Comparative Study of Metaheuristic Algorithms by Segmentation of Brain Tumor MR Images

MINOR PROJECT I

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Abstract

In recent times, the introduction of information technology and e-health care system in the medical field helps clinical experts to provide better health care to the patient. Brain tumor is one of the major causes for the increase in mortality among people. To detect infected tumor tissues from medical imaging modalities, segmentation is employed. This project is aim to implement Nature-inspired meta-heuristics algorithms to detect brain tumor. A previously used algorithm is used to prepare a comparative study with a non-implemented algorithm in the field of brain segmentation.

Gantt Chart

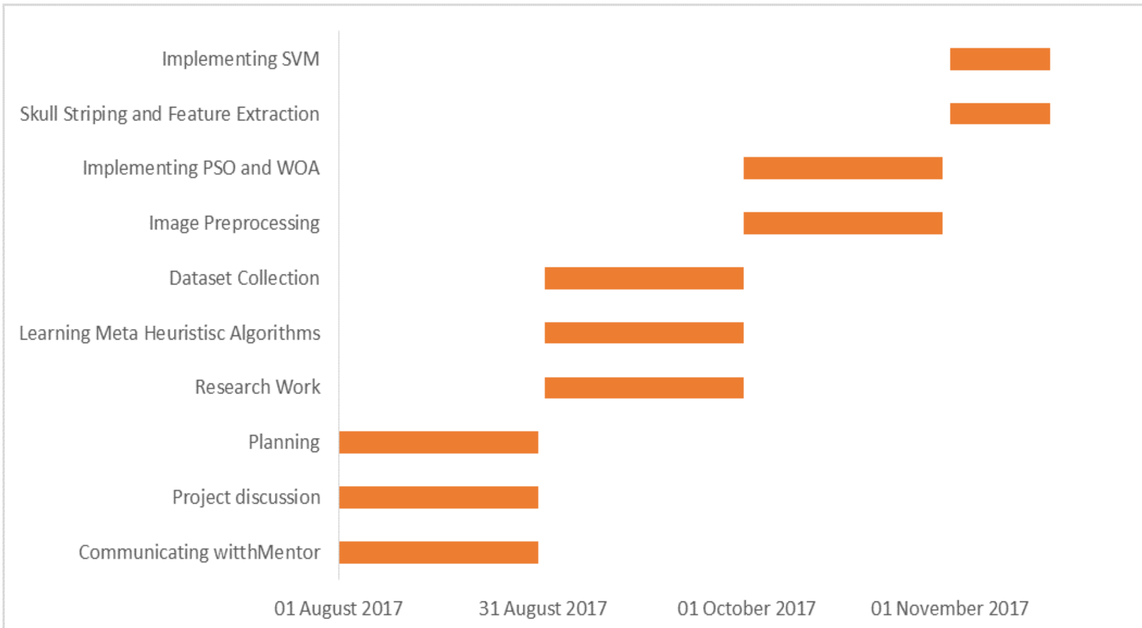

Figure: Gantt Chart

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List of Abbreviations

1	DICOM	Digital Imaging and Communications in Medicine
2	MRI	Magnetic Resonance Image
3	PSO	Particle Swarm Optimisation
4	CWM	Centre Weighted Median Filter
5	SVM	Support Vector Machine
6	WOA	Whale Optimisation Algorithm
7	GLCM	Gray Level Co-Occurrence Matrix

Contents

Chapter 1 Introduction

1.1 Overview

Today image processing plays an important role in medical field and medical imaging is a growing and challenging field. Medical imaging is advantageous in diagnosis of the disease. Many people suffer from brain tumor, it is a serious and dangerous disease. Medical imaging provides proper diagnosis of brain tumor. There are many techniques to detect brain tumor from MRI images. These methods face challenges like finding the location and size of the tumor. To detect the tumor from the brain is most important and difficult part, image segmentation is used for this. Already, various algorithms are developed for image segmentation.

1.1.1 Magnetic Resonance Images

MRI is a way of creating pictures of our body without using potentially harmful x-rays or radiation. Our body generates a naturally occurring magnetic field and an MRI scanner can take pictures of it. MRI pictures can show soft tissues of the body like the brain, muscles, and nerves. MRI is useful for detecting abnormalities of the brain, spinal cord, blood vessels, joints and organs. The MRI scanner is a big machine with a tunnel through the middle. During an MRI scan you have to lie very still in the tunnel, usually on you back. The magnetic field and radio waves used in an MRI scan are believed to be safe and no adverse effects have ever been reported.

