FUZZY IMAGE SEGMENTATION USING ANT COLONY OPTIMIZATION

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CERTIFICATE

This is to certify that **Sonam Arora (2k13/ISY/23)** has carried out the major project titled "**Fuzzy Image Segmentation using Ant Colony Optimization**" in partial fulfilment of the requirements for the award of Master of Technology degree in Information Systems by **Delhi Technological University**.

The major project is bonafide piece of work carried out and completed under my supervision and guidance during the academic session 2013-2015. To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any degree or diploma.

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ABSTRACT

Segmentation plays a vital role in medical image processing. Effective segmentation is necessary for structural analysis of an organ, diagnosis and detection of certain abnormalities. Magnetic Resonance Imaging (MRI) is an advanced technique used in field of medical imaging. Manual image segmentation is very tedious and time consuming. Also results of manual segmentation are subjected to errors due to huge and varying data. Therefore, automated segmentation systems are gaining enormous importance nowadays. This study presents an automated system for segmentation of brain tissues from brain MRI images. Segmentation of three main brain tissues is carried out namely white matter, gray matter and cerebrospinal fluid. In this work, we performed the initialization step for fuzzy C-means clustering algorithm using Ant Colony Optimization. Clustering results are often dependent upon the initial solution. ACO is a meta-heuristic approach inspired by the intelligent behaviour of real ants which provides close to optimal solution avoiding any trap in local minima. Spatial information is also considered in segmenting brain tissues as grouping of pixels into different clusters is influenced by its local neighbourhood. Also Mahalanobis distance metric is used instead of Euclidean distance metric in clustering process to avoid any relative dependency upon the geometrical shapes of different clustering classes. The results of the system are evaluated and validated against the ground truth images for both real and simulated database.

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Chapter 1

INTRODUCTION

Image segmentation plays a vital role in different image processing techniques. Segmentation is the process of splitting an images into its constituent regions depending upon certain property or characteristics. Each pixel in a region is similar to another in certain aspect such as intensity, texture, color, etc. The basic goal of segmentation is to extract the meaningful information and make things easier to analyze and visualize.

The process of Segmentation has spread its roots into different domains such as medical imaging, face recognition, machine vision, expert system, automatic traffic control system, and also to deal with satellite images, etc. Medical Image segmentation is of great focus nowadays due to its various practical applications. In its application to brain MRI, difference purposes can be dealt such as extraction of small specific structures such as brain tumor, or some main tissues(WM , GM, CSF), [8-10] or partitioning the brain into anatomical structures, etc.[11] It is a very challenging task as medical images exhibit higher complexity due to presence of various artifacts such as presence of noise, intensity inhomogenity i.e. bias field and also partial volume effect may further add on to its complex nature.

1.1 BACKGROUND

Different image segmentation techniques have been proposed and been applied to numerous applications in real world [12]. We are basically concerned with soft clustering in which an object can belong to more than one cluster/class with varying degree of membership. The most commonly studied soft clustering algorithm is Fuzzy C-means which was introduced by Bezdek in 1981 [13]. This approach is simple to implement and performs clustering in an efficient way. But in presence of noise FCM doesn't copes up with the expected results. Since it takes into account random values in its initialization step and also no spatial information is considered in complete algorithm. Several works has been done to include spatial data/information [14-15]. Ahmed at el. [16] introduced FCM-S in which the objective function was changed to include information of gray levels but this approach was computationally expensive. Chen and Zhang [15] proposed another variant of FCM in which the neighbouring term for each data point is computed well in advance to avoid computational delays. Also the Euclidean measure is used in FCM to calculate the distance between data points and cluster centres. Euclidean distance always takes into account the data

points in spherical shape from the point being examined. It does not consider the correlation among the data points. The possibility of data point belonging to same cluster is not only dependent upon the distance but also on the direction. Mahalanobis distance introduced by P.C. Mhalanobis in 1936 considered both these issues. Kim and Krishnapuram [17] tried to show that mahalanobis distance cannot be directly applied to any of the clustering process. Kesel and Gustafson(GK)[18] used mahalanobis distance with fuzzy terminology i.e. introduction of fuzzy co-variance matrix was done in this work. Also meta-heuristic approaches are introduced to deal with NP-hard problems and the problems for which the data is uncertain and not readily available. These optimization techniques include Particle swarm optimization, Genetic Algorithms(GA) , Ant Colony Optimization. [19] Thomas A. Runkler showed the extension of simplified ant colony system to be compatible with FCM. Yucheng Kao and Kevin Cheng [20] introduced ACOA in which array based graph is constructed and ants are moved randomly to from the solution set.

1.2 MOTIVATION

Medical Resonance Imaging(MRI) is an advanced technique being used in field of medical imaging as it provides abundant information regarding the anatomy of human soft tissues. MRI helps in diagnosis and evaluation of any abnormal change such as tumors, or any other focal lesions, in bodily parts and helps in early detection of diseases. MRI helps to achieve varying image contrast by making use of different pulse sequences and changing imaging parameters.

Manual segmentation of MRI images is very cumbersome as well as time consuming. It also involves variability depending upon the individual examining the results. It may vary from one observer to another and also within same individual/observer. Though manual segmentation by an expertise has proven to be of superior quality but automated methods can be very advantageous to deal with such variations and to handle large data. So there is a need to develop appropriate automated or semi-automated system to perform segmentation of medical images as per the requirement.

1.3 GOAL OF MASTER THESIS

Our focus is to segment brain MRI images into different tissue classes, namely white matter, cerebrospinal fluid and gray matter. Dealing with some of the image declension elements such as random noise during acquisition, bias field, partial volume effect is very tedious and

challenging. In this work Medical Image segmentation is performed using modified Fuzzy C-means clustering approach. Ant colony optimization is used to get initial values of cluster centres to avoid any local optimal results. Mahalanobis distance is used instead of Euclidean distance as data points may not be distributed every time in a spherical manner about the centre of mass. This algorithm is applied on medical image segmentation which usually contains some random noise. Therefore, spatial information is also included i.e. during clustering process local neighbourhood information is also considered. The results are compared with fcm as it doesn't perform effectively in case of noise.

1.4 THESIS ORGANIZATION

Chapter two gives the detail of the previously done work in this field and also the description of the segmentation techniques. This chapter also covers details about medical imaging and brain structure.

Chapter three presents the proposed work. The approach used for segmentation of brain tissues in MRI images is covered here. Also the applicability of ACO in segmenting an image to get global optimal results is shown.

Chapter four presents the results of our current approach and validate the results against ground truth. Comparison with FCM and discussion is also shown.

Chapter five concludes the thesis and further ideas for future work has been presented.

Chapter 2

LITERATURE REVIEW

2.1 DIFFERENT IMAGE SEGMENTATION TECHNIQUES

Image segmentation approaches can be broadly grouped into two classes:

1. Based on similarity

2. Based on Discontinuity [1]

In similarity based segmentation, the image is partitioned into several regions, each region having similar characteristics based on certain predefined criteria. The techniques in similarity based approach includes clustering, region growing, thresholding.

In discontinuity based segmentation, the image is grouped/partitioned on the basis of abrupt/sudden change in the intensity. The technique in similarity based approach includes edge detection.

2.1.1 Edge detection based segmentation:

In edge based segmentation, the result of segmentation is in form of edges/boundaries between different regions. Edges are formed where there is sharp and significant change in the pixel intensity. [1] A variety of edge operators can be used for edge detection. Some of the popular ones are Prewitt, Sobel, Canny, LoG (Laplacian-of-Gaussian), etc. This technique works well on images having good contrast between different regions. Some of its drawbacks include inadequate detection of areas with low contrast boundaries, inadequate detection of thin areas, etc.

2.1.2 Thresholding based segmentation

In this technique, a threshold value is selected and an image pixels having value less the threshold is grouped into one region and image pixels having values greater than and equal to threshold into another.[5] Various thresholding methods include global thresholding (GT), local thresholding (LT), adaptive thresholding (AT), etc. This method is very fast, simple and of course easy to implement. It is an effective and efficient approach for segmenting an image having light object and dark background or vice versa. Threshold can selection can either be done manually or automated threshold selection algorithms can be used.

2.1.3 Region based segmentation

It is further classified into:

Region growing: The process [4] starts with selecting a pixel(seed) or group of pixels. Subsequently, based on some predefined criteria neighbouring pixels that exhibit similar property are added to the region. This process is continued until no more pixels can be appended to the growing region. This process helps in getting the connected region that have certain structure of interest.

Region splitting and merging: This process [2] starts with few initial segmentation and then sub-dividing the regions that do not satisfy the predefined criteria. This is region splitting. This splitting of regions is further accompanied with region merging to add up the advantages of both the approaches.

2.1.4 Clustering based segmentation

Clustering is basically unsupervised learning scheme in which we need to find out the number of clusters to group the pixels of an image into those clusters. Based upon some similarity criteria, similar pixels are appended to a particular cluster.[6] The basic goal is to maximize the intra cluster similarity and to minimize the inter cluster similarity. Clustering is of two types- one is hard clustering and another is soft clustering. Clustering based approaches yields better results and are very efficient.

2.2 APPLICATION OF IMAGE SEGMENTATION IN MEDICAL IMAGING

Appropriate segmentation of medical images is very much necessary in planning radiotherapy. Various radiographic techniques are being used nowadays for diagnosis, planning various treatments, and in clinical studies aswell. These techniques include Computed Topography (CT), Magnetic Resonance Imaging(MRI), etc. Semi automated system assist the experts in examining the huge data and presents results easily and in less time. Need for medical image segmentation [1] can be summarised into following :

- To determine the anatomical structures of various bodily parts

- Diagnosing the abnormality and treatment planning

- Study of soft tissues of body

- Classification of main tissues of brain such as white matter, csf, gray matter

- Registration of 2D and 3D imaging data acquired at different times for further analysis

- To locate several abnormalities such as tumor in brain

- Helps in computer assisted surgery

-Measuring and correcting tissue volumes

2.3 MEDICAL BACKGROUND

2.3.1 Brain Anatomy

Brain is one of the most tangled organ in human body. It is our brain that controls our thoughts, memory, speech, and functions of various other organs in our body, etc. Brain anatomical structure can be classified by different means. In this section the brain anatomical structure and details of different tissues of the brain will be covered.

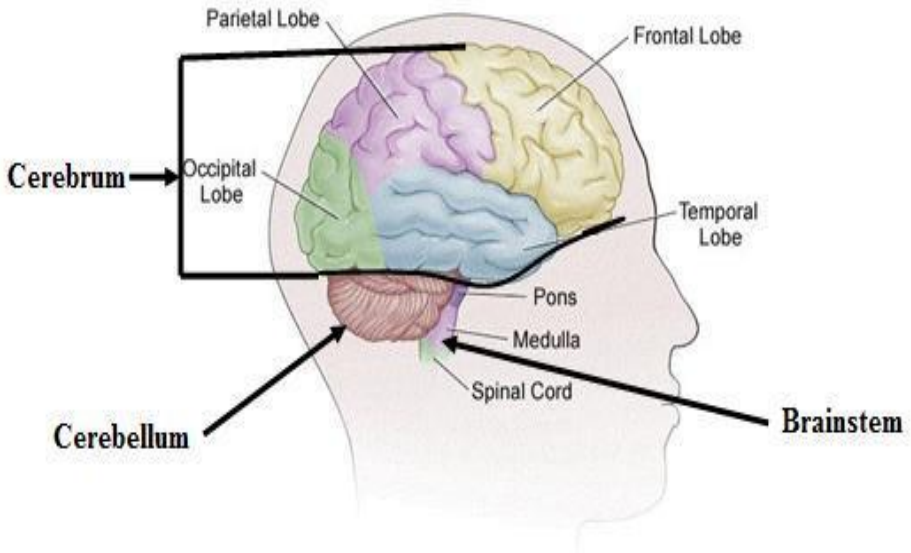


Fig 2.1. Human Brain Structure/Anatomy

Brain structure is comprised of Brainstem, Cerebellum, Cerebrum as shown in figure 1. 4 [3] Cerebrum is the largest and the major portion of the brain. It is subdivided into left and right cerebral hemispheres. This part of the brain controls and manages the conscious thoughts of brain, sensations, movement of human body, etc. Another important part of human brain is cerebellum which is located at the back of brain. Its function is to tune or

synchronise motor activity or we can say movement such as balancing, walking, etc. Brainstem is located at the lower bottom of the brain and in connection with spinal cord. Its function is to control reflexes, eye movement, passing messages to various parts of the body back and forth, etc.

2.3.2 Magnetic Resonance Imaging

MRI is very advanced and most famous medical imaging technique providing ample amount of information regarding human bodily soft tissues, bones, other organs, etc. It is basically used in detecting the abnormalities of body structure and determining the grimness of the disease. MRI uses strong magnetic fields and radio frequency waves to capture the images for further analysis and to diagnose any structural abnormality. MR images can be captured easily and they provide good contrast in images depending upon the way it is captured i.e. the parameters that were set during image acquisition.

