IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)
e-ISSN: 2278-2834,p- ISSN: 2278-8735.Volume 12, Issue 2, Ver. III (Mar.-Apr. 2017), PP 129-144
www.iosrjournals.org

Brain Tumor Segmentation and Detection using Firefly Algorithm

Ms. Pooja S. Deshpande[1], Prof. S.J. Honade[2]
[1]*(Electronics & Telecommunication, SGBAU, India)*
[2]*(Electronics & Telecommunication, SGBAU, India)*

Abstract: *Brain tumor is most severe disease; most of populations in world affected due to brain tumor. Now day death rate because brain tumor gradually increases. For that consideration, most prominent method implemented for brain tumor detection and segmentation. When most normal cells grow, old cells die or damaged and new cells take their place. Sometimes this process goes wrong. New cells form when the body does not need them, and old or damaged cell do not die as they should .The buildup of extras cells often forms a mass of tissue called a growth or tumor. Earlier detection, diagnosis and proper treatment of brain tumor are essential to prevent human death. An effective brain tumor detection and segmentation using MR image is an essential task in medical field.*

A number of research papers related to medical image segmentation methods are studied. Segmentation and detection plays an important role in the processing of medical images. There are various segmentation methods implemented for brain tumor detection. These methods include k-means clustering with watershed segmentation algorithm; optimized k-means clustering with genetic algorithm and optimized c- means clustering with genetic algorithm. Traditional k-means algorithm is sensitive to the initial cluster centers. Genetic c-means and k-means clustering techniques used to detect tumor in MRI of brain images etc.

The proposed work deals with the use of firefly algorithm (FA) for brain tumor detection and segmentation using MRI images. The FA gives more improved parameters like time delay, % of tumor and FPR will be under consideration.

Keywords: *MRI, brain tumor, segmentation, detection, FA*

I. Introduction

The properties of problem of semi-automatic tumor detection make it an excellent research challenge in the fields of medical image analysis and pattern recognition, in general. The main motivations for this investigated effort are as follows:

- The manual segmentation by qualified professionals has two major drawbacks. The first drawback is that producing manual segmentations is extremely time consuming, with higher accuracies more finely detailed volumes demanding increased time from medical experts .
- The second problem with manual segmentation methods is that the results are subject to variations. This is due to the fact that several anomalies in brain appear similar in MRI.A recent study quantified an average of 28% +_ 12% variation in quantified volume between the individual performing the brain tumour detection task, and quantified a 20%+_ 13% variation within the individuals repeating the task three times at one month intervals.
- Accurate segmentation methods may possibly also lead to new applications, including effective content based image retrieval in large medical databases. This could allow clinicians to find the similar images in historical data based on tumor location, size, simillare pattern of growth, or a variety of other factor.

In medical field accuracy and delay time plays vital role in every aspect of technology to achieve, access and accommodated desired response of system. The most eminent field of technology, which completely enhance and fulfills the primary need of society is proper diagnosis. Although after implementing verities of invitation research in segmentation and detection of brain tumor ; inventors are unable to develop system with high accuracy, With this unfortunate truth in medical field to provide Proper diagnosis is biggest challenge for inventors.

With this motivation being an engineer proposed work to developed system of brain tumor segmentation and detection which would provides better performance parameters.

Tumor defined as the abnormal growth of the tissues. Brain tumor shown in figure 1 is an abnormal mass of tissue in which cells grow and multiply uncontrollably, seemingly unchecked by the mechanisms that control normal cells. Brain tumors can be primary or metastatic, and either malignant or benign. A metastatic brain tumor is a cancer that has spread from elsewhere in the body to the brain Epilepsy is a brain disorder in which clusters of nerve cells, or neurons, in the brain sometimes signal abnormally. Neurons normally generate electrochemical impulses that act on other neurons, glands, and muscles to produce human thoughts, feelings, and actions. In epilepsy, the normal pattern of neuronal activity becomes disturbed, causing strange sensations, emotions, and behavior or sometimes convulsions, muscle spasms, and loss of consciousness.

Magnetic Resonance Imaging (MRI) is an advanced medical imaging technique used to produce high quality images of the parts contained in the human body MRI imaging is often used when treating brain tumors, ankle, and foot. From these high-resolution images, we can derive detailed anatomical information to examine human brain development and discover abnormalities. Nowadays there are several methodology for classifying MR images, which are fuzzy methods, neural networks, atlas methods, knowledge based techniques, shape methods, variation segmentation. MRI consists of T1 weighted, T2 weighted and PD (proton density) weighted images and are processed by a system which integrates fuzzy based technique with multispectral analysis. Pre-processing of MRI images is the primary step in image analysis, which perform image enhancement, and noise reduction techniques that used to enhance the image quality and then some morphological operations applied to detect the tumor in the image. The morphological operations applied on some assumptions about the size and shape of the tumor and then tumor is map onto the original gray scale image with 255 intensity to made it to visible the tumor in the image. The algorithm has tried on a number of patients MRI data of brain tumor images.

Figure 1: Illustration of a brain tumor

Segmenting brain tumors is a very difficult task. In the first place, there are a large class of tumor types, which have a variety of shapes and sizes. Appearance of brain tumors different locations in the brain with different image intensities is another factor that makes difficult automated brain tumor detection and segmentation. The intensity values seen on an MRI scan for a particular brain depends primarily on the content of that pixel versus neighboring tissue and on other factors including the presence of abnormality. In normal brain MR images intensity level of brain tissues in the order of increasing brightness is cerebrospinal fluid (CSF), gray matter (GM), white matter (WM) in T1-weighted (T1-w) and WM, GM and CSF in T2- weighted (T2-w) image. In tumorous brain MR images intensity level of tumorous tissues exhibit different intensity level on T1-w and T2-w images based on the type of tumor. On T1-w most tumors have low or intermediate signal intensity but for some tumors this does not hold true, for example, glioblastoma multiforme tumor has high signal intensity. On T2-w most tumors have bright intensity but there are tumors which have low intensity, the classic examples are lymphoma tumors.

Brain tumors are not a very common disease, but they are among the fatal cancers. DeAngelis reported an incidence of less than 1 h in the western population but life expectancy for an individual can be one year or even less for the most aggressive brain tumors. The causes of brain cancer are still largely unknown, the only environmental risk factors which could be identified so far, are exposure to certain chemicals or ionizing radiation .Early detection of brain tumors is difficult because the brain is covered by the skull and brain tumors do not exhibit very specific clinical symptoms. In general, three different categories of symptoms for brain tumors can be distinguished .First, increased cranial pressure can lead to headache, vomiting and alternation states of consciousness. Second, cognitive and behavioral impairment, personality or emotional changes attributed to brain dysfunction. Third, symptoms of irritation like absences, fatigue or seizures observed. However, no symptoms are specific for brain tumors only. Therefore, diagnosis usually starts with an interrogation of the patient for medical history and symptoms. If a brain tumor was suspect, imaging plays a central role. Currently, different modalities of magnetic resonance images (MRI) are state of the art for noninvasively diagnosing brain tumors. However, despite the crucial role of imaging, a definitive diagnosis cans confirm by histological examination of tumor tissue samples, which had been obtain by biopsy or surgery.