1.1.2 DICOM

The Digital Imaging and Communications in Medicine (DICOM) Standard specifies a data interchange protocol, digital image format, and file structure for biomedical images and image related information. The DICOM Standard exists primarily to address the long-standing requirement for communication interoperability among medical imaging devices. DICOM groups information into data sets. A DICOM data object consists of a number of attributes, including items such as name, ID, etc., and also one special attribute containing the image pixel data. A single DICOM object can have only one attribute containing pixel data.

1.1.3 Nature Inspired Algorithms

Meta-heuristic optimization algorithms are becoming more and more popular in engineering applications because they:

1. Rely on rather simple concepts and are easy to implement.
2. Do not require gradient information.
3. Can bypass local optima.
4. Can be utilized in a wide range of problems covering different disciplines.

Nature-inspired meta-heuristic algorithms solve optimization problems by mimicking biological or physical phenomena. They can be grouped in three main categories: Evolution-based, physics-based, and swarm-based methods. Evolution-based methods are inspired by the laws of natural evolution. The most popular evolution-inspired technique is Genetic Algorithms that simulates the Darwinian evolution. Physics-based methods imitate the physical rules in the universe. The third group of nature-inspired methods includes swarm-based techniques that mimic the social behaviour of groups of animals. The most popular algorithm is Particle Swarm Optimization.

1.2 Model Diagram

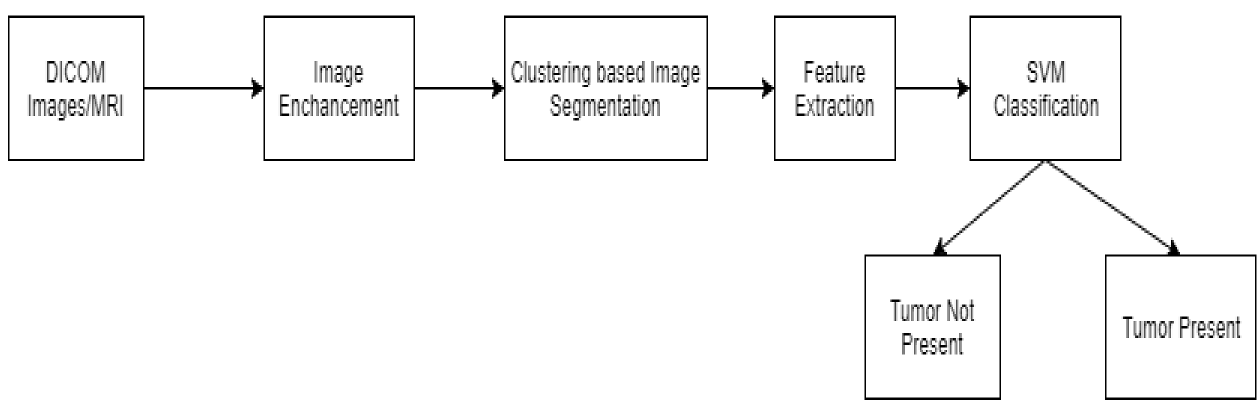

Figure: Model Diagram

1.3 Requirement Analysis

1.3.1 Software

i) Python
ii) Radiant (DICOM Viewer)
iii) Microsoft Office

1.3.2 Hardware

Laptop Specifications:
i) 2.2 GHZ Intel Core i5-5200U with Intel HD Graphics 5500
ii) Memory: 1TB hard drive with 5400 rpm
iii) 8GB RAM

1.3.3 Functional

1.3.4 Non Functional

i) The code that is used to compute throughput should be accurate enough to give the correct measurement of throughput.
ii) Project should be error free and should be able to complete in the stipulated time for the project.
iii) The project shall provide 100% accurate result.
iv) Project must give same result in any format of images.
v) Project gives output with same accuracy on different dataset.