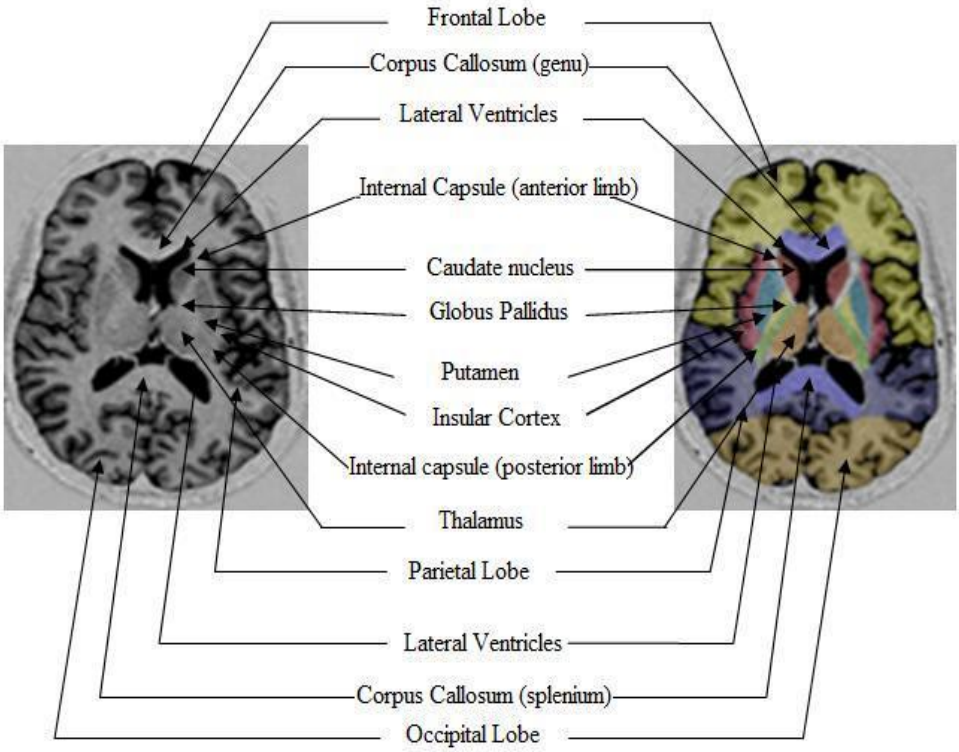


Fig 2.2. Human brain Magnetic Resonance Imaging(MRI) labelling

The amount of data acquired in MRI is so vast that it becomes difficult to handle and to analyse. Therefore, we need a semi-automated or fully automated system to overcome such

issues. MRI images can be segmented differently to solve different purpose. One of its purpose includes segmenting MRI image into different tissue classes. The main tissue classes are white matter(WM), gray matter(GM), Cerebrospinal fluid (CSF). [3]

Different techniques can be adopted in acquisition of MRI image. According to Pham *et al.* the properties and requirements of segmentation should be well known beforehand so as to make a well firmed decision. The density of tissues and its relaxation properties contributes to contrast in an image. The most common and maximum used weightings are T1 and T2.[7] Selection of appropriate one as per the demand of the problem is very crucial and an important step.

T1-weighted Images (T1W1)

T1 images exhibits higher contrast among WM and GM. T1 is the time till when X percent (X=63) of the longitudinal magnetization has been restored/recovered. In these types of images gray matter appears dark gray, white matter appears light gray, while some tissues possess low intensity such as CSF and some possess high intensity such as adipose tissue.

T2-weighted Images (T2W1)

T2 images possess higher contrast between CSF and bone. T2 is the time till when X percent (X=63) of the transverse magnetization has been diminished/decayed. In these types of images both white and gray matter are gray in color i.e. they possess similar intensities.

Dominance of MRI over other techniques:

- undergoes scanning easily without any pain
- provides the detail information of different body structures as well as body tissues
- It ensures better localization for particular lesion in a 3D structure of brain image.
- It do not make use of any ionizing radiations unlike other techniques and hence is suitable for capturing MRI images of children or pregnant women.
- The contrast agent used in MRI scanning is found to be less allergic unlike iodine type used in CT scanning.

Though MRI scanning is very advantageous, it has some negative side too which includes the following:

- The procedure is quite lengthy and person needs to stay still for that duration

- MRI scanners are very costly and hence are not found very easily
- Can't be carried out in presence of metallic bodies as magnetic field is generated during the process.

2.4 ANT COLONY OPTIMIZATION

Ant Colony Optimization (ACO) technique is influenced by the behaviour of ants in real life scenario. It is basically used in cases when the problem statement belongs to NP-hard class. [21] ACO is the probabilistic approach which focuses on providing solution to discrete optimization based difficult problems.[22]

In real world, ant locomote from one place to another in search of food.These ants are almost blind. They are generally influenced by the movement of other ants and try to find the shortest route to destination. The shortest path is ascertained by the pheromone trail deposited on that path by any of the ant. The more is the pheromone deposition on the path, the more is the chance/probability of that path being chosen. ACO tries to find out the optimal or close to optimal solution. It's solution might take time to converge but convergence is guaranteed.

ACO was firstly used for solving travelling salesman problem (TSP). To solve a new problem by using ACO, we try to find out whether that problem can be think of or mapped in travelling salesman problem or not.

Overview of ACO implementation :

-Parameter setting: Initialize pheromone matrix and other required data.

-DO While some defined stopping criteria is not met (Outer/cycle loop)

-Do Until every ant completes a move/tour (Inner/tour loop)

- Update the pheromone/trail locally

-End Do (Inner)

- Analyze the solution and trail
- Update the pheromone globally
- Get the best solution

-End Do (Outer)

Movement of ants from one node to another is dependent upon the probability of choosing that path. The higher the probability, the more likely is the path to be selected. The movement of an ant from node i to node j is judged by the following probabilistic equation:

$$p_{i,j} = (\tau_{i,j}{}^{\alpha})(\eta_{i,j}{}^{\beta}) \Big/ \left(\sum_{\Omega \in allowed} (\tau_{i,j})(\eta_{i,j}) \right)$$

Where,

$\tau_{i,j}$ denotes the amount of pheromone/trail laid by an ant on edge (i,j)

$\eta_{i,j}$ denotes the amount of heuristic matrix whose value is typically 1/d(i,j)

α regulates the impact of $\tau_{i,j}$

β regulates the impact of $\eta_{i,j}$

Pheromone Update

Updation in pheromone is done according to the equation:

$$\tau_{i,j} = (1 - \rho) * \tau_{i,j} + \Delta \tau_{i,j}$$

Where,

ρ is the rate of evaporation of pheromone

$$\Delta \tau_{i,j}{}^{k} = \begin{cases} 1/L_k, & \text{if } k^{th} \text{ ant travels/covers edge (i,j)} \\ 0, & \text{otherwise} \end{cases}$$

Where L_k denotes the length of the k^{th} ant travel/tour

2.5 FUZZY C-MEANS CLUSTERING

Clustering focuses on grouping the objects that exhibit similar properties/ characteristics into one cluster or group.[19] The objects belonging to other groups differ in certain aspects. There are various clustering algorithms that try to find out the interesting patterns for the data points. Grouping of data points is done based upon fulfilment of some similarity measure. Different measures can be used to solve the purpose of clustering such as distance, intensity, connectivity, etc. Clustering can be of two types: Hard clustering and Soft clustering.

In hard clustering, each data point/object is assigned to one and only one cluster. In soft clustering, each data point can be assigned to more than one cluster depending upon its membership value or belongingness to that cluster.

FCM [13] is a soft clustering algorithm developed by Dunn in 1973 and improved by Bezdek in 1981.

2.5.1 Algorithmic steps followed in fuzzy c-means clustering:

Given the set of data points say $X=\{x_1,x_2 .... x_n\}$

Step1: Define the number of clusters, say c. Select 'c' cluster centres randomly such that $V= \{v_1,v_2 .... v_n\}$ be the set of cluster centres.

Step2: Calculate the fuzzy membership matrix using the below mentioned formula

$$u_{i,j} = 1 / \sum_{k=1}^{c} d(i,j) / d(i,k)^{(2/m-1)}$$

Step3: Calculate and update the centres v_j using:

$$v_j = (\sum_{i=1}^{n} (u_{i,j})^m x_i) / (\sum_{i=1}^{n} (u_{i,j})^m), \forall j = 1,2...c$$

Step4: Repeat step2 and step3 until maximum iteration is reached or until $||U^{(k+1)} - U^{(k)}|| < \varepsilon$

Where,

$\boldsymbol{U} = [\boldsymbol{u}_{i.j}]_{n*c}$ is the membership matrix or fuzzy partition matrix

ε is the termination criteria/value whose value lies between [0, 1]

Advantages:

- As opposed to K-means algorithm in which each data point can belong to only one cluster, FCM permits data belongingness to more than one cluster i.e. data point may be assigned to more than one cluster depending upon its membership of being into that cluster.
- FCM provides very good results for the set of overlapped data points.

Disadvantages:

- Euclidean distance is subject to various limitations
- Number of clusters are to specified beforehand
- Results are better with lower value of ε but on expense of number of iterations

Chapter 3

PROPOSED APPROACH

In this work, an automatic framework for segmentation of brain tissue classes namely, white matter, gray matter and cerebrospinal fluid has been proposed. The brain MRI images are used for the purpose of segmenting these tissues. The results of segmentation are often dependent upon the initialization step. MRI images are often subjected to some random noise. Segmentation algorithm such as FCM is very sensitive to noise. To avoid any stuck in local optimal results, Ant Colony Optimization technique is used. ACO is used to determine the value of initial cluster centres. The centres thus obtained are fed into the system to perform segmentation. Modified Fuzzy C-means clustering approach is used to segment an image into WM, GM and CSF. In modified FCM, Mahalanobis distance is used instead of Euclidean distance as Euclidean distance takes into account only the super spherical shapes about the centre of mass for clustering the data points. Whereas, data points belonging to same cluster may not be located in that area only. Also the local neighbourhood information is also considered as neighbouring pixels are more likely to belong to same cluster.

3.1 INITIALIZATION STEP USING ANT COLONY OPTIMIZATION

ACO is the probabilistic based optimization technique inspired by the behaviour of ants in this real world. Various optimization problems can be reduced to finding the shortest path from source/nest to destination/food source depending upon the pheromone concentration on that path. In case of noisy problems,[19] Fuzzy c-means clustering algorithm can easily get stuck into local optimal solution as FCM is very sensitive to noise. One can run the algorithm many a times with different initial values each time to get the best solution by comparing the results each time with the best solution.[27] But this process is very cumbersome. Therefore, meta-heuristic approach can be used to solve this problem [21]. Meta-heuristic optimization techniques can be used to solve the problems when the available data is incomplete, noisy or uncertain. Main purpose of using Ant Colony Optimization technique is to get the global optimal solutions without getting trapped in local optimal results.

In the proposed approach, Ant Colony Optimization technique is mapped to our problem of segmentation of brain tissues. Basically, ACO is used to obtain the initial values of clusters required for segmenting the brain MRI images.

TABLE 3.1

Parameters values used in ACO initialization

Parameters	Values
$\alpha = \beta$	1.5
total_NumberOfAnts	10
Max_iteration	150
Rho (ρ)	0.1

3.1.1 Algorithm for initialization using ACO (ACO-FCM)

Requirements: Fix the number of clusters, initialize all the parameters mentioned in Table 1

Step1: Input data matrix/image say $X=\{x_1, x_2 \ldots x_n\}$ where n is the total number of pixels in an image.

Step2: Calculate another matrix X' of same dimension as X, such that value of each pixel in X' is the mean value of 4*4 neighbourhood of corresponding pixel in X

Step3: for iter =1 to max_iteration do

Step4: for ants=1 to total_NumberOfAnts do

Step5: Randomly initialize cluster centre values for all clusters 'c'

Step6: Calculate the heuristic matrix η, where η=1/D (D is the distance of pixels from all cluster centres)

Step7: Find the probability of belongingness of each pixel to a particular cluster using the formula:

$$p_{i,j} = (\tau_{i,j}{}^{\alpha})(\eta_{i,j}{}^{\beta}) \Big/ \left(\sum_{\Omega \in allowed} (\tau_{i,j})(\eta_{i,j}) \right)$$

Step8: Based on the indexing of each pixel into different clusters calculated using above probability, cluster centres are then updated using the formula:

$$v_j = (\sum_{i \subseteq S} (u_{i,j})^m x_i + \alpha * x'_i) / (\sum_{i \subseteq S} (1+\alpha) * (u_{i,j})^m), \forall j = 1, 2 \ldots nc$$

Where, S is the set of pixels having similar index i.e. cluster numbers

Step9: Calculate the Euclidean distance using the updated cluster centres.