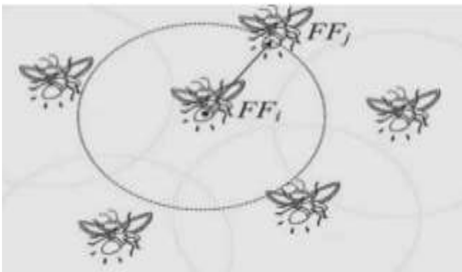


Figure 2: Firefly algorithm based on behavior of fireflies

In proposed work, soft computing method is use as a tool for extracting image components that are useful in the representation and description of region of tumor. Soft Computing is the fusion of methodologies designed to model and enable solutions to real world problems, which are not modeled or too difficult to model, mathematically. The segmentation technique employed has been base on firefly algorithm. Firefly algorithm is base on behavior fireflies shown in figure 2. Soft Computing is the fusion of methodologies that designed to model and enable solutions to real world problems, which are not modeled or too difficult to model, mathematically. In proposed work with help of firefly algorithm, achieve truthful parameters.

II. Related Research

This section, presents review of the selected literature in image segmentation techniques and their usage. The key objective is to highlight key strengths and limitations to these techniques.

A. S. Capelle et.al, introduced an automatic segmentation method for magnetic resonance images. The aim of this segmentation is to divide the brain into homogeneous regions and to detect the presence of tumors. This method divided into two parts. First, perform a pre-segmentation to extract the brain from the head. Then, a second segmentation did inside the brain. Several techniques combined like anisotropic filtering or stochastic model-based segmentation during the two processes. The paper describes the main features of the method, and gives some segmentation results [14].

The paper represented by Jehan Zeb et.al, discuss segmentation is in important step in the processing of MR images for the purpose of medical diagnosis, 3-D Visualization of the human brain. It was very difficult problem to segment multiple tissues in n single channel MR image. In this work, the features of the three Standard MR Images i.e. TI, T2 and PD weighted images had been employ that has not only improved the accuracy of the segmentation process but also enhanced its reliability. [13].

The clustering approach invented by D. Jude Hemanth et.al, was widely used in biomedical applications particularly for brain tumor detection in abnormal MRI. Fuzzy clustering using fuzzy C- means (FCM) algorithm prove to be superior over the other clustering approaches in terms of segmentation efficiency. However, the major drawback of the FCM algorithm is the huge computational time required for convergence. [13].

The edge detection was discuss by Xie Mei et.al, plays a critical role in medical application, Edges characterize boundaries are fundamental problem in image processing. The paper illustrated the way by Canny algorithm detected the weak edge of brain, then labeling all the 8-connected edge with a different number and classifying with the that edge, for the size of all the 8-connected edge circumference being different. Plot the histogram according to the size of the edge. At last, detect the sole weak edge by the histogram segmentation. This way could get the deformable edge such as brain tumor [11].

Gayatri Mirajkar et.al, introduced a fully automatic method for segmenting MR images showing tumor, both mass-effect and sensitive structures presented. The method uses UDWT and gabor wavelets. The method uses Tl, T2 images and produced appreciative results even in the presence of noise. A multiresolution approach using undedicated wavelet transform was employed which allows the low low, low high, high-low, and high-high sub-bands to remain at full size. Detection of tumor takes place in LL. [10].

N. Hema Rajini et.al, described clustering is the process of organizing data objects into a set of disjoint classes called clusters. The objective of this paper was to develop an enhanced k-means and kernelized fuzzy c-means for a segmentation of brain MRI images. In this paper, intend a new center initialization algorithm for measuring the initial centers of the proposed clustering algorithms. This algorithm based on maximum measure of the distance function, which found for cluster center detection process [16].

M. Usman Akram et.al, was present Computer Aided System for Brain Tumor Detection and Segmentation. MR images are a very useful tool to detect the tumor growth in brain but precise brain image segmentation is a difficult and time-consuming process. A automatic brain tumor diagnostic system from MR images. This system consists of three stages to detect and segment a brain tumor. [8].

Sarah Parisot et.al, was proposed conception based on Graph-based Detection, Segmentation & Characterization. In this manuscript proposed a novel approach for detection, segmentation and characterization of brain tumors. This method exploits prior knowledge in the form of a sparse graph representing the expected spatial positions of tumor classes [5].

Atiq Islam et.al, invented a stochastic model for characterizing tumor texture in brain MR images proposed. The efficacy of the model demonstrated in patient-independent brain tumor texture feature extraction and tumor segmentation in MRIs. Due to complex appearance in MRI, brain tumor texture formulated using a multiresolution-fractal model known as multi-fractional Brownian motion. Detailed mathematical derivation for mBm model and corresponding novel algorithm to extract spatially varying multi-fractal features are proposed. A multifractal feature-based brain tumor segmentation method is developed next. [6].

J.Vijay et.al, presented described an efficient method for automatic brain tumor segmentation for the extraction of tumor tissues from MR images. In this method, segmentation carried out using K-means clustering algorithm for better performance. This enhances the tumor boundaries more and is very fast when compared to many other clustering algorithms [4].

Sindhumol et.al, proposed Wavelet based Independent Component Analysis of brain Tissue Classification. Multispectral analysis is a promising approach in tissue classification and abnormality detection from MRIs. However, instability in accuracy and reproducibility of the classification results from conventional techniques keeps it far from clinical applications. Recent studies proposed Independent Component Analysis (ICA) as an effective method for source signals separation from multispectral MR data. The improvement of the proposed method over conventional ICA effectively demonstrates by segmentation and classification using k-means clustering [14].

I. Kailash Sinha et.al, published paper efficient Segmentation Methods for Tumor Detection in MRI images. This document presents a comparative study of three segmentation methods implemented for tumor detection. The methods include k-means clustering with watershed segmentation algorithm, optimized k-means clustering with genetic algorithm and optimized c- means clustering with genetic algorithm. Traditional k-means algorithm is sensitive to the initial cluster centers. Genetic c means and k-means clustering techniques used to detect tumor in MRI of brain images [3].

Praveen et.al, correspond to detection method of brain tumor in MRI Images, using Combination of Fuzzy C-Means and SVM. MRI is the most important technique, in detecting the brain tumor. In the paper data, mining methods used for classification of MRI images. A new hybrid technique based on the support vector machine (SVM) and fuzzy c-means for brain tumor classification is proposed. The algorithm is a combination of support vector machine (SVM) and fuzzy c-means, a hybrid technique for prediction of brain tumor [2].

Ishmam Zabir et.al, demonstrated automatic system of Brain Tumor Detection and Segmentation based on Multi-Modal MRI Images Based on Region Growing and Level Set Evolution. Glioma is a type of brain tumor, originates from glial cells [1].

These are the methods used for the implementation for the brain tumor detection and segmentation. The proposed report gives the most efficient but the fastest method for the brain tumor detection and segmentation, which gives the parameters under consideration like time delay, % of tumor, mean, standard deviation, entropy, sensitivity, specificity and accuracy. This proposed paper has the easiest step of image processing. The method easily implemented simply by using MATLAB tool with the simple image processing toolbox.

III. Proposed method

This section presents proposed methodology of image segmentation for extraction of tumor in MRI images. The tumor diagnosis system implemented using the soft computing technique, which act as feature extraction method. This technique explained with following block diagram. This system consists of database training and database testing.

3.1 Database Training

For creating database for brain tumor, segmentation and detection images are available in multispectral suite. Database training process shown in figure 3 clarified below:

3.1.1 MRI Images

In Database training both synthetic and clinical images considered in the evaluation of the proposed system. Synthetic MRIs collected from Brain Web database. Slices of abnormal data set, containing Multiple Sclerosis details selected to form the multispectral suite. Axial T1-Weighted Images shown in figure 4 with parameter settings 1-mm slice thickness, intensity non-uniformity 20% and noise level 0% were included in the set.