1.4 UML Diagram

1.4.1 Activity Diagram

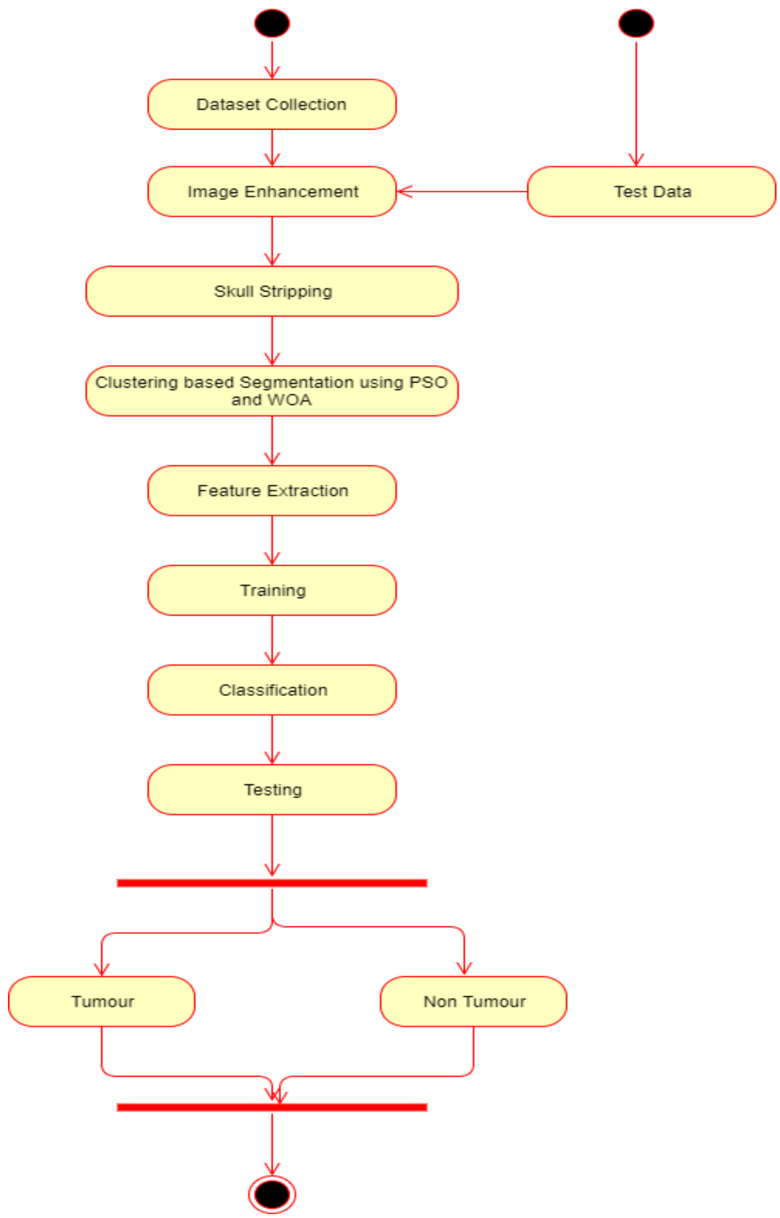

Fig:Activity Diagram

Chapter 2 Literature Review

1. Improved Fuzzy C-Means based Particle Swarm Optimization (PSO) initialization and outlier rejection with level set methods for MR brain image segmentation [1]

   (a) Introduction:
   In this paper Author purposes classification techniques used for brain MRI images. Several basic techniques are used for clustering in image segmentation. He purposes Fuzzy C-Means(FCM) algorithm with many modifications he improvise it to kernel possibilistic c-means (KPCM).These algorithm mainly suffers from bad initialization of cluster centres. To overcome this problem he uses Particle Swarm Optimisation (PSO) with KPCM to improve clustering and provide Improvised kernel possibilistic c-means (IKPCM) which initializes cluster centres initially.

   (b) Result:
   The results reveal that the algorithm shows a significant improvement concerning the robustness to noise. For medical images, IKPCM was used to find the initial contour for the level set evolution. A fine segmentation and the extraction of the various tissues were achieved.

   (c) Drawbacks:
   The disadvantages of using PSO algorithm are that it easy to fall into local optimum in high-dimensional space has a low convergence rate in the iterative process. Initialisation of fitness function vary the optimisation of algorithm.

2. The Whale Optimisation Algorithm [2]

   (a) Introduction
   The paper proposes a novel nature inspired meta-heuristic optimisation algorithm, which mimics the hunting strategy of humpback whales.

Natureinspired meta-heuristics algorithms solve optimisation problems by mimicking biological or physical phenomena. The proposed method included three operators to stimulate the search for prey, encircling prey, and bubble-net foraging behaviour of humpback whales. An extensive study was conducted to analyse exploration, exploitation, local optima avoidance, and convergence behaviour of the proposed algorithm. The numerical efficiency of the WOA algorithm developed in the study was tested by solving mathematical optimisation problems.

(b) Result

It was observed from the findings that the present algorithm is always the most efficient or the second best algorithm in the majority of the test functions used to evaluate exploration and exploitation. Convergence curves of WOA, PSO and GSA were compared and it was observed that WOA is competitive enough with other state-of-the-art meta-heuristic algorithms.

3. A Simple Skull Stripping Algorithm for Brain MRI [3]

(a) Introduction:

The paper proposes a simple skull stripping algorithm S3 to remove non cerebral tissues from a brain MRI image. It uses adaptive intensity thresholding followed by morphological operations, for increased robustness, on brain MRI. The threshold value is calculated based on intensity distribution in brain MRI.

(b) Result:

The proposed algorithm provides accurate results for T1-weighted brain MR images. Experimental results show that the proposed S3 method is suitable on both synthetic as well as real images. THis method is based on brain anatomy ans image intensity characteristics and can be implemented as a part of any automatic brain image processing system.