Step10: Calculate the objective function using the above calculated distance:

$$J = \sum_{i=1}^{n} \sum_{j=1}^{c} (u_{i,j})^m d^2(x_i, c_j) + \alpha \sum_{i=1}^{n} \sum_{j=1}^{c} (u_{i,j})^m d^2(x'_i, c_j)$$

Step11: Compare the value of objective function with the best fitness. Our goal is to minimize the fitness function. Update best fitness, best centres and corresponding index for each pixel of an image

Step11: END for (Loop at Step4)

Step12: Calculate the distance using the best centres after each iteration

Step13: Update the membership matrix using the updated distance as

$$u_{i,j} = (d^2(x_i, c_j) + \alpha d^2(x'_i, c_j))^{(1/m-1)} / \sum_{k=1}^{nc} (d^2(x_i, c_k) + \alpha d^2(x'_i, c_k))^{(1/m-1)}$$

Step14: Calculate the best index of each pixel using the best solution obtained after each iteration

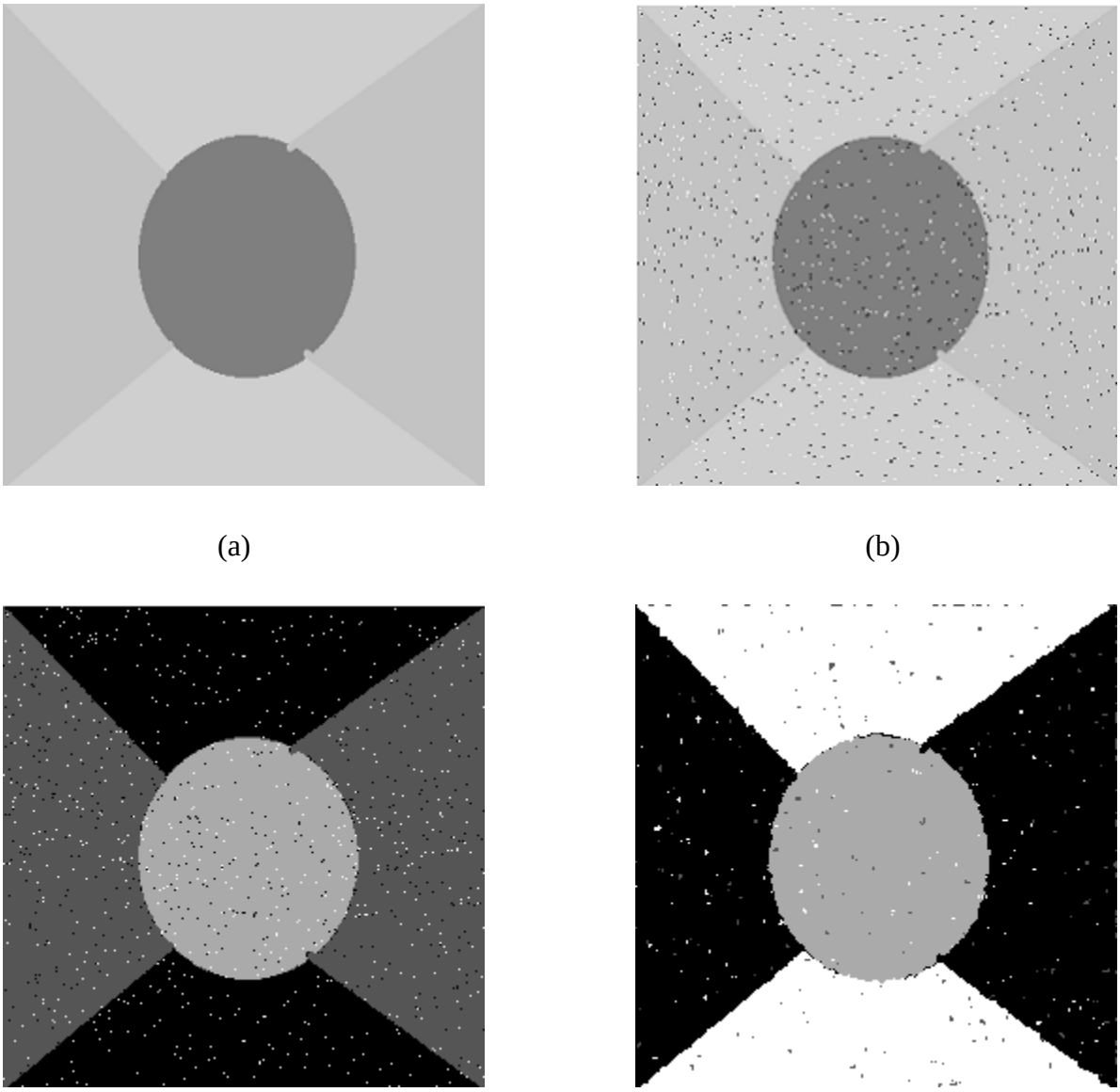
Step15: Update the pheromone matrix using the best indexes obtained in previous step:

$$\tau_{i,j} = (1 - \rho) * \tau_{i,j} + \Delta \tau_{i,j}$$

$\Delta \tau_{i,j}$ equals to 1/distance corresponding to same location where updation of pheromone is being done

Step16: END for (Loop for max_iteration Step3)

Step17: Return the best centres obtained and membership matrix corresponding to those best centres.



(a) (b)

(c) (d)

Fig. 3.1 (a) Original image (synthetic), (b) image corrupted with salt and pepper noise (level 0.02), (c) result of segmentation using FCM with random initialization, (d) result of segmentation using FCM with ACO based initialization

Simply running FCM for a noisy image doesn't make any difference in segmentation result. Resultant image does not show any reduction in noise thus quality of segmentation is degraded. Using ACO based initialization rather than random initialization, significant

improvement can be noticed in segmented image. Reduction in noise and better segmentation quality can be observed.

3.2 CLUSTERING ALGORITHM

3.2.1 Mahalanobis Distance

Unlike Euclidean distance, Mahalanobis distance takes into consideration the co-relation among data points or data sets. P.C. Mahalanobis introduced this distance in 1936.[26] It gives the measurement of distance of a data point say M and a distribution say D. It is also defined as the distance of the test point p from the centre of mass q divided by the width of ellipsoid measured in the direction of test point.

$$D(p,q) = \sqrt{(p-q)^T C^{-1} (p-q)}$$

Where, C is the covariance matrix of vector P

When the data points are distributed or spread in a non-spherical manner, then the possibility of data point belonging to a particular cluster or set is not only dependent upon the distance of data point from the centre of mass or we can say the average of sample points but it is also dependent upon the direction of the data point in consideration. Data point must be closer in shorter axis of ellipse and farter in longer/major axis of ellipse. This state can be formulated by defining the covariance matrix of the sample data points.

Firstly we try to frame out the covariance matrix of sample points belonging to each class. Then distance of given test point is calculated from all N classes. The test point is classified to a particular cluster for which the distance is minimal. The mahalanobis distance involving fuzzy logic is described by G&K[18] and is given as:

$$d^2(x_j, c_i) = (x_j - c_i)^T C_i (x_j - c_i)$$

$$C_i = |\sum_i|^{1/p} \sum_i$$

$$\sum_i = \sum_{j=1}^{N} \sum_{i=1}^{nc} u_{i,j}{}^m (x_j - c_i)(x_j - c_i)^T \Big/ \sum_{j=1}^{N} \sum_{i=1}^{nc} u_{i,j}{}^m$$

3.2.2 Spatial information for clustering

As we know that MRI images are subjected to random noise during its acquisition. It sometimes becomes difficult to view its anatomy or analyze the brain main tissues in the presence of noise in an image. FCM converges to local solution in case of noise. So, performing clustering of data points using FCM will not be effective. As FCM does not takes into account the spatial information of the data points to be clustered. The pixels surrounding the particular pixel are more likely to be segmented into same class. Therefore, we include the information of 4*4 neighbouring pixels surrounding the pixel being examined for clustering. This spatial information is the average of the neighbouring pixels in the defined window and is included in the process of clustering or assigning labels to pixels [16].

3.2.3 Clustering Algorithm

Requirements: Cluster centres and membership matrix returned by algorithm1, total number of iterations (max_iter=100), error (10^{-6})

Step1: for ij=1:max_iter

Step2: Calculate the mahalanobis distance using the equation

Step3: Update the membership degree/matrix using the equation given below:

$$u_{i,j} = (d^2(x_i, c_j) + \alpha d^2(x_i^{'}, c_j))^{(1/m-1)} / \sum_{k=1}^{nc} (d^2(x_i, c_k) + \alpha d^2(x_i^{'}, c_k))^{(1/m-1)}$$

Step4: Update the cluster centres as:

$$v_j = (\sum_{i=1}^{N} (u_{i,j})^m x_i + \alpha * x^{'}_i) / (\sum_{i=1}^{N} (1+\alpha) * (u_{i,j})^m), \forall j = 1, 2 \ldots nc$$

Step5: If $||U^{(ij+1)}-U^{(ij)}||$ < error, then go to Step8

Step6: END If

Step7: END for (loop for maximum iteration)

Step8: Return U, perform clustering using degree of belongingness of each pixel in clusters.

Chapter 4

EXPERIMENTAL RESULTS

The following system configuration has been used while conducting the experiments:

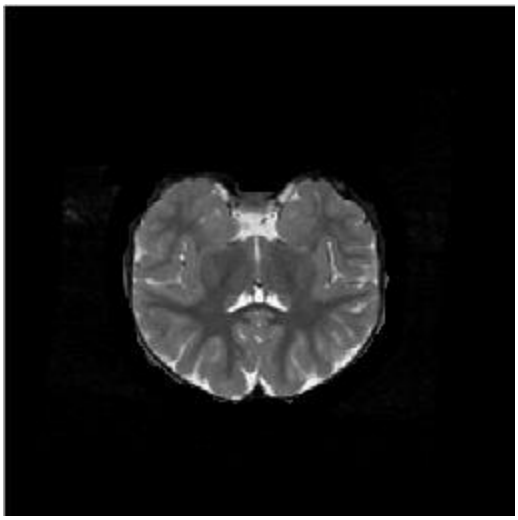
- Processor: Intel Core i3
- Clock Speed: 2.40 GHz
- Main Memory: 4 GB
- Hard Disk Capacity: 512 GB
- Software Used: MATLAB R2010a

The real time database of Brain MRI images has been taken from Insight Journal. Insight Journal is an Open Access on-line publication that covers domain of medical image processing and visualization. One of its journals is MIDAS. Midas community include National Alliance for medical image computing (NAMIC) which presents the data for two autistic and two normal children (male and female).[29] The data is re-collected after two years of time span. Three type of MRI scanning is presented i.e. T1 weighted, T2 weighted, PD weighted images. Coronal slices are obtained with slice thickness of 1.5mms. Also the tissue segmentation label map is presented with the database. This tissue label is atlas based segmentation by making use of expectation-maximization scheme. The quantitative analysis of MRI brain images is done in comparison with the ground truth images and is presented in Table 2. True positive gives the measure of the correctly classified pixels. Whereas False positive counts the total number of pixels that our system classifies but is not present in ground truth and True negative counts the total number of pixels that our system doesn't classifies but is present in the ground truth as belonging to particular cluster.

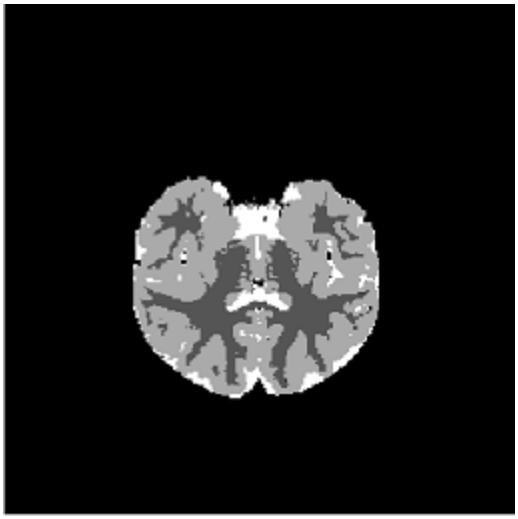
TABLE 4.1

Classification of pixels for ACO-FCM

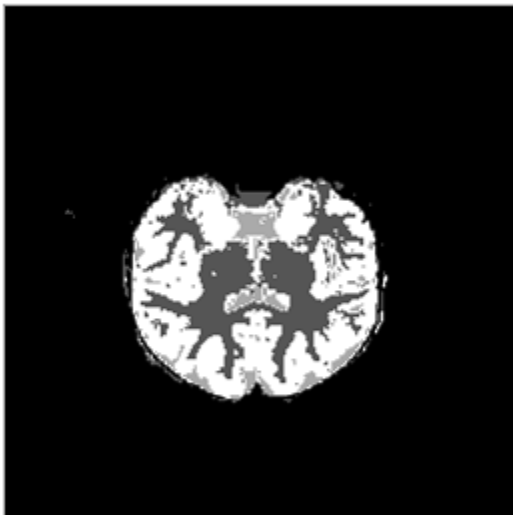
Patient #	**Ground True**	**True positive**	**False negative**	**False Positive**
Autistic Female slice100	34482	29779	4703	2172
Autistic Female slice140	33936	29829	4017	4449
Control Female slice80	33056	30733	2323	3581
Control Female slice114	28503	24764	3739	3946
Control Male slice110	33528	28973	4555	5197
Control Male slice67	39125	34822	4303	4442
Autistic Male slice70	30248	28660	1588	3036
Autistic Male slice160	10960	10183	777	809