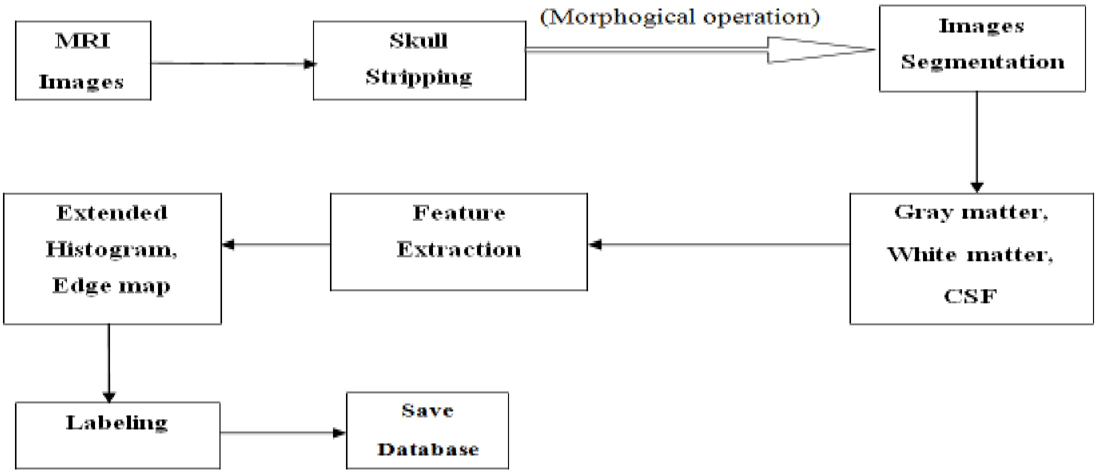


Figure 3: Block diagram of database training.

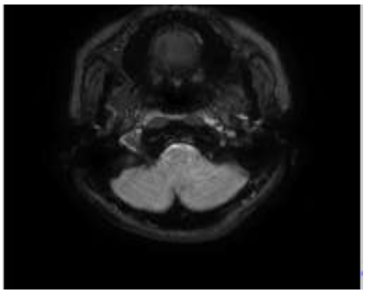


Figure 4: Axial T1-Weighted MRI

3.1.2 Skull Stripping

Skull stripping is important process in biomedical image analysis. It needed to make only in brain image shown in figure 5 (a) but not needed to make in other medical image analysis such as heart, lung, etc. It must be do before other image-processing step. It is a process of eliminating all non-brain tissues from brain image. In skull stripping, it is removed extra cerebral tissues such as skull, fat, skin, etc. Skull stripping did by various methods. They are automatic skull stripping using image contour, skull stripping based on region growing and mathematical morphology, skull stripping based on histogram analysis, skull stripping based on resonance principle and skull stripping based on threshold value. Skull stripping shown in figure 5 (b) based on threshold value used to remove the skull tissues in this report. In the skull stripping based on threshold value, the threshold value of the skull tissues and that of normal brain tissues are manually determined for every image.

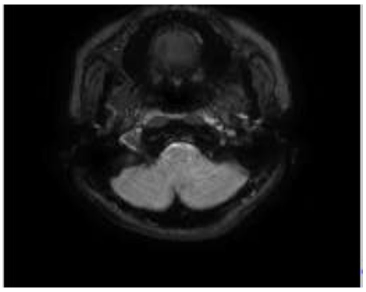


Figure 5: (a) Original MRI

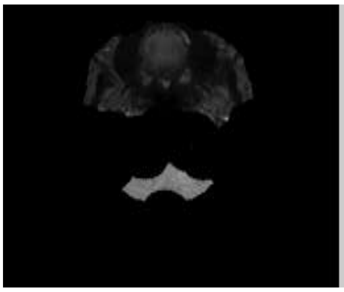


Figure 5: (b) Skull stripped image

3.1.3 Morphological Operation

Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. A morphological operation shown in figure 6 on a binary image creates a new binary image in which the pixel has a non-zero value. Morphological operations transform the image. In this paper, erosion applied to detect the tumor. The erosion of A by B is given by the expression:

$$A \ominus B = \{(i , j) : B(i, j)\} \quad (4.1)$$

Where, A= the binary image, B= the structuring element, (i, j) = the center pixel of structuring element.

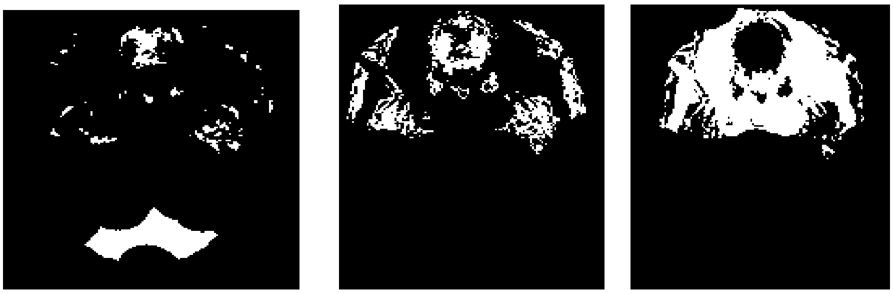


Figure 6: (a) White matter **Figure 6: (b)** Gray matter **Figure 6: (c)** CSF
Figure 6: Morphological Operation

3.1.4 Image segmentation

Segmentation is the technique of separating an image into multiple slices and object region. The skull stripes images used in image segmentation. This provides good result for tumor segmentation. In this work, fuzzy c-means algorithm used in MRI image segmentation. Fuzzy C-Means (FCM) algorithm used to find out the suspicious region from brain MRI image. This fuzzy c-means clustering method provides good segmentation result. Image segmentation is important role in medical image segmentations. The image segmentation shown in figure 7 of brain tumor from magnetic resonance images is an important task. The image segmentation is one of the techniques for finding tumor from the MRI. It is time consuming but also generates errors.

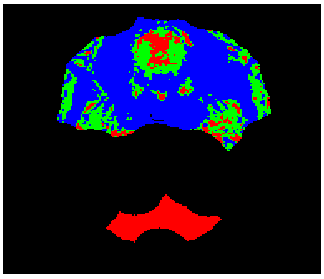


Figure 7: Segmented MRI Image

The image Segmentation by expert is variable. Segmentation takes at least three hours to complete. Several automated technique had been develop for MRI image segmentation. Segmentation of MR images into different tissue classes, especially gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF), is an important task. Brain MR Images have the number of features, especially the following: There are several automate image segmentation techniques are discuses below:

3.1.4.1 Threshloding

Threshloding is one of the simple image segmentation techniques. It is process of separating the pixels classes depending on their pixels gray levels. A thresholding method determines the intensity value, called threshold, which separate the desired classes. Segmentation achieved by taking threshold value. On basis of threshold value, the pixels grouping with intensity greater than the threshold into one class and remain pixels grouping into another class. The main disadvantage is the simplest form only two classes generated and it could not be apply to multichannel images. In thresholding technique, image having only two values black and white. The MR image contains 0 to 255 grey values.

3.1.4.2 Region Growing

It is a region based image segmentation method. This process is first requirement of manually select the seed points. Selection of the seed points based on user criteria. It is also an iteration-based method, like clustering algorithms. The algorithm steps for region growing technique described below:

- In the first step manually selects the seed points.
- In next steps, pixels in the region of seeds examined and it added to the region accordance with the homogeneity criteria. This process continued until all the pixels belong to some region.
- In last step, the object illustration did by growing the regions of pixels. The region growing technique applied in medical image segmentation. In medical field, it applied in kidney segmentation, extraction of brain surface and cardiac images. The main disadvantage of this method requires the user interface for selection of seed the points. Thus for each region that selection of the seed is requires the user interface and very time consuming process.