4. MRI Brain Image Enhancement Using Filtering Techniques [4]

   (a) Introduction:
   In this paper Author purposes several filtering techniques for pre-processing of brain MRI images for better segmentation. Several techniques has been used for image enhancement for better analysis of image. Methodology includes histogram modelling and then by using median filter for removal of high intensity of noise.

   (b) Result:
   After acquisition the brain MRI is given to the pre-processing stage, here the film artefacts are removed. Next, the high frequency components are removed using CWM. Hence we obtain the enhanced brain MRI image.

   (c) Drawbacks:
   It is very difficult measure to the improvement of the enhancement objectively. If the enhanced image can make observer perceive the region of interest better, then we can say that the original image has been improved. Otherwise, there is no use to enhance images.

Chapter 3 Implementation

3.1 Dataset Description

The proposed brain tumour detection method is evaluated using the MR brain tumour images from REMBRANDT database [5]. The database contains pre-surgical MR images from 130 Rembrandt patients. The magnetic images are available in DICOM format in the database, which are converted into jpeg format and stored in a local database after processing. A total of 100 normal and 200 tumour MR images are used for this work.

Collection Statistics	Updated 09/12/2014
Modalities	MR
Number of Patients	130
Number of Studies	174
Number of Series	1483
Number of Images	110020
Image Size(GB)	9.9

Table 1: Dataset [6] [5]

3.2 Pre-Processing

Pre-processing of all the MR images in the database is carried out to increase the quality of the images. The MR images are first converted into grayscale format and resized to make all images of a single size. The MR images are further enhanced using noise removal and histogram equalization methods to improve the contrast and the overall quality of images.
Skull stripping methods are used to remove non cerebral tissues like the skull from brain MR images. Simple Skull Stripping algorithm [3], termed as S3 is used for this purpose. Steps implemented:

1. Apply median filtering with a window of size 3*3 to the input image.
2. Compute the initial mean intensity value T_i of the image.
3. Identify the top, bottom, left, and right pixel locations, from where brain skull starts in the image, considering gray values of the skull are greater than T_i.
4. Form a rectangle using the top, bottom, left, and right pixel locations.
5. Compute the final mean intensity value T_f of the brain using the pixels located within the rectangle.
6. Approximate the region of brain membrane, based on the assumption that the intensity of skull is more than T_i and that of membrane is less than T_f.
7. Set the average intensity value of membrane as the threshold value T.
8. Convert the given input image into binary image using the threshold T.
9. Apply an opening morphological operation to the binary image in order to separate the skull from the brain completely.
10. Find the largest connected component and consider it as brain.
11. Apply an closing morphological operation to fill the gaps.

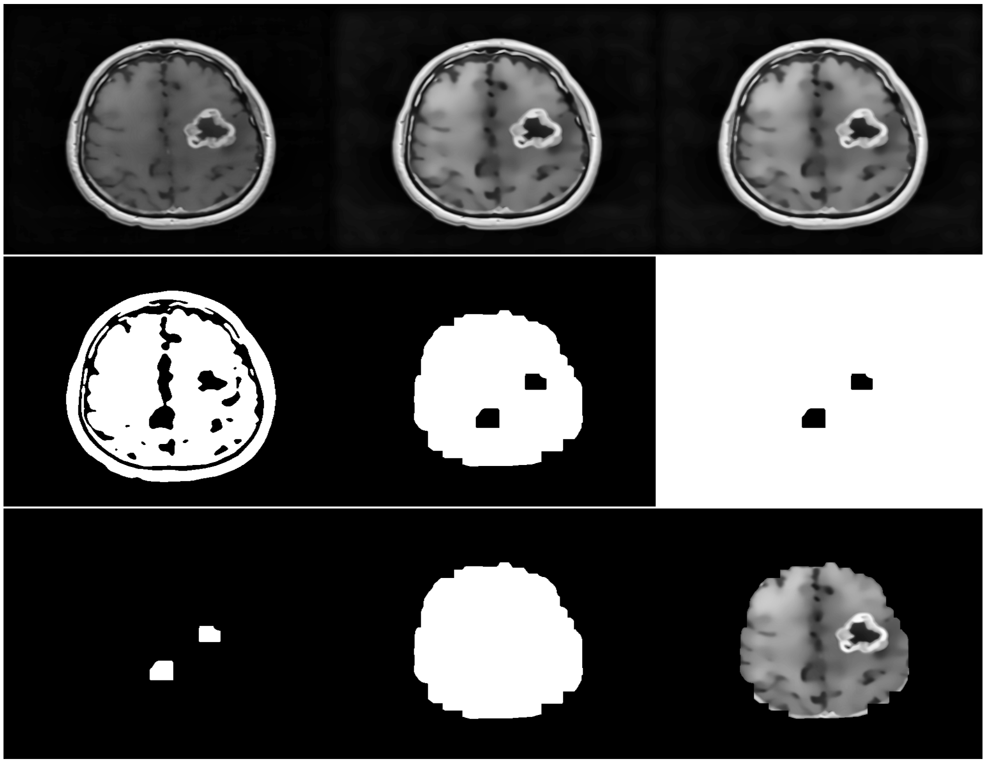

Figure: (From top left to Bottom right) Original Image, Enhanced Image, MedianBlur, Threshold, Morphological Operation, Floodfill, Floodfill Inverse, Mask, Skull Stripped