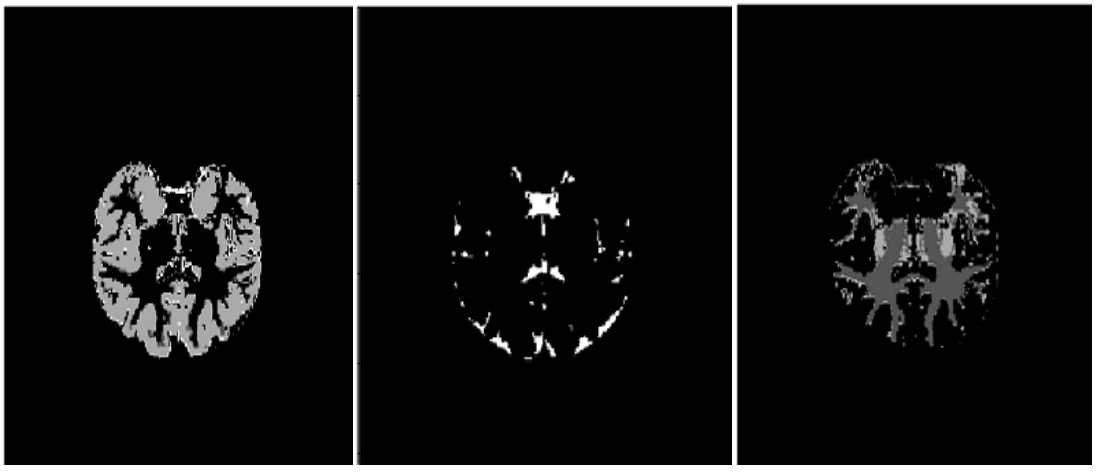
(a)



(b)

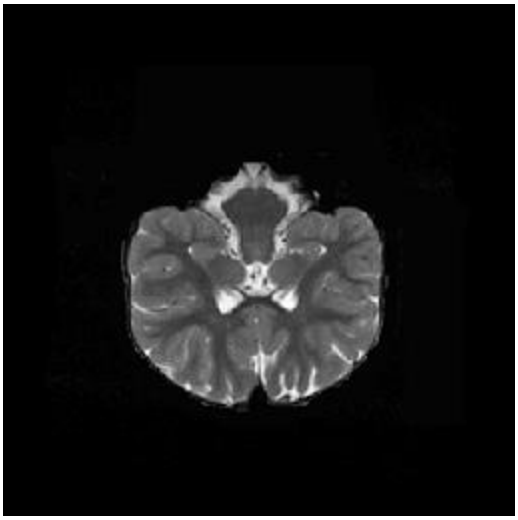


(c)

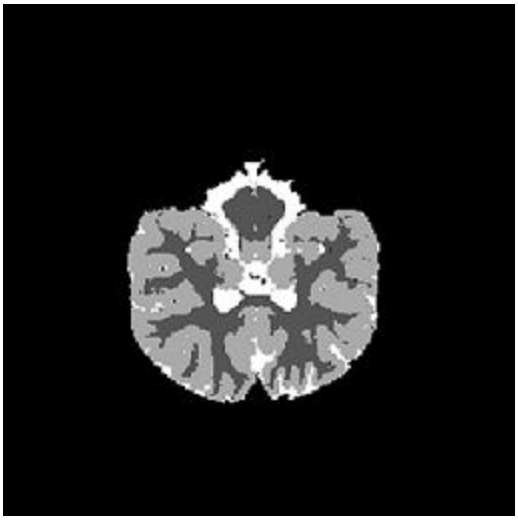


(d) (e) (f)

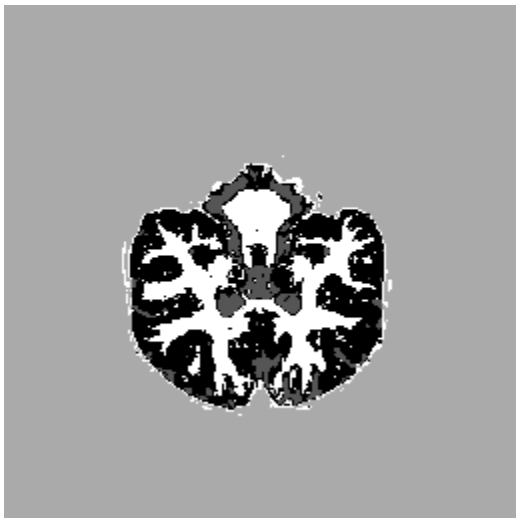
Fig 4.1 (a)Autistic Female T2weighted MRI(slice 100), (b)Ground truth, (c) Segmentation result, (d) Gray matter, (e) CSF, (f) White matter



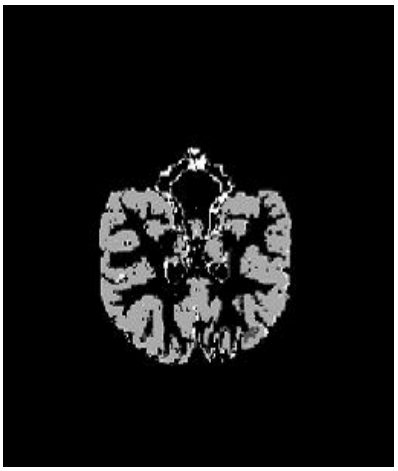
(a)



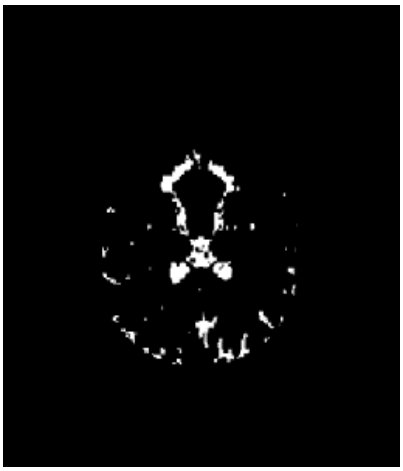
(b)



(c)



(d)



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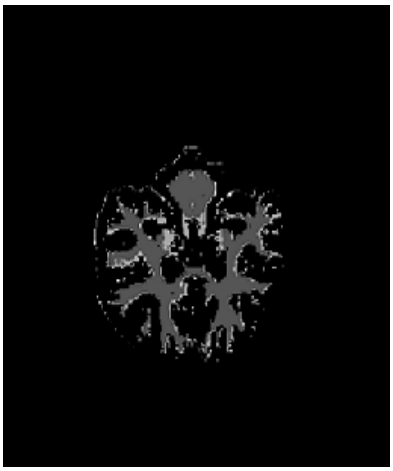
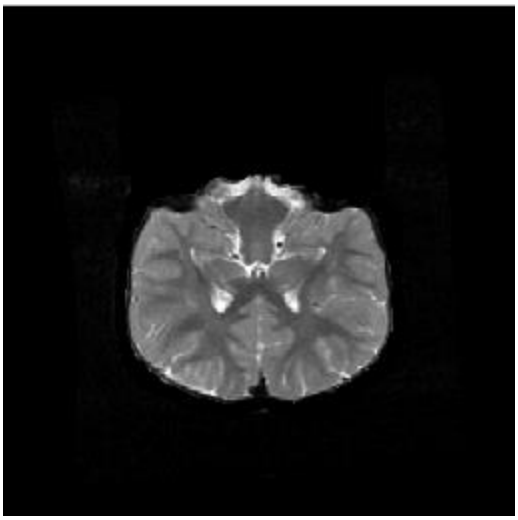
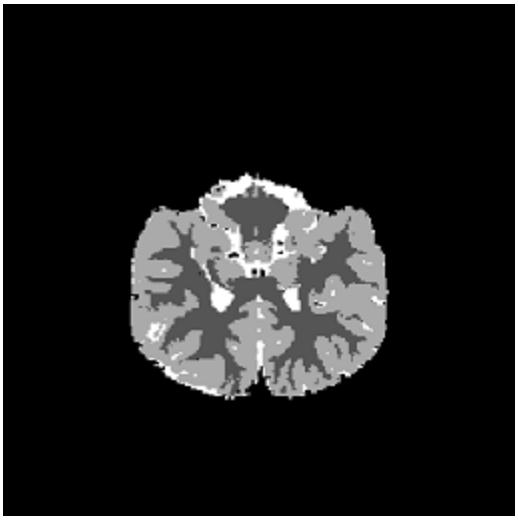


(f)

Fig 4.2 (a)Autistic Female T2weighted MRI(slice 140), (b)Ground truth, (c) Segmentation result, (d) Gray matter, (e) CSF, (f) White matter



(a)



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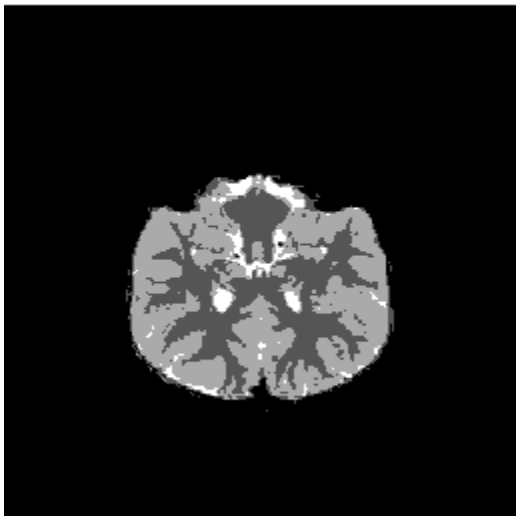
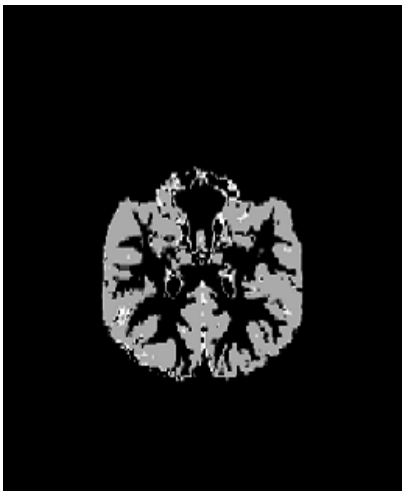
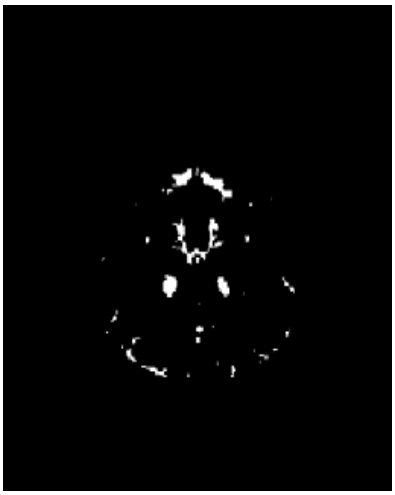
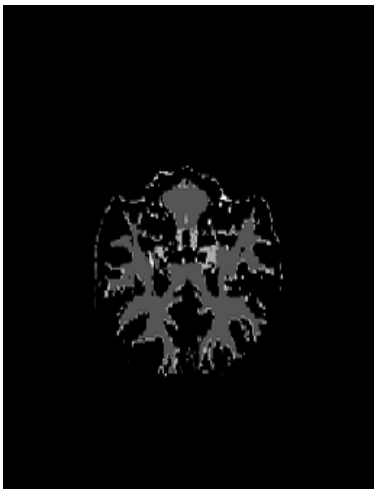


(c)







(d) (e) (f)

Fig 4.3 (a)Control Female T2weighted MRI(slice 80), (b)Ground truth, (c) Segmentation result, (d) Gray matter, (e) CSF, (f) White matter