3.1.4.3 Fuzzy C-Means Clustering

Fuzzy C-means clustering is the overlapping clustering technique. One pixel value depending upon the two or more clusters centers. It is also known as soft clustering method. Most widely used the fuzzy clustering algorithms are the Fuzzy C-means (FCM) algorithm. The FCM algorithm is the partition of the n element X={x1,...,xn} into a collection of the c fuzzy clustering with respect to the below given criteria

It based on the minimization of the following objective function:

$$J=\sum_{i=1}^{N}\sum_{j=1}^{c}u_{ij}^{m}\,|x_i-y_i|^2 \qquad (4.2)$$

Where,

m = level of the fuzziness and real number greater than 1.
uij= degree of the membership of xi in the cluster cj
x = data value

Fuzzy C-means is the popular method for medical image segmentation but only considers the image intensity thereby producing unsatisfactory results in noisy images. Its use the preprocessing step for filtering the noise and other artifacts .A fuzzy c-mean is slower than the K-means in efficiency but gives the accurate prediction of tumor cells which are not predicted by the K-means algorithm.

3.1.5 Feature Extraction

Feature extraction calculates features based on which image easily classified as normal or abnormal one. The feature extraction is the process to represent raw image to facilitate decision making such as pattern classification. Features extracted from the tumor regions from MRI images. Feature extraction shown in figure 4.6 involves reducing the amount of data required to describe a large set of data accurately. Features used as inputs to classifiers that assign them to the class that represent. The intention of feature extraction is to reduce the original data by measuring positive properties, or features, that discriminate one input sample from another sample.

3.1.5.1 Extended Histogram based on Threshold Techniques

The classification of each pixel depends on its own information such as intensity and color information. Those techniques are efficient when the histograms of objects and background clearly separated. Thresholding technique is the classification of each pixel depends on its own information such as intensity and color information. Those techniques are efficient when the histograms of objects 19 and background clearly separated. In thresholding based segmentation scheme, each image divided into a number of segments by defining some threshold value. Thresholding is a very known and simple approach for segmentation in computer vision and image analysis. As the computational complexity is low, thresholding based scheme considered for real time computer vision systems. Thresholding schem broadly classified into two categories as contextual (depends on second order gray level statistics or co-occurrence matrix of the image) or non-contextual (depends on gray level distribution of image). If only one threshold used for entire image then it called global thresholding. On the other hand if the image partitioned into a number of sub-regions and threshold value is determined for each sub regions, it referred to as local or adaptive thresholding. Further thresholding scheme divided into bi-level thresholding (when the processed output image will have two region types as background and foreground) or multi-level thresholding (when the processed output image will contain more than two region type). A simple approach of determining the threshold value/s is by analyzing peaks and valleys of the histogram of the image. These peaks and valleys used for selecting threshold/s by minimizing the probability of error using Bayesian risk formulation.

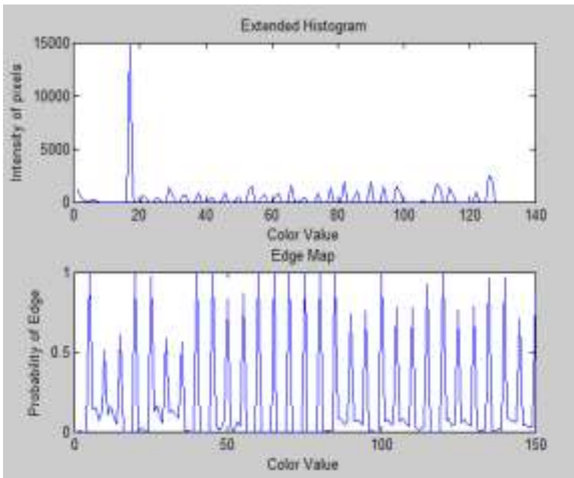


Figure 8: Feature Extractions method

3.1.5.2 Edge map based on Edge Extraction Technique

Edge-based methods focused on detecting contour. It fails when the image is blurry or too complex to identify a given border. The most important feature in an image is the contrast. Contrast described as discontinuities in the gray values of an image or variations in scene illumination. In vision based analysis edge considered as a very good descriptor of contrast. Different approaches of edge detection in an image includes gradient based edge (includes Sobel, Perwitt and Robert operators), Canny edge, Fuzzy edge, Laplacian of Gaussian (LOG), Laplacian edge etc. Most of the edge extraction based object detection scheme depends on the luminance information of the image. In an ancient work, H. Tang considered the purpose of the multi-resolution image analysis is to decompose the image into multi-frequency representations to visualize contents of interest in variable resolutions. Multi-scale filtering such as the Canny operator and the Monga-Deriche filter can detect the edges in the low contrast or low S/N images. Edges detectors are good because follow the optimal filter design criteria: good localization and high S/N output. By adjusting the scale from low to high, edges from fine to coarse obtained. Here employ a multi-resolution segmentation concept to segment both edges and structures. Instead of using the local statistic standard deviation as the edge strength detector, define a new Ti/ as the edge strength detector using the Monga-Deriche low-pass filter that can be realized using recursive digital filter design. Edge extraction based scheme provides an efficient object detection result against illumination variation in the scene but it has its own drawbacks. The major limitation of the edge-based approach of object detection scheme is its inability to produce a reasonable solution in cluttered background. In case of two or more objects present (overlapped with each other) in the scene, the effect of silhouette is also likely to occur, as one of the objects may not able to be identifying in the image. The edge detection problem was eliminating by the active contour detection schemes. It is high sensitive to starting point.

3.1.6 Labeling:

Labeling is used to told system that the brain image is healthy or Disease image (tumor image).After labeling, images are save as database.

Database images used in testing part for segmentation and detection tumor for achieving more improve parameters.

3.2 Database Testing

The process of testing the database mentioned in figure 9. First, an MRI image applied as an input for testing purpose. The skull stripping operation performed on input MRI image. Skull stripping performs on MRI images. Skull stripping is a vital process in brain image analysis, which involves removal of the scalp tissue, skull and Dura. In the proposed technique, skull stripping used for the segmentation of brain tissues. The steps involved in the skull stripping process are:

- Binarization via Thresholding
- Morphological Operation
- Tumor region identification

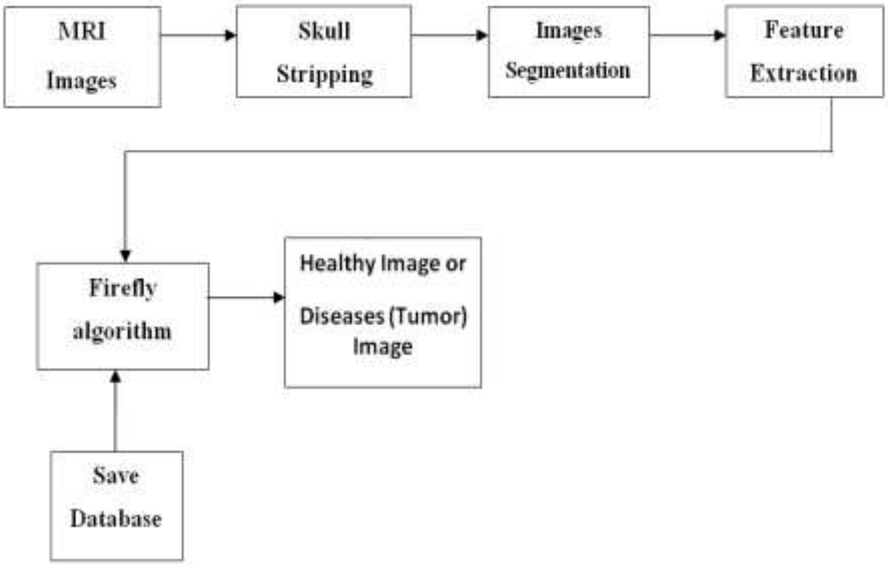


Figure 9: Block diagram for database testing

3.2.1Image Segmentation using Fuzzy C-Means

The skull stripped images applied to image segmentation as input. Image segmentation performed on image with help of fuzzy c-means algorithm. The fuzzy logic is a way to processing the data by giving the partial membership value to each pixel in the image. The membership value of the fuzzy set is ranges from 0 to 1. Fuzzy clustering is a multi valued logic that allows intermediate values i.e., member of one fuzzy set can also be member of other fuzzy sets in the same image. There is no abrupt transition between full membership and non-membership. The membership function defines the fuzziness of an image and defines the information contained in the image. These are three main basic features involved in characterized by membership function. They are support, Boundary. The core is a fully member of the fuzzy set. The support is non-membership value of the set and boundary is the intermediate or partial membership with value between 0 and 1.