3.3 Clustering based Image Segmentation

3.3.1 Particle Swarm Optimisation

Particle swarm optimization belongs to the class of swarm intelligence techniques that are used to solve optimization problems. PSO simulates the behaviors of bird flocking. Means, a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But they know how far the food is in each iteration. So the best way to find the food is to follow the bird which is nearest to the food. Steps followed:

1. For each particles position, evaluate fitness.
2. Initialize particles with random position and velocity.
3. If fitness(p) is better than fitness(pbest) then update pbest.
4. Set best of pbest as gbest.
5. Update particles velocity and position. [7]

3.3.2 Whale Optimisation Algorithm

WOA can be considered a global optimizer because it includes exploration / exploitation ability. The WOA algorithm starts with a set of random solutions. At each iteration, search agents update their positions with respect to either a randomly chosen search agent or the best solution obtained so far. The a parameter is decreased from 2 to 0 in order to provide exploration and exploitation, respectively. A random search agent is chosen when A is greater than 1, while the best solution is selected when A is less than 1 for updating the position of the search agents. Depending on the value of p , WOA is able to switch between either a spiral or circular movement. Finally, the WOA algorithm is terminated by the satisfaction of a termination criterion.

$$\vec{D} = |\vec{C}.\vec{X^*}(t) - \vec{X}(t)| \qquad \vec{A} = 2\vec{a}\cdot\vec{r} - \vec{a}$$

$$\vec{X}(t+1) = \vec{X^*}(t) - \vec{A}\cdot\vec{D} \qquad \vec{C} = 2\cdot\vec{r}$$

$$\vec{X}(t+1) = \begin{cases} \vec{X^*}(t) - \vec{A}\cdot\vec{D} & if \;\; p < 0.5 \\ \vec{D'}\cdot e^{bl}\cdot\cos(2\pi l) + \vec{X^*}(t) & if \;\; p \geq 0.5 \end{cases}$$

3.4 Feature Extraction

Feature Extraction is the process of collecting higher level information of an image such as shape, texture, color, and contrast. It is used effectively to improve the accuracy of diagnosis system by selecting prominent features.

The technique used for feature extraction is Gray Level Cooccurrence Matrix (GLCM) and texture feature. This technique follows two steps for feature extraction from the medical images. In the first step, the GLCM is computed, and in the other step, the texture features based on the GLCM are calculated. [8] The features extracted are:

First order histogram features:

1. Mean
2. Variance
3. Skewness
4. Kurtosis
5. Energy
6. Entropy

Second Order Co-Occurrence Matrix Based Features

7. Angular Second Moment
8. Correlation
9. Inertia
10. Absolute Value
11. Inverse Difference
12. Entropy
13. Maximum Probability

3.5 Classification

Classification is the next step after feature extraction and it is a supervised learning procedure. It involves two steps training and testing. During the training phase, the classifier is trained with features from training images. In testing phase, an unknown images features are given to the classifier and it has to classify the image as tumor affected or tumor not affected.
Support Vector Machine is used for the classification. SVM classifier is used to find a hyper plane which separates the data into two classes. SVM contains two classes namely tumor affected and tumor not affected as its output. During the training phase the SVM classifier is trained with a training dataset which contains feature vectors extracted from the training images and their respective class labels. During the testing phase if an unknown images feature vector is given as an input to the trained classifier, it classifies the test image as belonging to one of classes. Experiments are conducted with support vector machine classifier using quadratic kernel function. [9]

- polynomial: $(\gamma \langle x, x' \rangle + r)^d$. d is specified by keyword `degree`, r by `coef0`.

Chapter 4 Result

From the above implemented procedures it is observed that Particle Swarm Optimisation provides better results as compared to Whale Optimisation Algorithm. While WOA gives results quicker than PSO, but the overall quality of the results obtained are not up to the level of results obtained from PSO. WOA relies on a number of probabilistic variables and the results are uncertain.