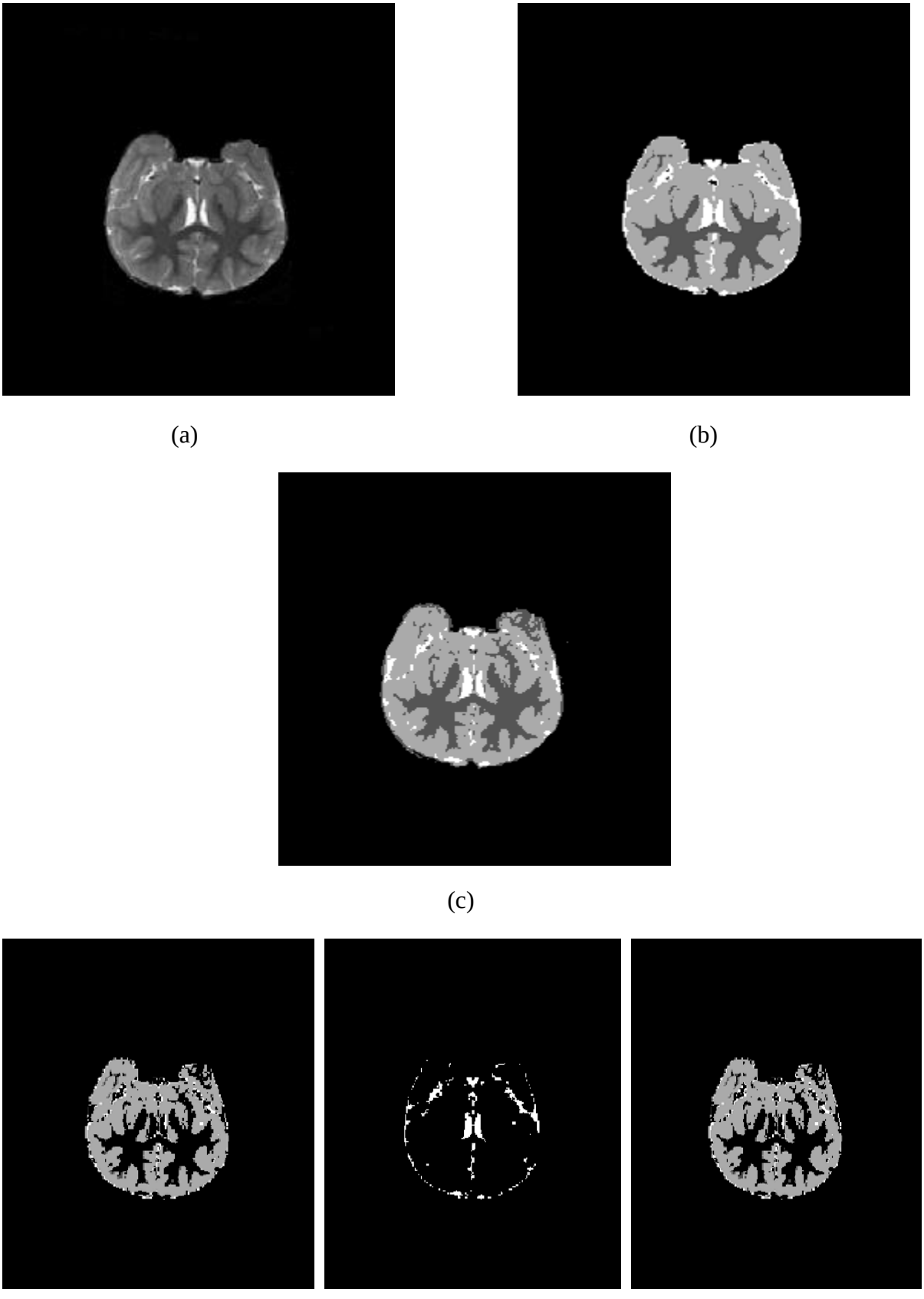
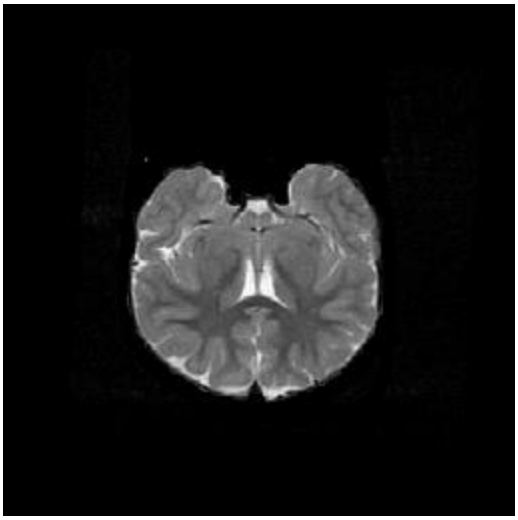
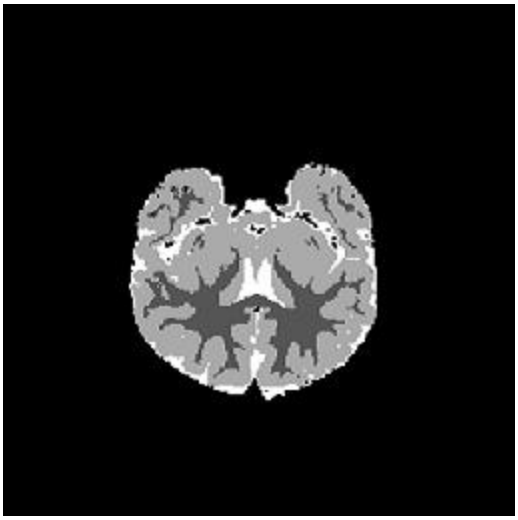


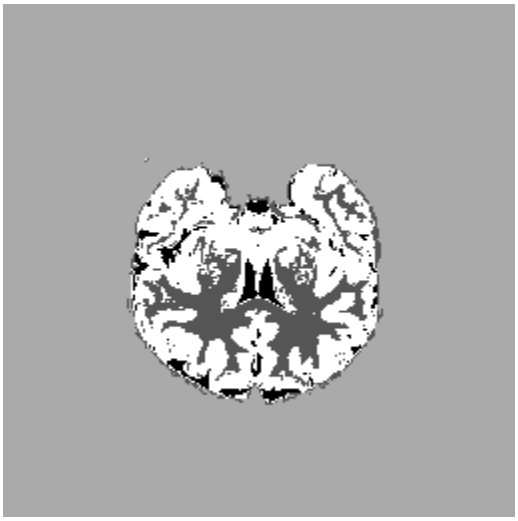
Fig 4.4 (a)Control Female T2weighted MRI(slice 114), (b)Ground truth, (c) Segmentation result, (d) Gray matter, (e) CSF, (f) White matter



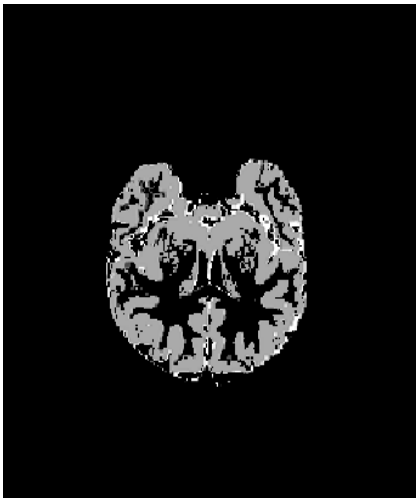
(a)



(b)



(d)



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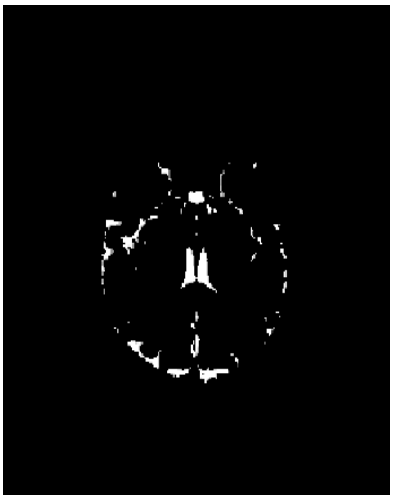
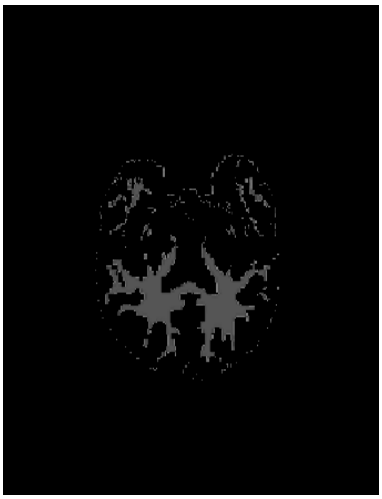
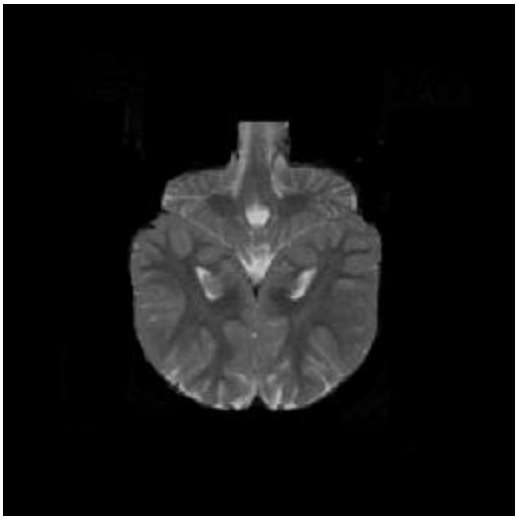


(e)

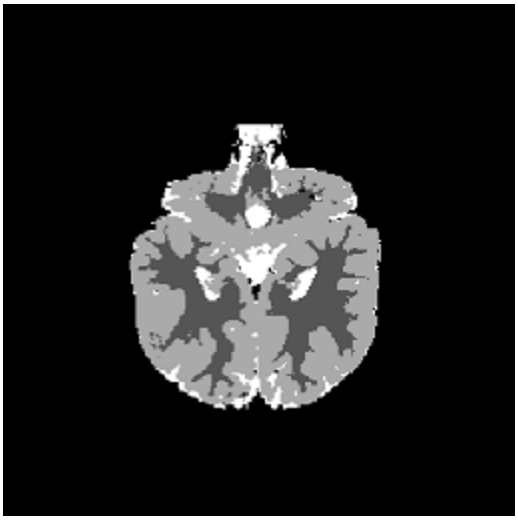


(f)

Fig 4.5 (a)Control Male T2-weighted MRI(slice 110), (b)Ground truth, (c) Segmentation result, (d) Gray matter, (e) CSF, (f) White matter



(a)



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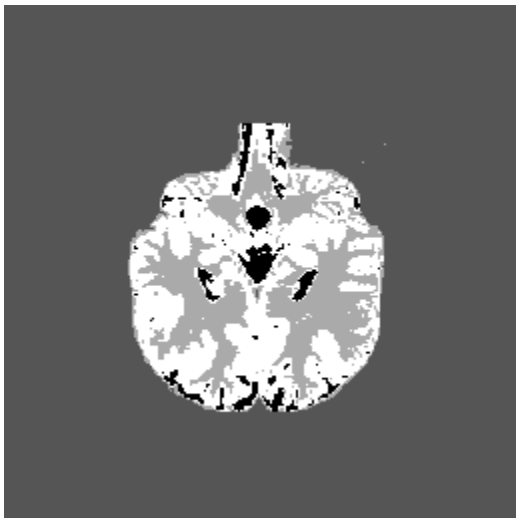
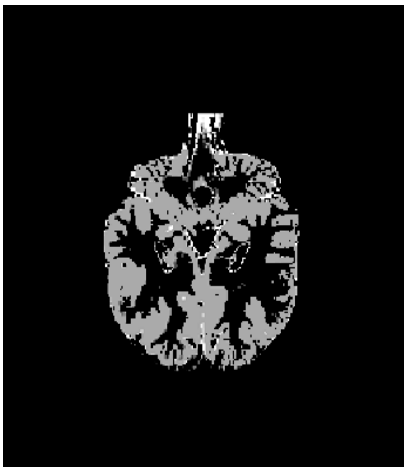
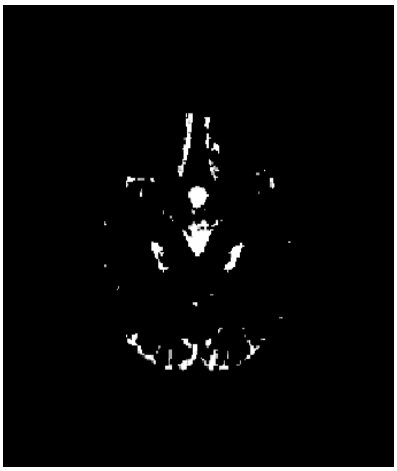


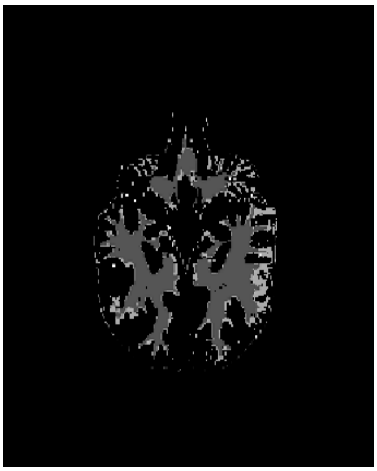
(c)



(d)

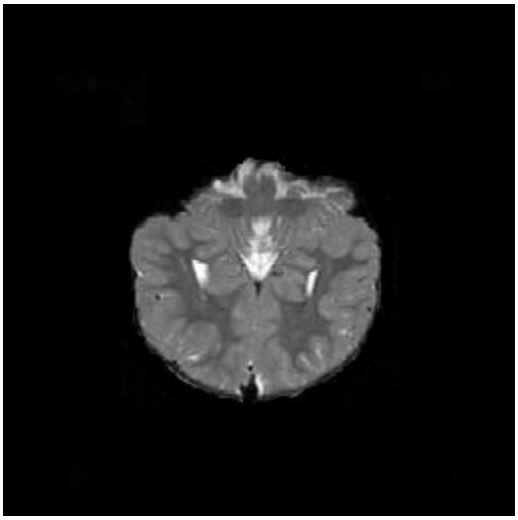


(e)

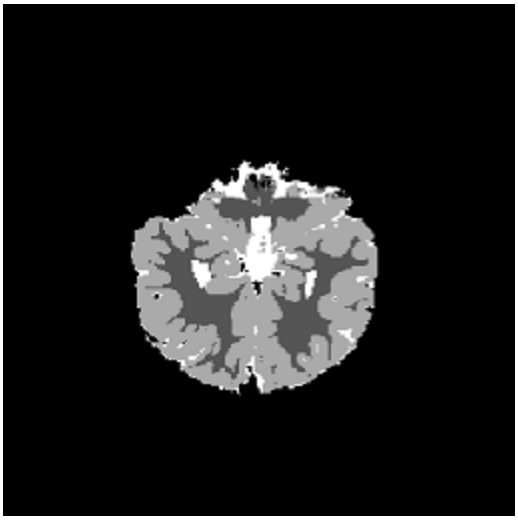


(f)

