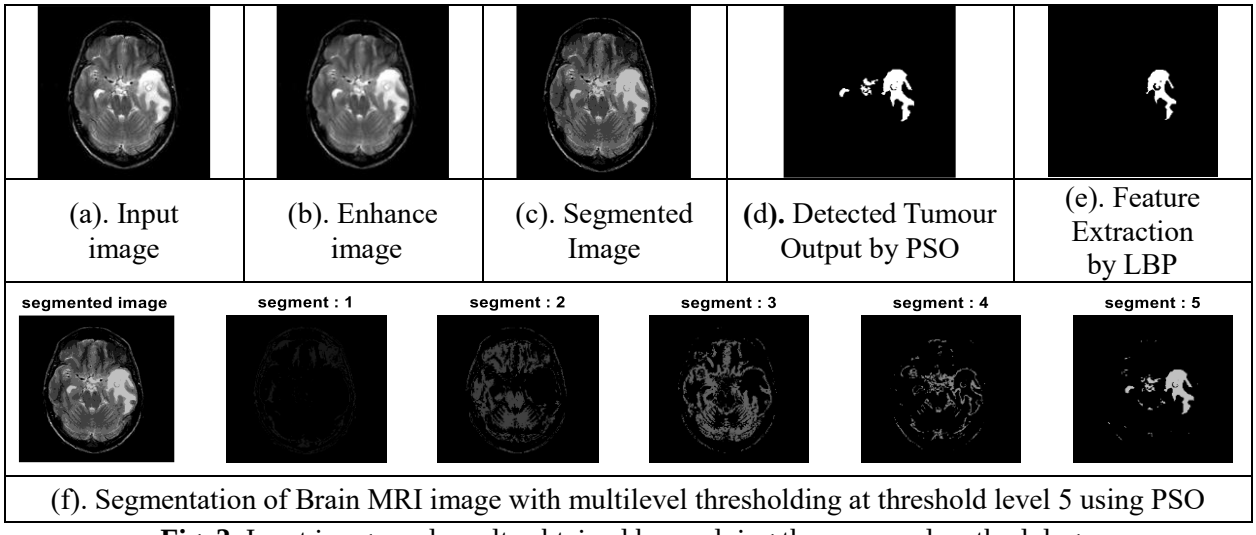
4. RESULTS AND DISCUSSION

The proposed study has been carried out and developed them on an Intel Core i3-5005U CPU processing at 2.00 GHz under Windows 8.1 employing MATLAB R2016a for image processing toolboxes. The onboard RAM, or memory, capability is 4GB. The proposed method was applied to a dataset containing over 235 brain MRI screened images. The proposed system's performance is assessed and evaluated using multiple indicators of effectiveness, and the findings produced at each stage are presented in the following section.

Table 1. Initialized parameter values proposed system

Parameters	PSO	Description
L_{max}	255	Pixel value with the greatest intensity
I	150	Size of optimal iterations (Best)
N	150	The population size required for successive segmentation
c_1	0.8	Particle cognitive/personal weight
c_2	0.8	Particle weight in socially available sphere
r_1, r_2	[0,1]	Random variables lie between [0,1]
ω	1.2	Inertial factor
V_{max}	5	Maximum positional mobility of the particle.
V_{min}	-5	Minimum positional mobility of the particle.
L	6	Total quantity of PSO algorithm layers
$L-1=Th$	5	Count of thresholding technique levels

The research is carried out on T2-W brain MRI images, which were attained from "Harvard Medical School" (HMC) website [14] publicly available databases, and real images collected from SRS Diagnostics, Kadapa.



(a). Input image | (b). Enhance image | (c). Segmented Image | **(**d**).** Detected Tumour Output by PSO | (e). Feature Extraction by LBP

(f). Segmentation of Brain MRI image with multilevel thresholding at threshold level 5 using PSO

Fig. 3. Input image and results obtained by applying the proposed methodology

To ease further processing, a stage of preprocessing of images applied to reduce noise within images, emphasizing edges, and displaying digital images. The median filter approach was used in this work to

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improve picture quality and safeguard the borders of brain MR images. Figure 3 (a) illustrations the acquired input image and figure 3 (b) shows the results of pre-processing with the median filter. To get rid of the brain tumour MRI tests in this suggested system, the Otsu's based multilevel threshold PSO method is used. Figure 3 (c) to (e) are the results obtained by segmentation, detected tumour output and feature extraction respectively. The success of applying Otsu's based multilevel threshold along with PSO has been employed to image segmentation is dependent on proper attention of innumerable factors which are available in the table 1. The table describes all of these limits as well as their initial values for our task. A tumour was spotted in the MRI image by determining the global best value from PSO related threshold rate. Figure 3 (f) shows the different thresholding levels from 2 to 7 using Otsu's method based and PSO segmentation. This offers segregation different tissues in the brain accurately. So, the segmentation method is able to segregate the desired tumour part and make easy and efficient further stages of the processing.