3.2.2Feature Extraction

The feature extraction is extracting the cluster, which shows the predicted tumor at the FCM output. The extracted cluster is give to the thresholding process. It applies binary mask over the entire image. It makes the dark pixel become darker and white become brighter. In threshold coding, each transform coefficient compared with a threshold. If it is less than the threshold value then it considered as zero. If it is larger than the threshold, it considered as one. The thresholding method is an adaptive method where only those coefficients whose magnitudes are above a threshold retained within each block. Edge-based methods focused on detecting contour. It fails when the image is blurry or too complex to identify a given border.

3.2.3 Firefly Algorithm (FA)

The feature are extracted such as extended histogram and edge map with help of thresholding method applied to FA for getting brain tumor region.

3.2.3.1Behaviors of Fireflies

Firefly algorithm is one of the components of soft computing Techniques. The flashing light of fireflies is an amazing sight in the summer sky in the tropical and temperate regions. There are about two thousand firefly species and Firefly Algorithms for Multimodal Optimization most fireflies produce short and rhythmic flashes. The pattern of flashes is often unique for a particular species. The flashing light produced by a process of bioluminescence, and the true functions of such signaling systems are still debating. However, two fundamental functions of such flashes are to attract mating partners (communication), and to attract potential prey. In addition, flashing may also serve as a protective warning mechanism. The rhythmic flash, the rate of flashing and the amount of time form part of the signal system that brings both sexes together. Females respond to a male's unique pattern of flashing in the same species, while in some species such as photuris, female fireflies can mimic the mating flashing pattern of other species to lure and eat the male fireflies who may mistake the flashes as a potential suitable mate. We know that the light intensity at a particular distance *r* from the light source obeys the inverse square law. That is to say, the light intensity I decreases as the distance *r* increases in terms of $I \propto 1/r^2$. Furthermore, the air absorbs light, which becomes weaker and weaker as the distance increases. These two combined factors make most fireflies visible only to a limited distance, usually several hundred meters at night, which is usually good enough for fireflies to communicate. The flashing light formulated in such a way that it is associated with the objective function to be optimized, which makes it possible to formulate new optimization algorithms. In the rest of this document, we will first outline the basic formulation of the Firefly Algorithm (FA) and then discuss the implementation as well as its analysis in detail

3.2.3.4 Firefly Algorithm

Now idealize some of the flashing characteristics of fireflies to develop firefly-inspired algorithms. For simplicity in describing our new Firefly Algorithm (FA), we now use the following three idealized rules:

- all fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex;
- Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less bright one will move towards the brighter one. The attractiveness is proportional to the brightness and both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly;
- The brightness of a firefly affected or determined by the landscape of the objective function. For a maximization problem, the brightness can simply be proportional to the value of the objective function.

Other forms of brightness defined in a similar way to the fitness function in genetic algorithms. Based on these three rules, the basic steps of the firefly algorithm (FA) summarized, as the pseudo code shown in figure 4.9. In certain sense, there is some conceptual similarity between the firefly algorithms and the bacterial foraging algorithm. In BFA, the attraction among bacteria is based partly on their fitness and partly on their distance, while in FA, the attractiveness is linked to their objective function and monotonic decay of the attractiveness with distance. However, the agents in FA have 172 X.-S. Yang adjustable visibility and more versatile in attractiveness variations, which usually leads to higher mobility and thus the search space is explored more efficiently.

Firefly Algorithm

Objective function f(**x**), **x** = (x1, ..., xd)T
Generate initial population of fireflies **x**i (i = 1, 2, ..., n)
Light intensity Ii at **x**i is determined by f(**x**i)
Define light absorption coefficient γ
while (t <MaxGeneration)
for i = 1 : n all n fireflies
for j = 1 : i all n fireflies
if (Ij > Ii), Move firefly i towards j in d-dimension; **end if**
Attractiveness varies with distance r via exp[−γr]
Evaluate new solutions and update light intensity
end for j
end for i
Rank the fireflies and find the current best
end while
Postprocess results and visualization

Figure.10: Pseudo code of the firefly algorithm

3.2.3.5 Attractiveness

In the firefly algorithm, there are two important issues: the variation of light intensity and formulation of the attractiveness. For simplicity, we can always assume that the attractiveness of a firefly determined by its brightness, which in turn is associated with the encoded objective function. In the simplest case for maximum optimization problems, the brightness *I* of a firefly at a particular location **x** can be chosen as I(**x**) ∝ f(**x**). However, the attractiveness *β* is relative; it should saw in the eyes of the beholder or judge by the other fireflies. Thus, it will vary with the distance rij between firefly i and firefly j. In addition, light intensity decreases with the distance from its source, and light is absorbed in the media, so we should allow the attractiveness to vary with the degree of absorption. In the simplest form, the light intensity *I*(*r*) varies according to the inverse square law *I*(*r*) = Is /r2 where Is is the intensity at the source. For a given medium with a fixed light absorption coefficient *γ*, th light intensity *I* varies with the distance *r*. That is I(r) = I(0) $e^{-\gamma r2}$, where I(0) is the original light intensity. In order to avoid the singularity at *r* = 0 in the expression I_s/r^2, the combined effect of both the inverse square law and absorption can be approximated using the following Gaussian form

$$I(r) = I(0)\, e^{-\gamma r2} \qquad (4.3)$$

3.2.3.6 Distance and Movement

The distance between any two fireflies *i* and *j* at x_i and y_j, respectively, is the Cartesian distance

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{j=1}(x_{i,k} - x_{j,k})} \qquad (4.4)$$

where x_i, *k* is the k^{th} component of the spatial coordinate **x***i* of *i*th firefly. In 2- D case, we have

$$r_{ij} = (x_i - xj)^2 + (yi - yj)^2 \qquad (4.5)$$

The movement of a firefly *i* is attracted to another more attractive (brighter) firefly *j* is determined by

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2}(x_i - x_j) + \alpha(rand - \tfrac{1}{2}), \qquad (4.6)$$

the second term is due to the attraction while the third term is randomization with α being the randomization parameter. rand is a random number generator uniformly distributed in [0, 1]. For most cases in our implementation, X.-S. Yang can take $\beta_0 = 1$ and $\alpha \in [0, 1]$. Furthermore, the randomization term can easily be extended to a normal distribution *N*(0, 1) or other distributions. In addition, if the scales vary significantly in different dimensions such as −105 to 105 in one dimension while, say, −0.001 to 0.01 along the other, it is a good idea to replace α by αSk where the scaling parameters *Sk* (*k* = 1, ..., *d*) in the *d* dimensions should be determined by the actual scales of the problem of interest. The parameter γ now characterizes the variation of the attractiveness, and its value is crucially important in determining the speed of the convergence and how the FA algorithm behaves. In theory, $\gamma \in (0,\infty)$, but in practice, $\gamma = O(1)$ is determined by the characteristic length Γ of the system to be optimized. Thus, in most applications, it typically varies from 0.01 to 100.