Fig 4.6 (a)Control Male T2-weighted MRI(slice 67), (b)Ground truth, (c) Segmentation result, (d) Gray matter, (e) CSF, (f) White matter



(a)



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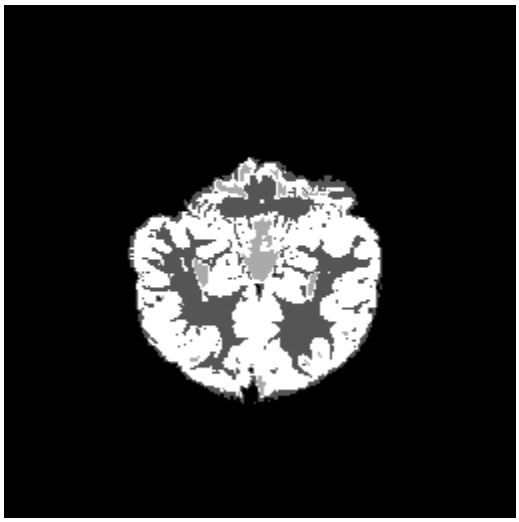

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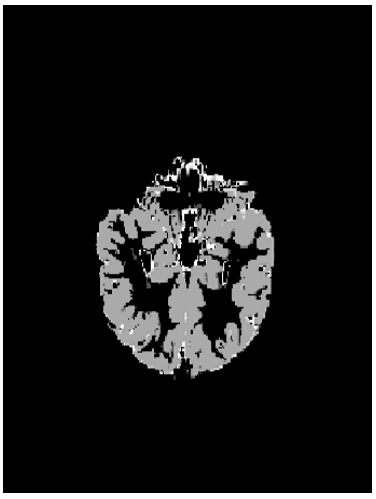
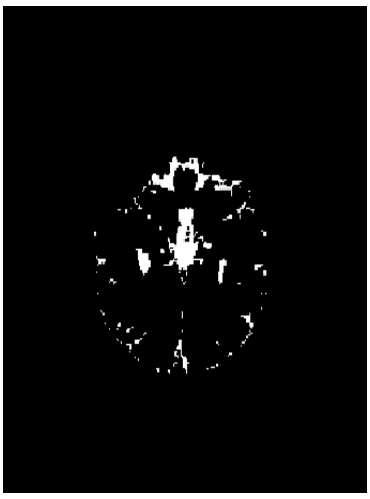
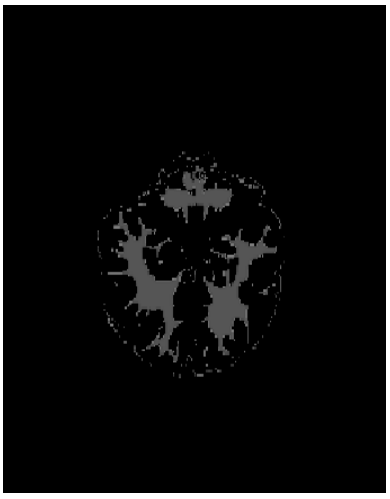






(d) (e) (f)

Fig 4.7 (a)Autistic Male T2-weighted MRI(slice 70), (b)Ground truth, (c) Segmentation result, (d) Gray matter, (e) CSF, (f) White matter

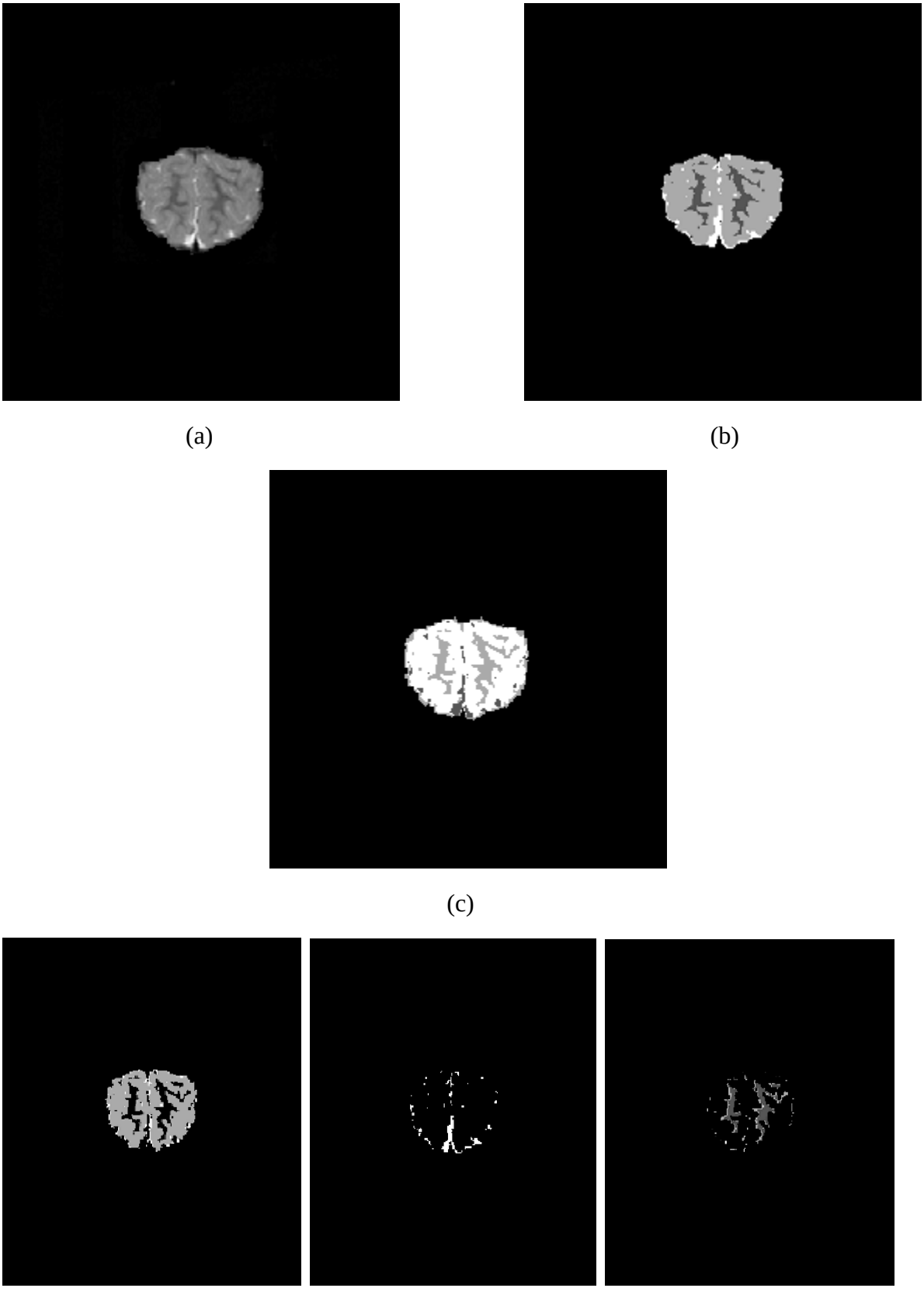


Fig 4.8 (a)Autistic Male T2-weighted MRI(slice 160), (b)Ground truth, (c) Segmentation result, (d) Gray matter, (e) CSF, (f) White matter

In order to measure the accuracy of segmentation results, several quantitative evaluation schemes can be used.[24][25] Some of them are as follows:

1. Dice Coefficient

D(P,Q)=2(|P and Q|)/(|P|+|Q|)

Where P and Q are two sets and |.| represents the size of the set.

The value of dice coefficient lies between 0 and 1. 0 signifies no match/overlap and 1 signifies complete match/overlap. In terms of segmentation P represents the segmented image and Q represents the gold standard/ ground truth.

2. Jaccard's Coefficient

J(P,Q)=(P intersection Q)/(P union Q)

The value of Jaccard similarity also lies within 0 and 1. 0 signifies no match/overlap and 1 signifies complete match/overlap.

Relationship between Dice coefficient and Jaccard similarity is as follows:

D=2*J/(1+J)

3. True positive fraction (Sensitivity)

TPF=TP/(TP+FN)

Where TP- True Positive, FN- False negative

4. Fuzzy Partition Coefficient (fPC) and Fuzzy Partition Entropy (fPE)

Clustering algorithms can be evaluated quantitatively using the cluster validity functions. Clustering results are best obtained when the value of partition coefficient is maximal and partition entropy is minimal. These two parameters only consider the fuzzy partition but do not takes into consideration specific featuring properties.

$$fPC(U) = (1/N) * \sum_{p=1}^{N} \sum_{q=1}^{nc} u_{p,q}^{2}$$

$$fPE(U) = -(1/N) * \sum_{p=1}^{N} \sum_{q=1}^{nc} (u_{p,q}) * \log(u_{p,q})$$

TABLE 4.2

This table presents the value of Dice Coefficient for three brain tissues namely, Gray matter, White matter, CSF for Fig. 4.1 - 4.8 using our approach(ACO-FCM) and standard FCM

	ACO-FCM				FCM				
	Dice Coefficient				Dice Coefficient				
Patient #	**GM**	**WM**	**CSF**	**Avg.**	**Patient #**	**GM**	**WM**	**CSF**	**Avg.**
P11	0.928	0.889	0.755	0.857	P11	0.917	0.848	0.570	0.778
P12	0.860	0.927	0.785	0.857	P21	0.838	0.848	0.680	0.788
P21	0.902	0.933	0.878	0.904	P21	0.849	0.830	0.784	0.821
P22	0.899	0.806	0.759	0.821	P22	0.872	0.751	0.617	0.746
P31	0.887	0.802	0.796	0.828	P31	0.841	0.793	0.652	0.762
P32	0.903	0.888	0.798	0.863	P32	0.852	0.817	0.716	0.795
P41	0.924	0.940	0.859	0.907	P41	0.887	0.846	0.838	0.857
P42	0.954	0.814	0.853	0.873	P42	0.918	0.744	0.697	0.786
Average	**0.907**	**0.874**	**0.810**	**0.863**	**Average**	**0.871**	**0.809**	**0.694**	**0.791**

Dice Coefficient is the volume overlap metric that evaluates the segmentation results quantitatively given the segmentation volumes pairs. The algorithm is run over several slices of both normal and autistic male and female dataset provided by NIMAC. The average of several runs was calculated using Dice Coefficient.

It is observed that the significant improvement can be seen in the result obtained from our approach (ACO-FCM) as compared to standard FCM .The classification of brain tissues is more promising in case of ACO-FCM as there are more number of correctly classified pixels. Our approach uses spatial information which helps in better classification of such tissues.

The more the value of dice coefficient is close to 1, the better is the segmentation accuracy. It is studied that dice coefficient's value >0.7 implies good segmentation.

Similar to Dice Coefficient is the Jaccard's similarity measure. Both these parameters are not sensitive to volume overestimations and underestimations. However, Dice Coefficient is more famous than jaccard ratio as it may sometimes result in a mismatch when there is a strong volumetric overlap. We have presented below the estimated results using Jaaccard's ratio as well to have a better outlook of classification system.

$J=D/(2-D)$

J- Jaccard's ratio

D- Dice coefficient

TABLE 4.3

This table presents the value of Jaccard's overlap ratio for three brain tissues namely, Gray matter, White matter, CSF for Fig. 4.1 - 4.8 using our approach(ACO-FCM) and standard FCM

ACO-FCM					FCM				
	Jaccard's Similarity					Jaccard's Similarity			
Patient #	**GM**	**WM**	**CSF**	**Avg.**	**Patient #**	**GM**	**WM**	**CSF**	**Avg.**
P11	0.865	0.800	0.606	0.757	P11	0.846	0.736	0.398	0.660
P12	0.754	0.863	0.646	0.754	P12	0.721	0.736	0.515	0.657
P21	0.821	0.874	0.782	0.825	P21	0.737	0.709	0.644	0.696
P22	0.816	0.675	0.611	0.700	P22	0.773	0.601	0.446	0.606
P31	0.796	0.669	0.611	0.692	P31	0.725	0.657	0.483	0.621
P32	0.823	0.798	0.663	0.761	P32	0.742	0.690	0.557	0.663
P41	0.858	0.886	0.752	0.832	P41	0.796	0.733	0.721	0.75
P42	0.912	0.686	0.743	0.780	P42	0.848	0.592	0.534	0.658
Average	**0.830**	**0.781**	**0.676**	**0.762**	**Average**	**0.773**	**0.681**	**0.537**	**0.663**

TABLE 4.4

This table presents the value of Sensitivity (True positive fraction) for three brain tissues namely, Gray matter, White matter, CSF for Fig. 4.1 - 4.8 using our approach(ACO-FCM) and standard FCM

ACO-FCM					FCM				
	Sensitivity					Sensitivity			
Patient #	**GM**	**WM**	**CSF**	**Avg.**	**Patient #**	**GM**	**WM**	**CSF**	**Avg.**
P11	0.879	0.907	0.686	0.824	P11	0.869	0.866	0.518	0.751
P12	0.862	0.980	0.701	0.847	P12	0.845	0.896	0.615	0.785
P21	0.911	0.981	0.810	0.900	P21	0.857	0.873	0.724	0.818
P22	0.873	0.940	0.650	0.821	P22	0.847	0.876	0.529	0.750
P31	0.874	0.923	0.678	0.825	P31	0.831	0.862	0.555	0.749
P32	0.868	0.981	0.702	0.850	P32	0.820	0.921	0.629	0.790
P41	0.951	0.984	0.757	0.897	P41	0.913	0.885	0.729	0.842
P42	0.940	0.920	0.790	0.883	P42	0.904	0.840	0.646	0.796
Avg.	**0.894**	**0.952**	**0.721**	**0.855**	**Avg.**	**0.860**	**0.877**	**0.618**	**0.785**

It can be noticed that classification/segmentation accuracy is highly dependent upon the classification of cerebrospinal fluid. The accuracy of both gray matter and white matter tissues is also improved but significant change can be seen in case of segmentation of CSF tissue. CSF is a very complex tissue (fluid flowing in our brain). It is sometimes difficult to segment such a flowing matter from brain MRI. Therefore there is a requirement to get better classification of data points belonging to CSF class. This improvement can be seen in our approach as compared to standard FCM.