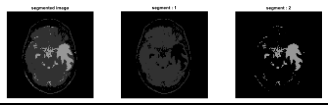
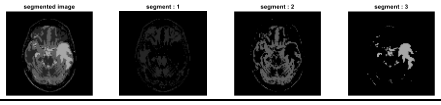
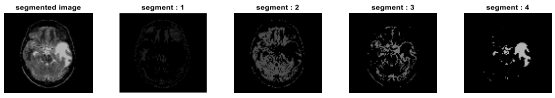
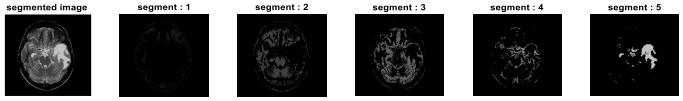
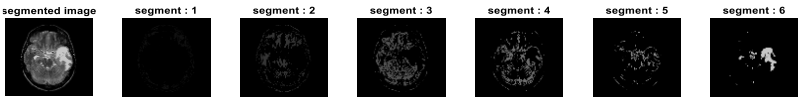
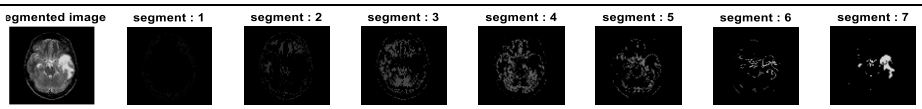
Image	Th	Segmented Image
Image R1	2	
	3	
	4	
	5	
	6	
	7	

Fig. 4. Segmented image obtained by applying different thresholding using Otsu's and PSO methods

Table 2 provides the comparison of performance metrics of the test images of brain tumour using FCM, GA, ACO and PSO methods. It is observed that the proposed Otsu's thresholding based PSO determined the better results than the existing FCM, GA and ACO methods.

Table. 2. Comparison of performance metrics of the test images of brain tumour using FCM, GA, ACO and PSO

Technique	MSE	PSNR	Sensitivity	Specificity	Accuracy	Detected Cells	Tumour Area	Processing Time
FCM	98.2419	27.3390	75.5684	50.0257	74.9986	1750	11.0439	110.0322
GA	25.4521	34.0735	86.2457	54.0542	85.5249	1984	11.7591	75.0203
ACO	16.5263	48.9826	93.8465	57.6594	93.2419	2018	11.8595	12.6845
Proposed PSO	0.0465	61.4526	97.9543	60.0000	95.3461	2111	12.1296	7.7886

Various statistical features determined by GLCM are provided in the table 3. The features helped to know the structural characteristics of the images.

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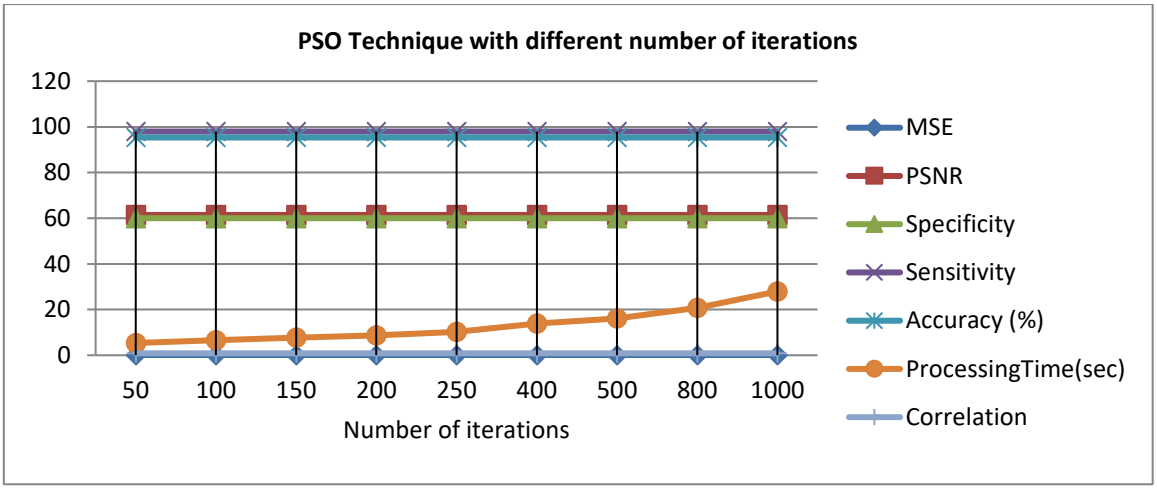