3.2.3.7 Scaling and Asymptotic Cases

It is worth pointing out that the distance *r* defined above is *not* limited to the Euclidean distance. Define many other forms of distance *r* in the *n* dimensional hyperspace, depending on the type of problem of our interest. For example, for job scheduling problems, *r* defined as the time lag or time interval. For complicated networks such as the Internet and social networks, the distance *r* defined as the combination of the degree of local clustering and the average proximity of vertices. In fact, any measures that can be effectively characterize the quantities of interest in the optimization problem used as the 'distance' *r*. The typical scale Γ should be associated with the scale in the optimization problem of interest. If Γ is the typical scale for a given optimization problem, for a very large number of fireflies *n* >> *m* where *m* is the number of local optima, then the initial locations of these *n* fireflies should distribute relatively uniformly over the entire search space in a similar manner as the initialization of quasi-Monte Carlo simulations. As the iterations proceed, the fireflies would converge into all the local optima (including the global ones) in a stochastic manner. By comparing the best solutions among all these optima, the global optima easily be achieved.

Extracted features of test MRI image is applied FA and these extracted features forms correlation matching with database images features. If maximum brightness obtained then input test MRI image is (tumor) Diseases image otherwise for minimum brightness test input MRI image is healthy image.

IV. Results And Discusstion

This section portrays some experimental results on real data on brain MRI. The entire input database (total images are 50 for abnormal and normal) used for segmentation consists of T1 weighted, 256x256 pixel MR images.

In proposed dissertation time delay and percentage of brain tumor considered as comparison parameters. The proposed dissertation developed most proficient method for segmentation and detection, which gives better performance parameters than reference methods like linear SVM, radial base SVM and quadratic SVM. In order to taste the algorithm developed, an MRI of brain having tumor considered. The outputs of the program resulted the following images and parameters obtained after the simulation are shown in the next sections.

4.1 Experimental Results

4.1.1 Experimentation of T1 weighted MRI image using Firefly algorithm (FA)

Step1: Open classiflyfirefly.m code press run button of editor window after that select the MRI image shown in figure 11 from test input folder.

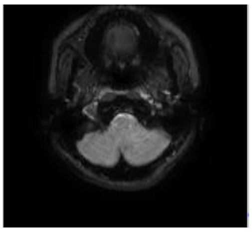


Figure 11: T1 weighted MRI image of brain (FA)

Step 2: By applying test input MRI image menu window get display on editor window shown in figure 12. On menu window four classifications types are available from that classifications types press firefly algorithm. The graph of extracted features like extended histogram and edge map, segmented image and tumor region, parameter percentage of tumor and delay time display as shown in figure 13, 14 and 15 resp.

Figure 12: Menu window (FA)

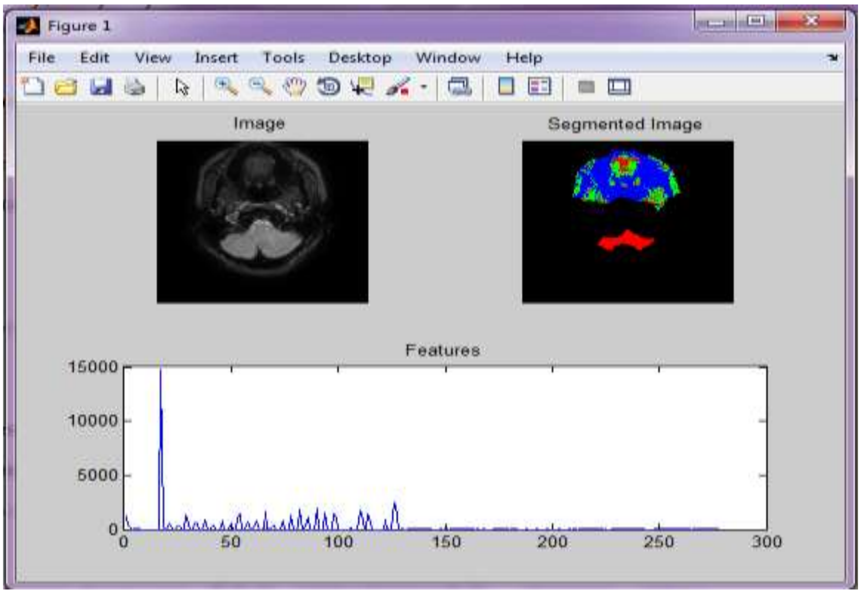
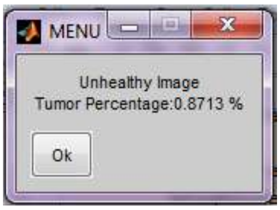


Figure 13: Input MRI image of brain, Segmented Image, Extracted feature graph (FA)



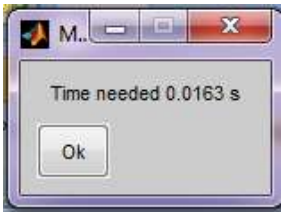


Figure 14: Tumor percentage (FA) **Figure 15:** Delay time (FA)

From above figure, it is clear that input MRI image unhealthy image means that it has brain tumor.

Step 3: For others parameters, cropping the boundary of the tumor with MATLAB command imtool(seg_img) in command window. After this command crop the region of tumor with help of crop image button from entire image shown figure 16, then copy the position of pixels in performance m.file then press run button of editor window, the parameters are displayed on command window shown figure 17.

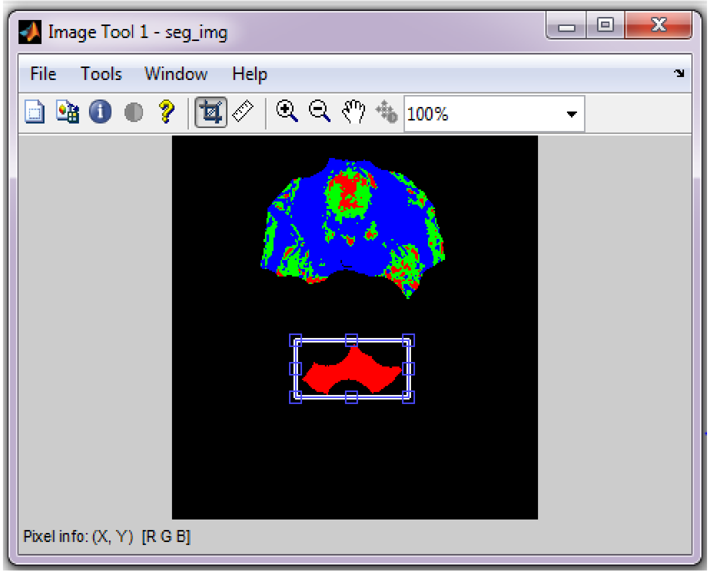


Figure 16: Crop Image of MRI Image (FA)

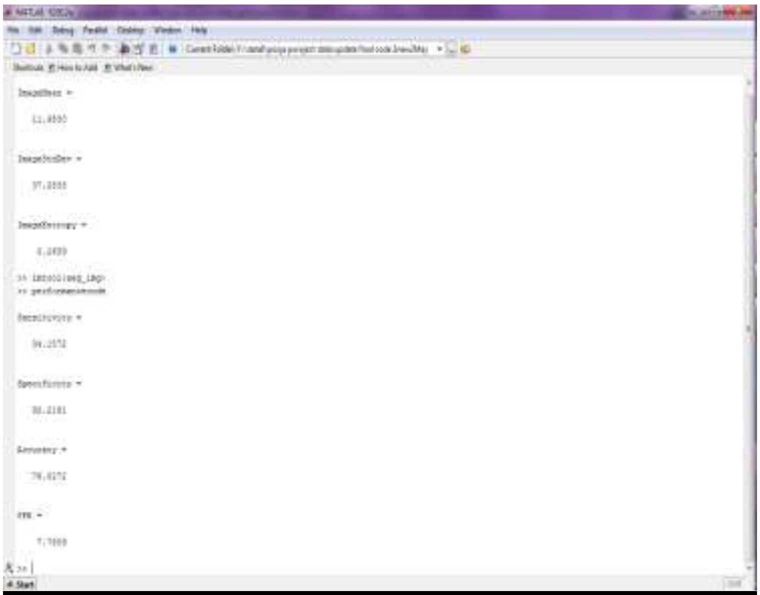


Figure 17: Parameters displayed on command window (FA)