The ACO-FCM approach for segmenting brain MRI images is also applied and validated for simulated 3D brain MRI images with varying level of noise from brain web database. The simulated dataset from brain web is provided by McGill University and can be obtained with different file extensions. [28] It contains normal anatomical brain structures with size of each image is 181*217. The results are tested and validated for T1-weighted images with 3%, 5% noise levels and slice thickness of 1mm.

TABLE 4.5

This table presents the value of Dice Coefficient for three brain tissues namely, Gray matter, White matter, CSF for Fig. 4.9 – 4.13 using our approach(ACO-FCM) and standard FCM

		ACO-FCM						FCM			
		Dice Coefficient						Dice Coefficient			
Slice#	**Noise**	**GM**	**WM**	**CSF**	**Avg.**	**Slice#**	**Noise**	**GM**	**WM**	**CSF**	**Avg.**
60	3%	0.962	0.911	0.812	0.895	60	3%	0.947	0.845	0.675	0.822
88	3%	0.929	0.963	0.890	0.927	88	3%	0.879	0.933	0.822	0.878
100	3%	0.900	0.970	0.837	0.902	100	3%	0.880	0.948	0.793	0.873
AVG.		**0.930**	**0.948**	**0.846**	**0.908**	**AVG.**		**0.902**	**0.908**	**0.763**	**0.857**
99	5%	0.915	0.967	0.841	0.907	99	5%	0.900	0.955	0.818	0.891
126	5%	0.934	0.902	0.874	0.903	126	5%	0.896	0.841	0.849	0.862
100	5%	0.902	0.962	0.835	0.899	100	5%	0.876	0.948	0.764	0.862
AVG.		**0.917**	**0.943**	**0.850**	**0.903**	**AVG.**		**0.890**	**0.914**	**0.810**	**0.871**

It can be noticed from the above table that ACO-FCM performs better for both levels of noise as compared to standard FCM. The efficiency of FCM is reduced with higher level of noise. This can be seen from the slice 100 corrupted with both 3% and 5% noise. Accuracy of FCM reduces significantly whereas ACO-FCM performs efficiently in higher level of noise as well.

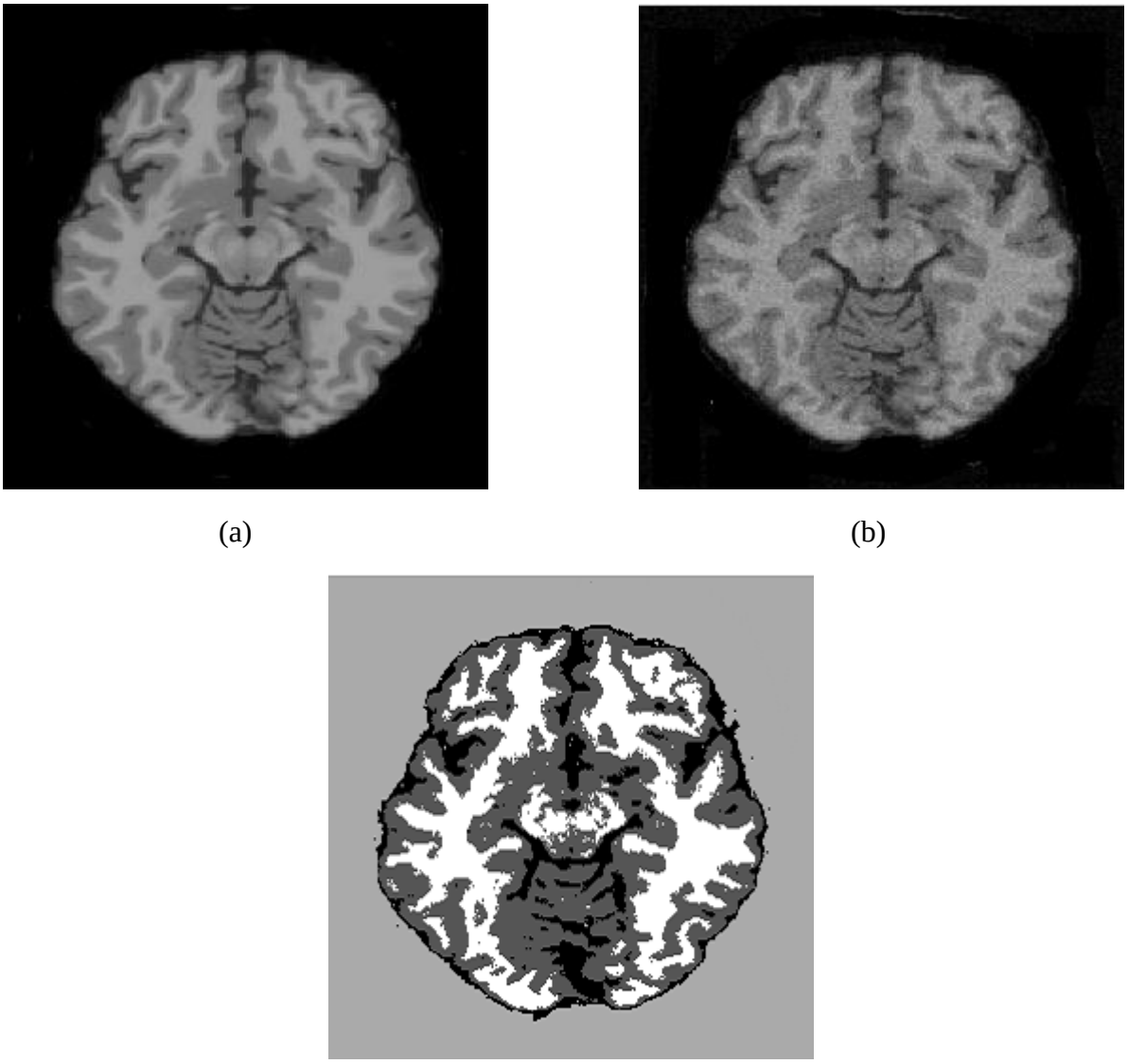
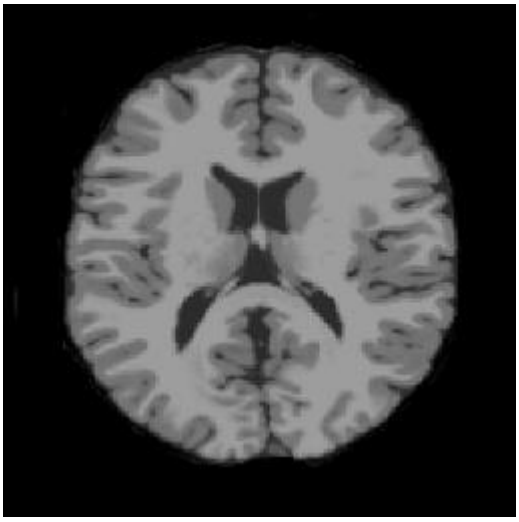
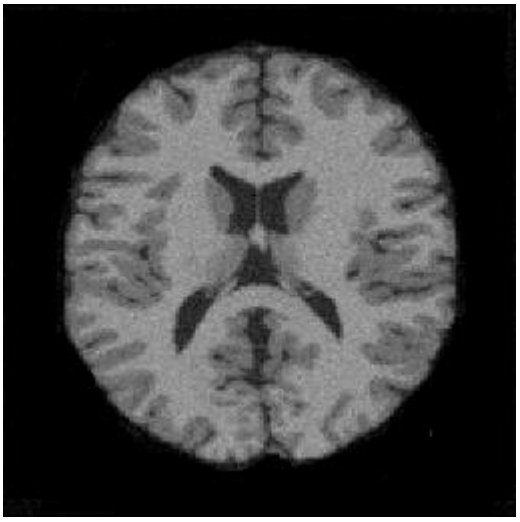


Fig4.9. (a) Normal Brain(T1-weighted slice 60), (b) Normal brain (noise 3%), (c) Segmented result using ACO-FCM, (d) Gray matter, (e) CSF, (f) White matter



(a)



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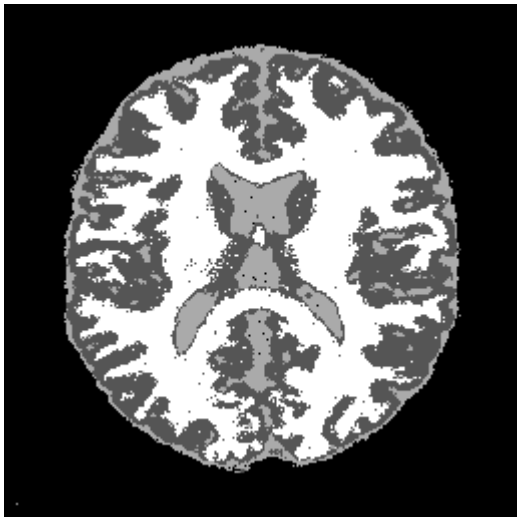
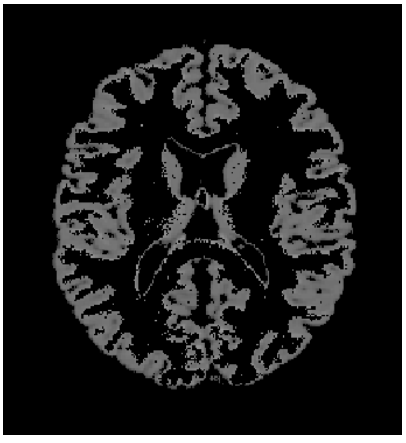
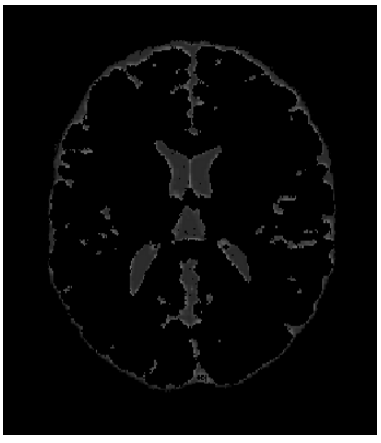
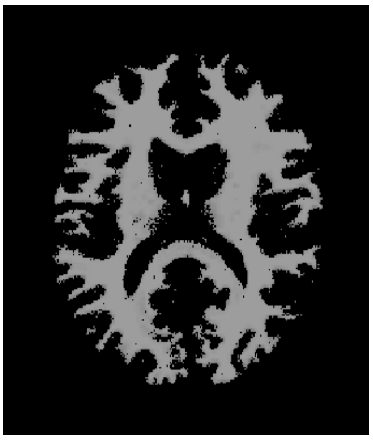


(c)

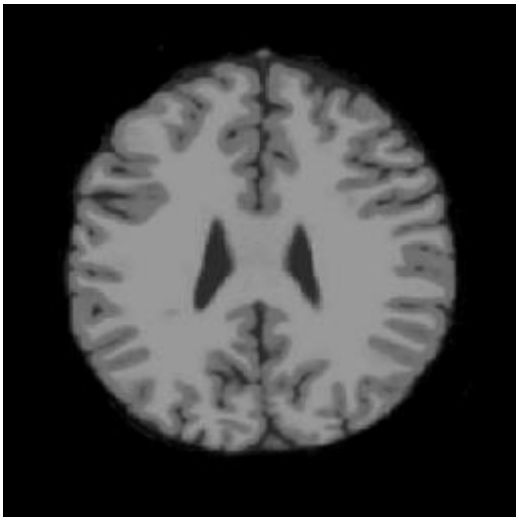






(d) (e) (f)

Fig4.10. (a) Normal Brain(T1-weighted slice 88), (b) Normal brain (noise 3%), (c) Segmented result using ACO-FCM, (d) Gray matter, (e) CSF, (f) White matter