Fig. 5. Parameters at various iterations

Table 3. Various statistical features of FCM, GA, ACO and PSO

Feature of the image	FCM	GA	ACO	Proposed PSO
Mean	10.59	9.65	6.98	6.18
Standard Deviation	35.96	35.54	35.01	33.89
Energy	0.86	0.85	0.86	0.92
Homogeneity	0.69	0.82	0.95	0.99
Contrast	0.65	0.54	0.28	0.29
Correlation	0.75	0.84	0.81	0.86

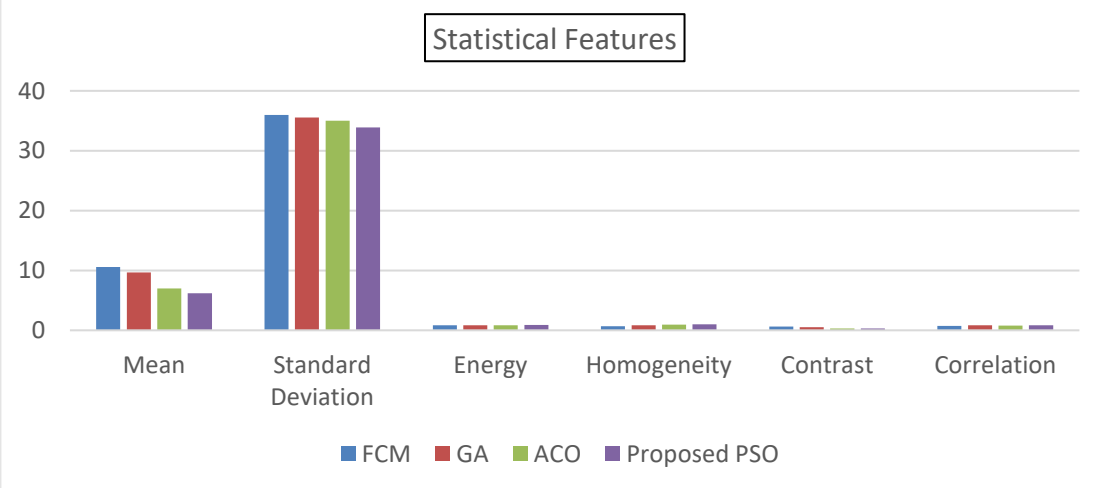

Fig. 6. Graphical representation of various statistical features of FCM, GA, ACO and PSO

5. Conclusion and Future Scope

Brain cancer remains one of the foremost death origins among the human of all ages which is caused with different work tensions and genetic issues. In our research, we used optimization strategies for tumour or anomaly dissection and classification. Images of brain MRI slices are initially acquired from publicly accessible websites. To avoid the complexity given by colour photographs, the preprocessing has done image resizing to change the proportions of the image, transforming the RGB images into grayscale. The median filter reduces noise and retains edges without affecting picture size characteristics; the noise was removed and the collected images were upgraded. The PSO along with Otsu's technique distinguishes the tumour from different tissues of the brain in the MRI scans. The

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GLCM feature extraction algorithms extract the tumour and tumour performance characteristics (parameters) successfully. The SVM classifier determines if the extracted tumour is normal or pathological. The suggested methodology's results are compared to FCM, GA, ACO based segmentation. When compared to existing techniques, the suggested system detects and classifies tumours effectively and provides good and accurate findings for brain MRI images. This work can be expanded in the future utilizing hybrid image processing techniques and need obtain the good and accurate statistical values. The same technique can also be applied to 3D brain MRI scans to increase statistical parameters.

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