In this way in proposed work seven test input MRI images apply to firefly algorithm and resulted parameters are tabulate as below;

Table 1 Parameters obtained from Firefly Algorithm

Test I/p Images	% of tumor	Delay Time	Mean	Standard Deviation	Entropy	Sensitivity	Specificity	Accuracy	FPR
Img1	0.8713	0.0163	11.983	37.2833	0.2639	34.1572	92.2191	76.0272	7.7809
Img2	1.3418	0.0238	14.7663	40.7075	0.3036	41.8033	99.004	75.6411	0.996
Img3	1.5274	0.0193	16.49	42.1184	0.3299	42.7029	99.2133	75.9435	0.7867
Img4	1.534	0.0193	15.9699	41.5605	0.3215	42.2672	97.0459	74.972	2.9541
Img5	1.563	0.0199	14.1801	39.1794	0.2926	42.3617	96.3235	72.3038	3.6765
Img6	1.3667	0.0189	11.2112	35.5071	0.2459	41.5711	96.4228	69.5541	3.5772
Img7	1.6073	0.01915	10.6808	33.3217	0.231	43.3827	102.3805	66.7546	2.3805
Avg	1.4016429	0.0195214	13.6116	38.52541429	0.28406	41.1780143	97.515586	73.028	3.16456

4.1.2 Comparative Analysis Of Soft Computing Algorithms:
The various soft computing algorithm studied under the proposed dissertation experimented for the number of MRI images and their performance comparison in terms of parameters like below:

4.1.2.1 % of Tumor

Table 2: Comparison of % Tumor with respective Algorithms

Algorithm	% of tumor
FA	1.4016429
LSVM	1.4016429
RBF SVM	1.40164286
QSVM	1.40164286

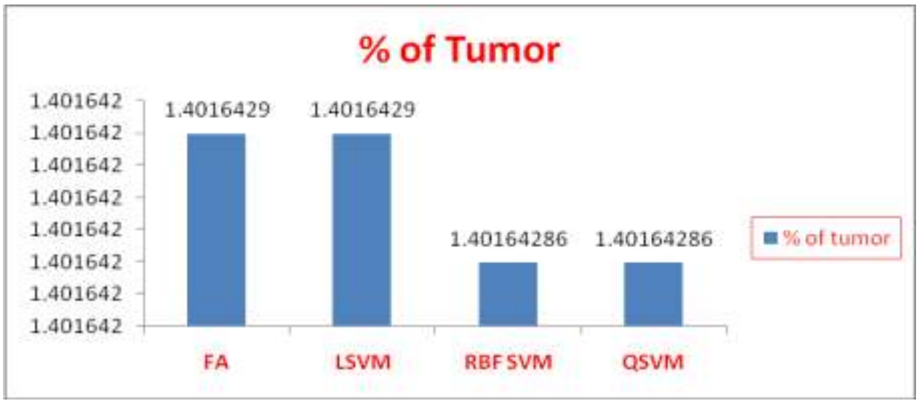


Figure 18: Graphical representation of algorithm in terms of % Tumor

The algorithms were compared in terms of % of tumor which has been reported in figure 18. The % of tumor in FA is better than reference algorithms.

4.1.2.2 Delay Time

Table 3: Comparison of Delay time with respective Algorithms

Algorithm	Delay Time
FA	0.0195214
LSVM	1.178486
RBF SVM	1.4578214
QSVM	3.29225

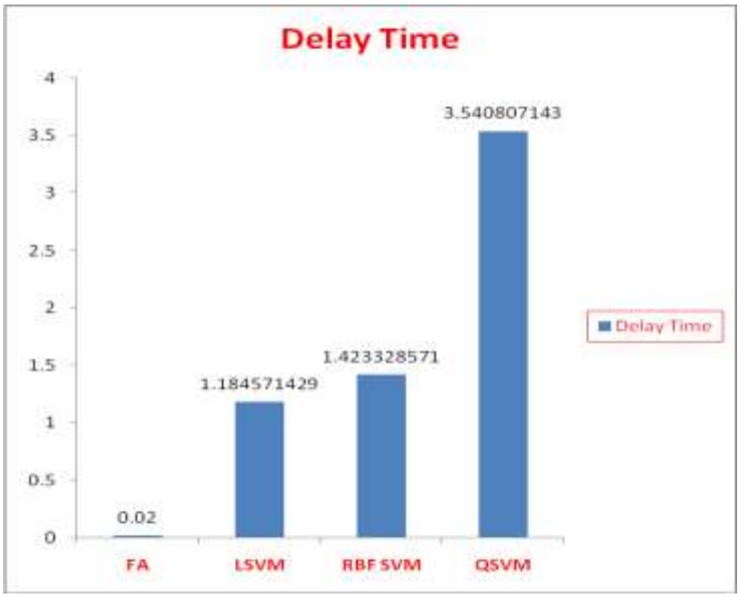


Figure 19: Graphical representation of algorithm in terms of Delay Time

Delay time required for FA is very less as compared to reference algorithms as shown in figure 19. It means that searching time of tumor detection and segmentation more efficiently obtained.

4.2.2.3 FPR

Table 4 Comparison of FPR with respective Algorithms

Algorithm	FPR
FA	3.16456
LSVM	2.59401
RBF SVM	3.00841
QSVM	2.42835

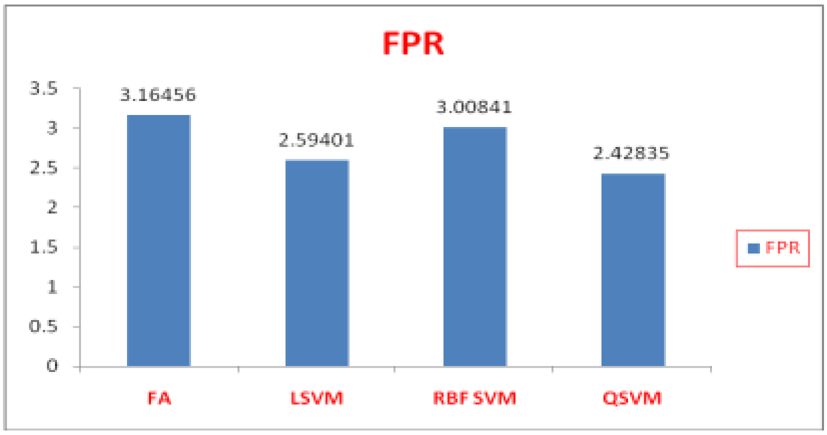


Figure 20: Graphical representation of algorithm in terms of FPR

FPR shown in figure 20 valve obsered to be less for proposed LSVM. Considerable reduction in FPR explains the rubstness and reliability of new approch in clinical field.

The algorithms were compared in tems of % of tumor , delay time, FPR and so on parameters which has been reported in above tables and graphs. The level of segmentation and parameters is better than that of traditional SVM' s algorithm. The comparision was done on basis of % of tumor, Delay Time , FPR and so on parameters.