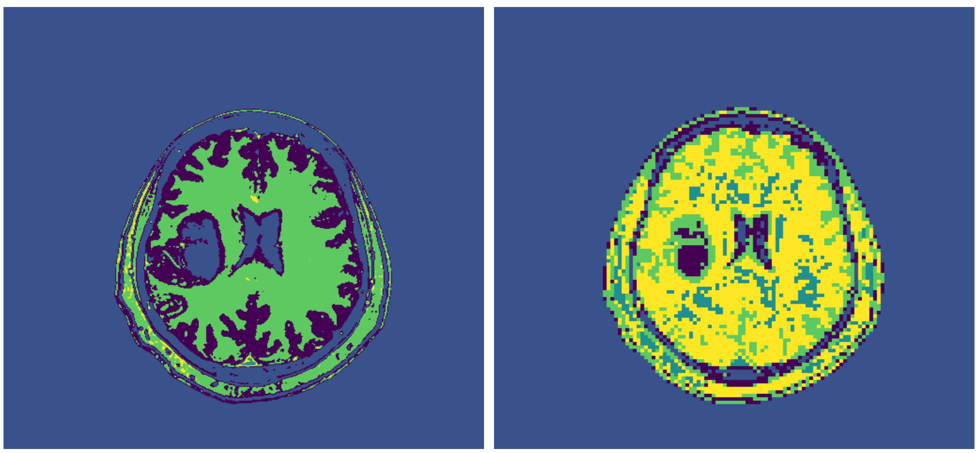

Fig:PSO and WOA

Sensitivity	97.18%
Specificity	0%
Accuracy	66.34%

Table 2: Results for WOA

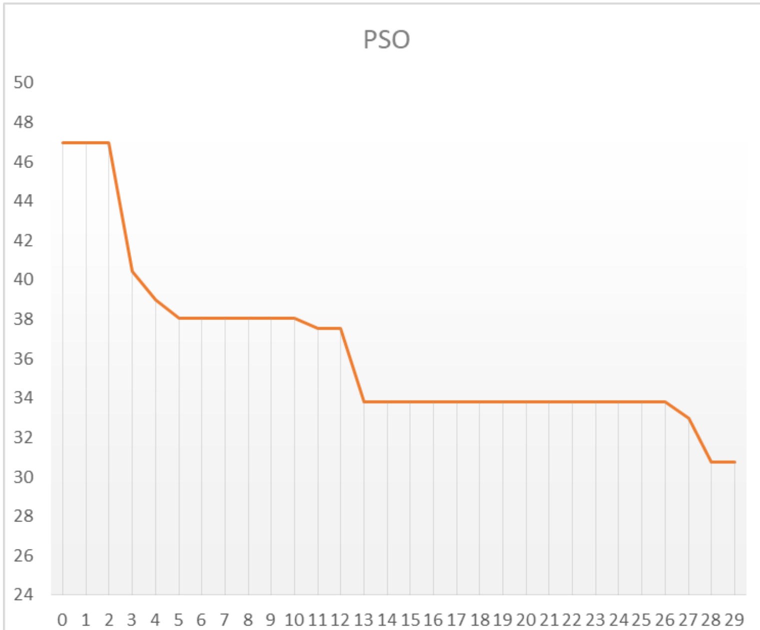

Fig:PSO (Fitness value vs Iteration)

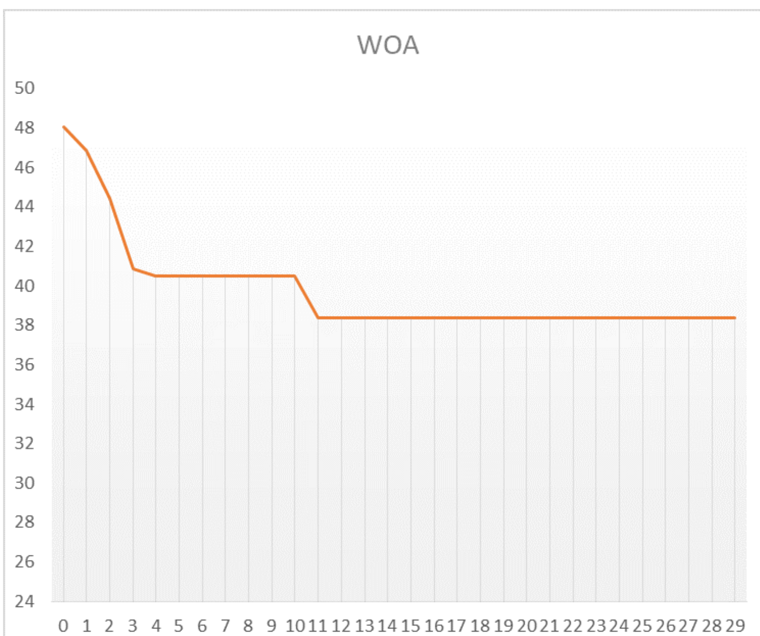

Fig:WOA (Fitness value vs Iteration)

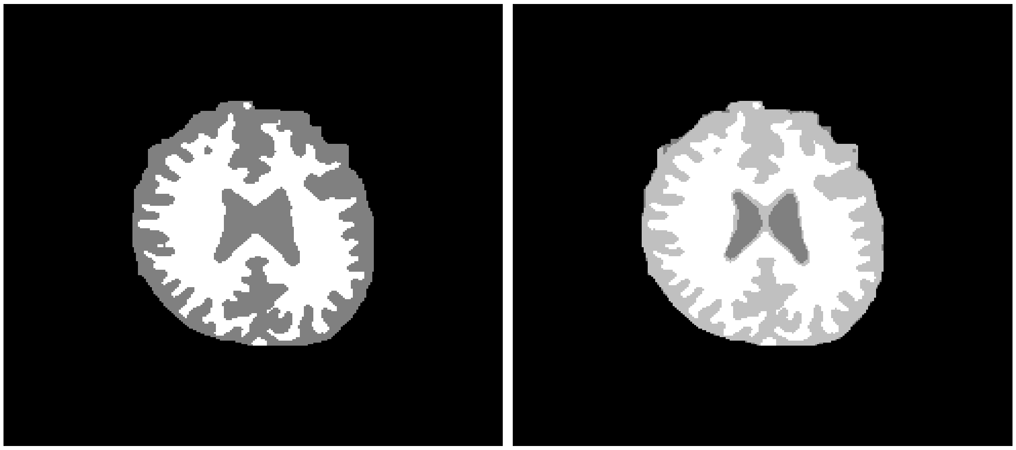

Fig: Segmentation of Non-Tumor MRI with WOA and PSO

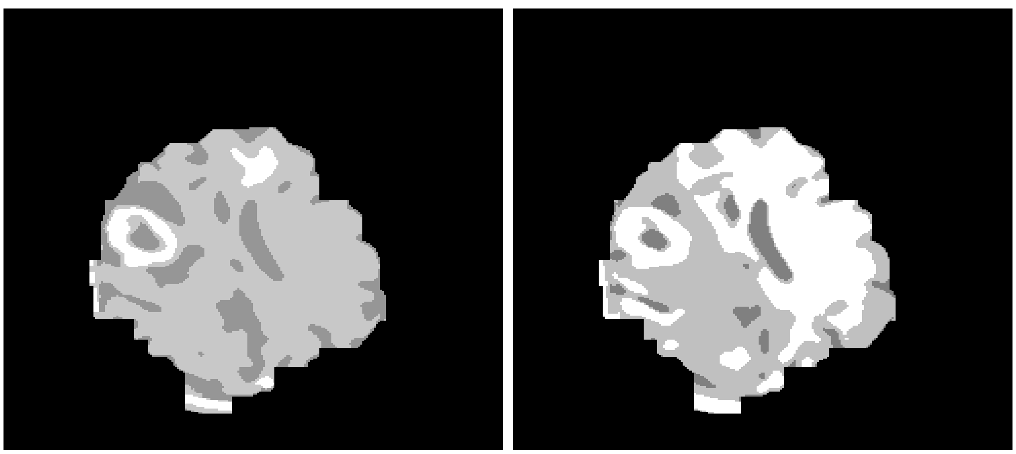

Fig: Segmentation of Tumor MRI with WOA and PSO

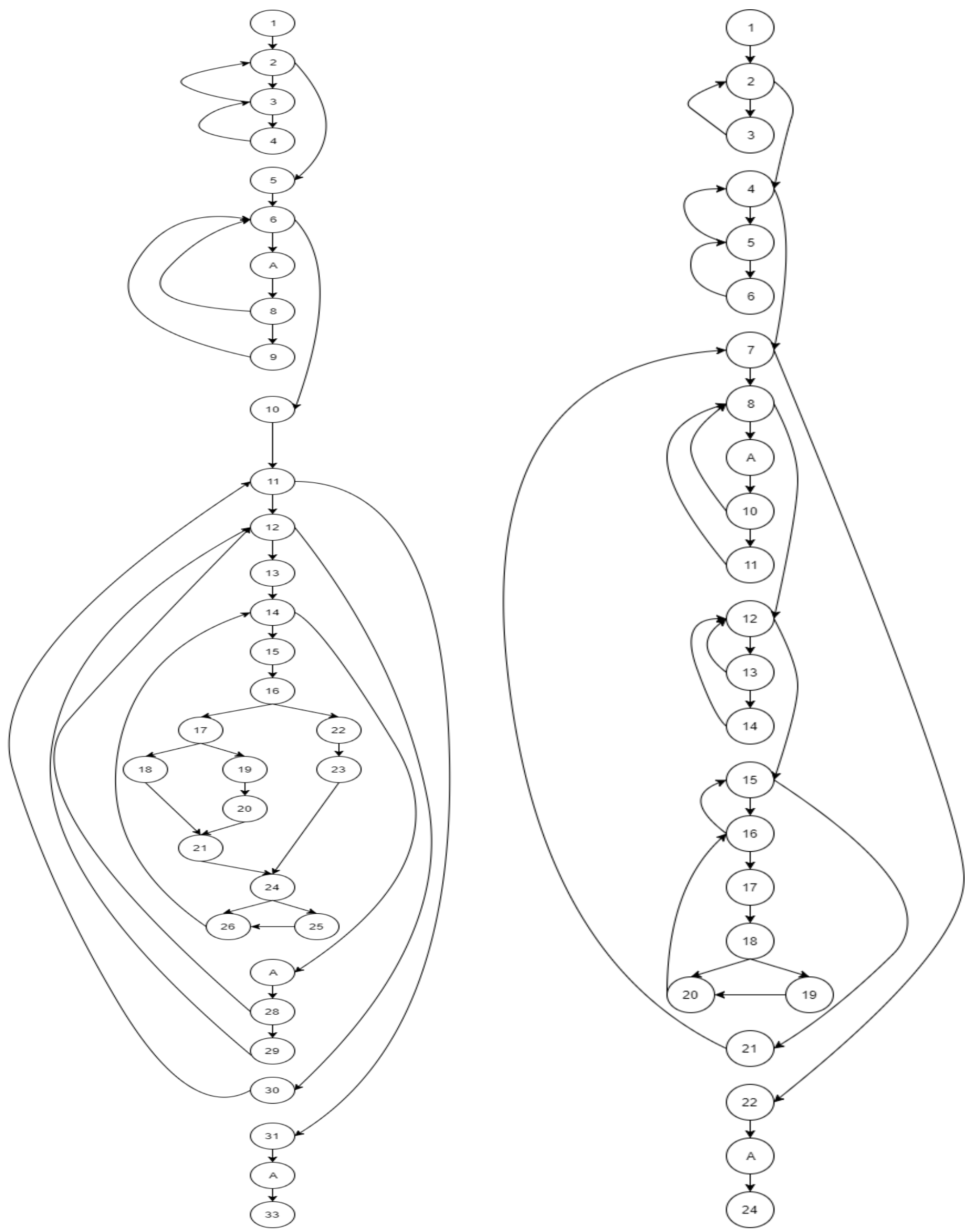

Fig: Decision to Decision graph of WOA and PSO

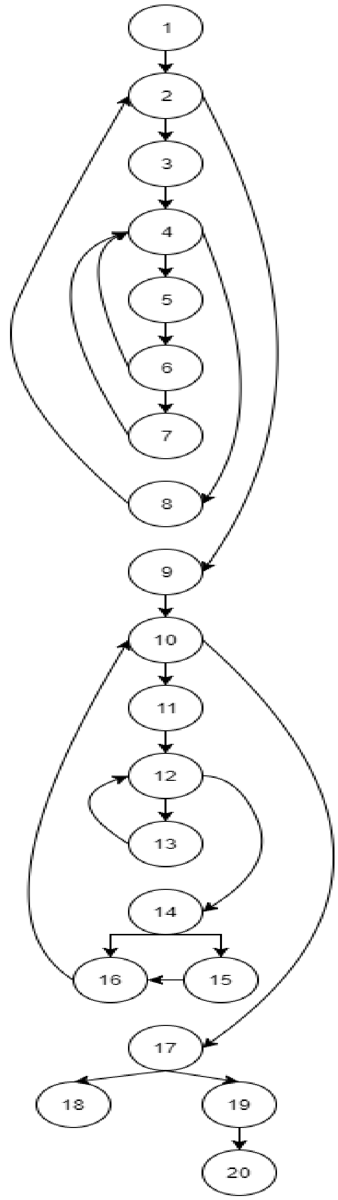

Fig: Decision to Decision graph of Fitness Function

Cyclomatic Complexity of Fitness Function:
No. of nodes = 20
No. of edges = 25
Complexity = E - N + 2P = 25 - 20 + 2 = 7

Cyclomatic Complexity of WOA Algorithm:
No. of nodes = 33
No. of edges = 43
Complexity = E - N + 2P = 43 - 33 + 2 + 3*(1+7-2) = 24
Cyclomatic Complexity of PSO Algorithm:
No. of nodes = 24
No .of edges = 34
Complexity = E - N + 2P = 34 - 24 + 2 + 2*(1+7-2) = 20

This research, if published, will contribute to further research in this field for other researchers and for us as well. We will continue our search for better algorithm for brain tumour detection process as it will be a help to many doctors and patients.

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