From above results it can be conclude that Firefly algorithm produces sharp results for brain tumor segmentation and detection of MRI images. It can be seen that firefly algorithm perform better that of SVM's algorithm; as the segmented region (% of Tumor) and level of detected region is better in Firefly algorithm. The time (delay time) required is less in Firefly algorithm as compared to linaer SVM algorithm , Radial basis SVM and Qudratic SVM algorithm. Therfore, Firefly algorithm can be considered as more powerful than linaer SVM algorithm , Radial basis SVM and Qudratic SVM algorithm.

V. Conclusion

Magnetic Resonance Imaging (MRI) is an important examination and diagnosis method for brain tumors in medical imaging. With a sound mechanism and clear imaging of soft tissues, the doctor on the patient's diagnosis can be scientific and rational, to grasp the exact progression of the disease state, which would set out the appropriate treatment, surgery and following-up to a series of disease control measures. Computer-aided analysis is to reduce the workload of doctors, to improve the diagnostic accuracy of the paramedical analysis, and meanwhile to improve the automatic degree in practice.

The proposed dissertation presents a semi-automatic and Soft computing technique based tumor detection and segmentation system, which can deal with multiple input MRI sequences and track on the patient's condition in the whole therapeutic treatment. The system only requires interactive participation once the sample points in the analysis of data of the first examination randomly selected and all the processing is in next examinations can be carried out semi automatically by the system itself. The segmentation algorithm works in an ordered manner, from tumor to tissues. That is, a first classification consists of segmenting the area of the entire tumor, and then separating the abnormal tissues based on the obtained tumor area. The firefly algorithm gives better results than linear, RBF and Quadratic SVM algorithm in terms of delay time (0.0195214 Sec.), percentage of tumor (1.4016429%), which used for brain tumor diagnosis using MRI images.

References

[1]. Ishmam Zabir, Sudip Paul et.el, "Automatic Brain Tumor Detection and Segmentation from Multi-Modal MRI Images Based on Region Growing and Level Set Evolution" IEEE International Confererance on Electrical and Computer Engg., Dhaka , Bangladesh, 2015, PP. 503-506.

[2]. Praveen and Amritpal Singh "Detection of Brain Tumor in MRI Images, using Combination of Fuzzy C-Means and SVM", IEEE, Dept. of computer science and engineering ,Govt. women engineering college Ajmer, India, 2015, PP.98 -101.

[3]. Kailash Sinha1, G.R.Sinha , "Efficient Segmentation Methods for Tumor Detection in MRI Images", IEEE, Student's Conference on Electrical, Electronics and Computer Science,ShriShankaracharya Technical Campus Bhilai, India, 2014, PP. 1-6.

[4]. J.Vijay,J.Subhashini "An Efficient Brain Tumor Detection Methodology Using K-Means Clustering Algorithm",IEEE, International conference on Communication and Signal Processing, Chennai, India, 2013, PP.653-657.

[5]. Sarah Parisot, Hugues Duffau, St´ephane Chemouny,"Graph-based Detection, Segmentation & Characterization of Brain Tumors", IEEE, Center for Visual Computing, Ecole Centrale de Paris, France, 2013, PP.988-995.

[6]. Atiq Islam, Syed M. S. Reza and Khan M. Iftekharuddin, "Multi-fractal Texture Estimation for Detection and Segmentation of Brain Tumors" Department of Electrical and Computer Engineering, Old Dominion University, Norfolk, VA 23529, USA, 2013.

[7]. K.S.Tamilselvan, Dr.G.Murugesan and B.Gnanasekaran, "Brain Tumor Detection from Clinical CT and MRI Images using WT-FCM Algorithm" Department of ECE Velalar College of Engineering and Technology, Erode, Anna University, India, 2013, PP.260-263.

[8]. M. Usman Akram and Anam Usman,"Computer Aided System for Brain Tumor Detection and Segmentation" ,IEEE ,Department qf Computer and Software Engineering, Bahria University, Islamabad, Pakistan , 2011,PP.299-302.

[9]. Ms.T.K. Sreeja and Ashmi Mohammed "A Skull-Stripping Method Based on Modified Morphological Processing" , International Conference on Signal Processing, Communication, Computing and Networking Technologies, IEEE, Noorul Islam University Kumaracoil, Tamil Nadu,India,2011,PP.313-316.

[10]. Gayatri Mirajkar, Balaji Barbadekar, "Automatic Segmentation of Brain Tumors from MR Images using Undedicated Wavelet Transform and Gabor Wavelets" 2010 IEEE, PP. 648-652.

[11]. Xie Mei, Zhen Zheng, Wu Bingrong, Li Guo, "The Edge Detection of Brain Tumor" School of Electronic Engineering,University of Electronic Science and Technology of China Chengdu,IEEE, Sichuan, China, 2009, PP 477-479.

[12]. D.Jude J Hemanth, D.Selvathi and J.Anithal, "Effective Fuzzy Clustering Algorithm for Abnormal MR Brain Image Segmentation",IEEE International Advance Computing Conference (IACC 2009), Karunya University, Coimbatore Mepco Schlenk Engineering College, Sivakasi, India, 2009, PP.609-614

[13]. Jehan Zeb Shah, Syed Afaq Husain " A fuzzy based Adaptive BPNN Learning Algorithm for Segmentation of thevBrain MR images" University of' Techno logy ,IEEE,Malaysia, SZABIST Is+, Flamahad, 2004, PP.86-90.

[14]. A. S. Capelle, 0. Alata, C. Femandez, S. Lefevre "Unsupervised Segmentation for Atomatic Detection of brain tumors in MRI ,Univ. Poitiers, Bat., Futuroscope Chasseneuil Cedex, FRANCE,IEEE,2004,PP. 613-613.

[15]. Mangipudi Partha Sarathi, Mohammed Ahmed Ansari, Vaclav Uher, RadimBurget, and Malay Kishore Dutta "Automated Brain Tumor Segmentation using Novel Feature Point Detector and Seeded Region Growing" IEEE,2013, PP. 648-652.

[16]. N. HemaRajini , R.Bhavani, "Enhancing K-means and Kernelized Fuzzy C-means Clustering with Cluster Center Initialization in Segmenting MRI brain images" Department of Computer Science and Engineering, Annamalai University, AnnamalaiNagar, Tamilnadu, , IEEE, 2011, PP. 259-26.

[17]. Sindhumol S., Anil Kumor and Kannan Balakrishnam, "Wavelet based Indepentent Component Analysis for Multispectral Brain Tissue Classification" , Dept.of computer application, kochi, India, IEEE, 2013, PP.415-418.

[18]. Xin-She Yang, "Firefly Algorithms for Multimodal Optimization",Department of Engineering, University of Cambridge, Trumpington Street, Cambridge, PP 169-179.

[19]. Xin-She Yang "Firefly Algorithm: Recent Advances and Applications", School of Science and Technology, Middlesex University, The Burroughs, London.

[20]. Dmitry bystrov "lecture notice introduction to soft computing"

[21]. Henry Han, Xiao-Li Li,"Multi-resolution independent component analysis for high- performance tumor classification and biomarker discovery, BMC Bioinformatics", 2011.

[22]. Abdullah N, Lee Wee Chuen, Ngah U K, Ahmad K A, "Improvement of MRI brain classification using principal component analysis", Proc IEEE IntConf on Control System, Computing and Engineering (ICCSCE), 2011, 557-561.

[23]. Eyal E, Bloch B N, Rofsky N M, Furman-Haran E, Genega E M, Lenkinski R E, DeganiH.,"Principal Component Analysis for Dynamic Contrast-Enhanced MRI in Human Prostate Cancer, Invest Radiol", 2010, PP. 174–181.