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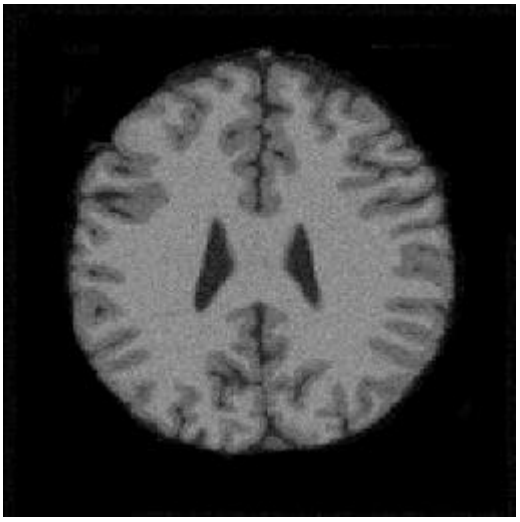
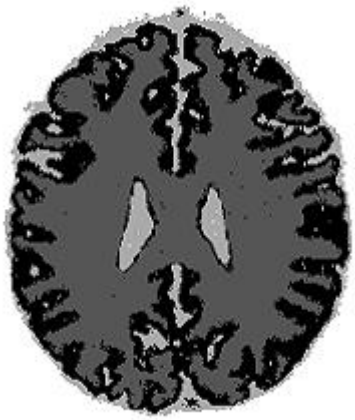
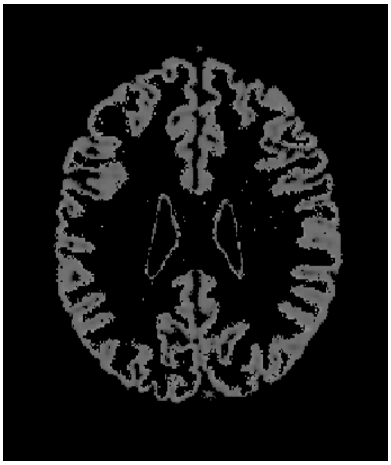
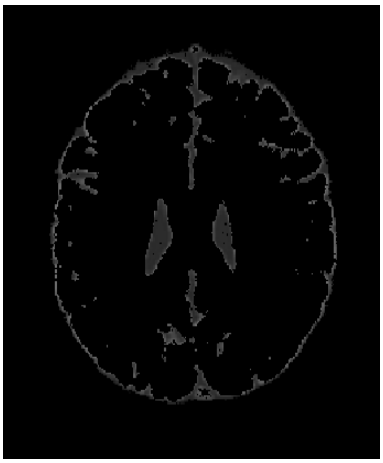


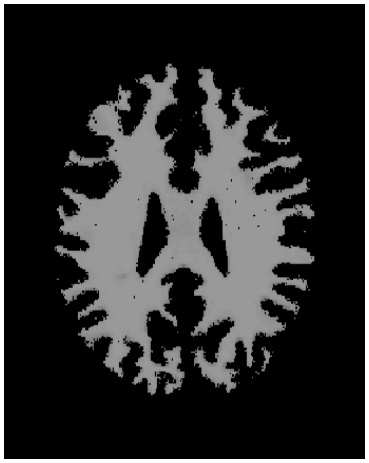
(b)



(c)

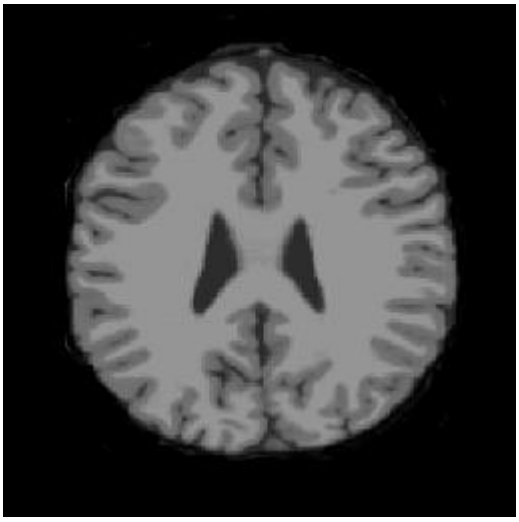




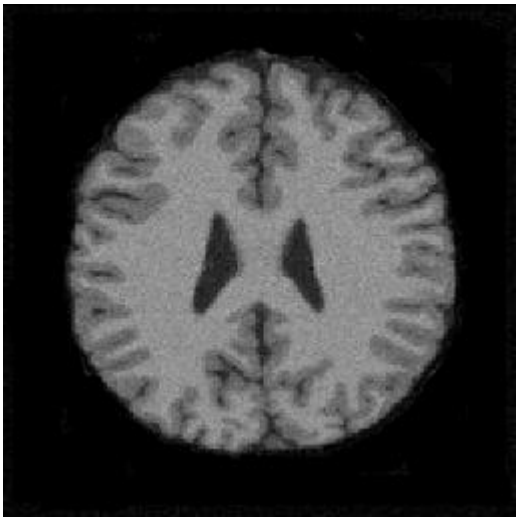


(d) (e) (f)

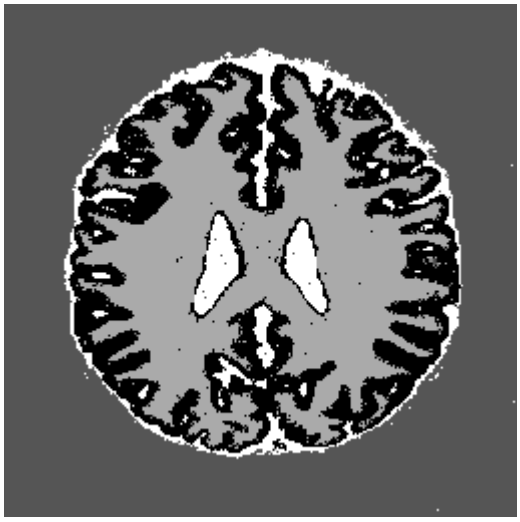
Fig4.11. (a) Normal Brain(T1-weighted slice 100), (b) Normal brain (noise 3%), (c) Segmented result using ACO-FCM, (d) Gray matter, (e) CSF, (f) White matter



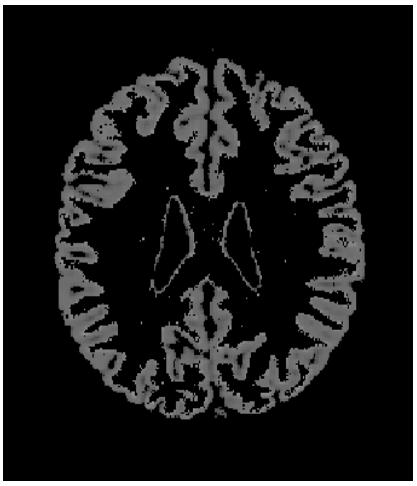
(a)



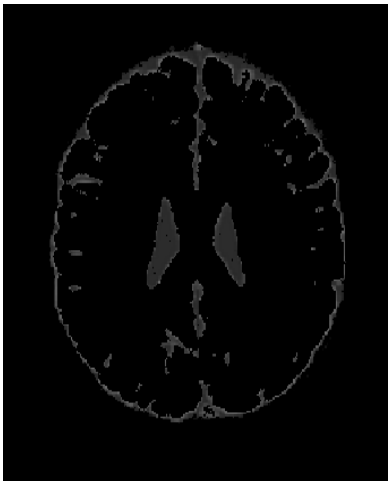
(b)



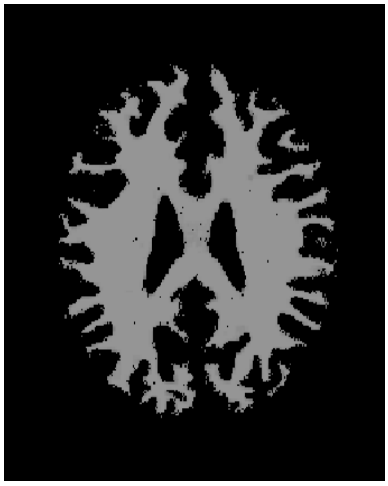
(c)



(d)



(e)



(f)

Fig4.12. (a) Normal Brain(T1-weighted slice 99), (b) Normal brain (noise 5%), (c) Segmented result using ACO-FCM, (d) Gray matter, (e) CSF, (f) White matter

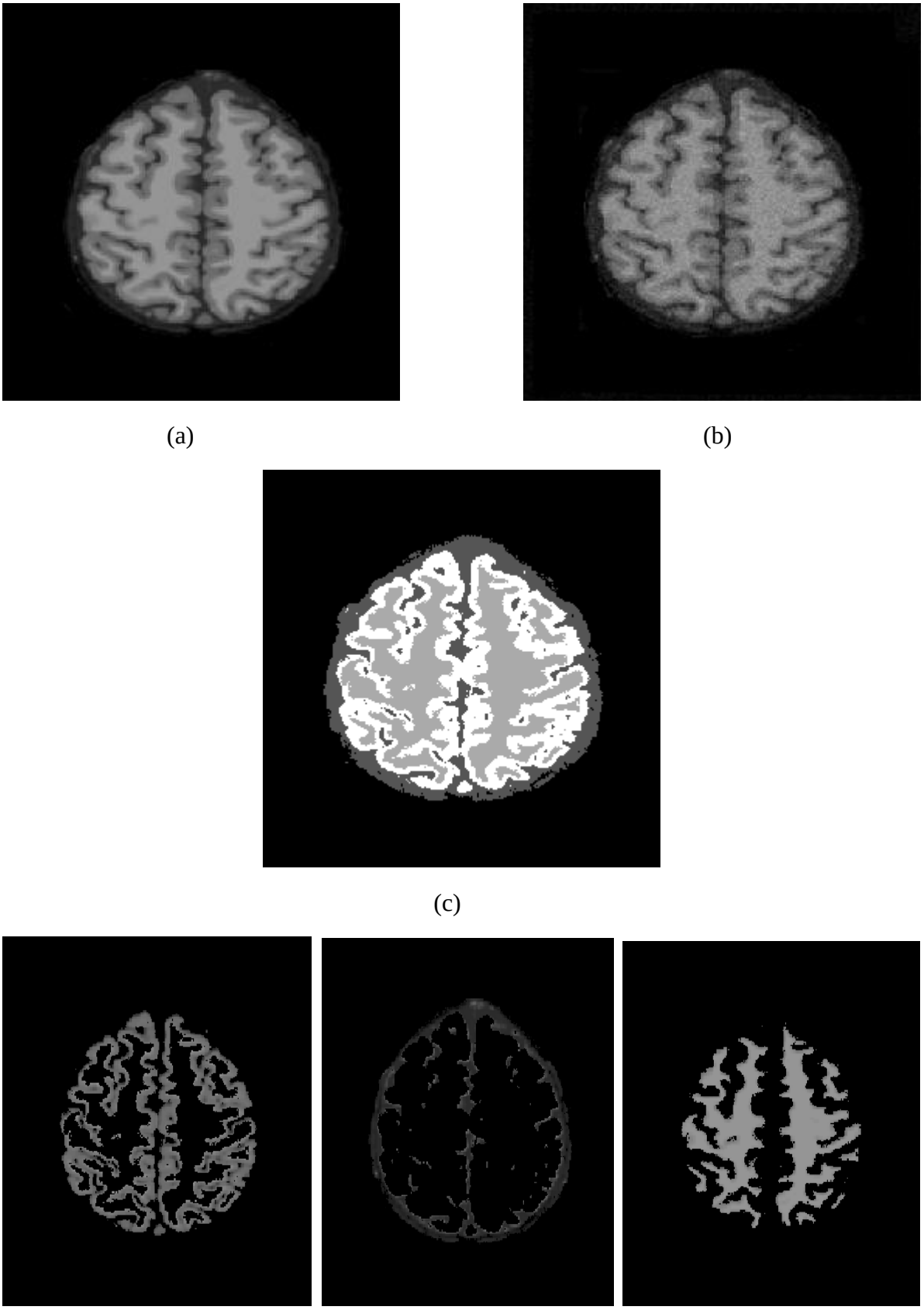
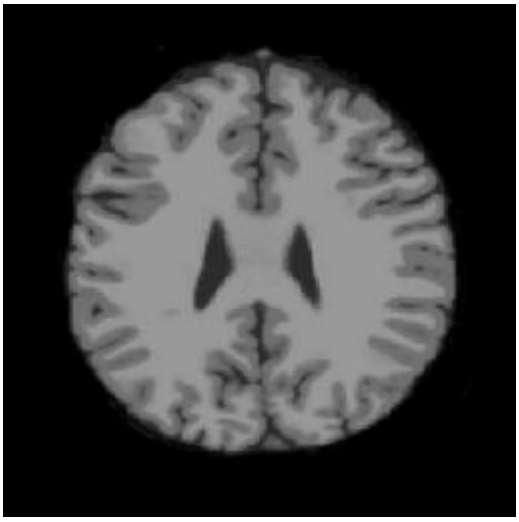
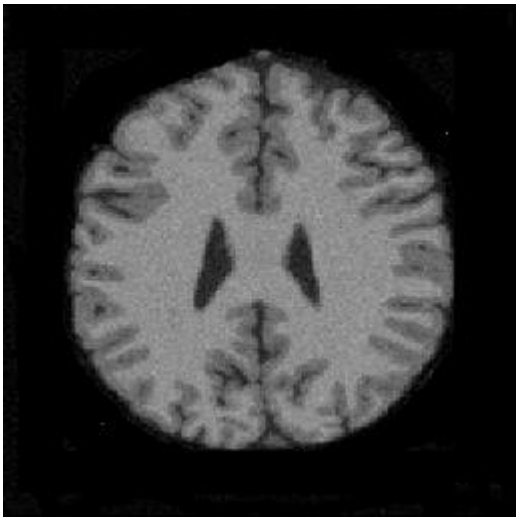


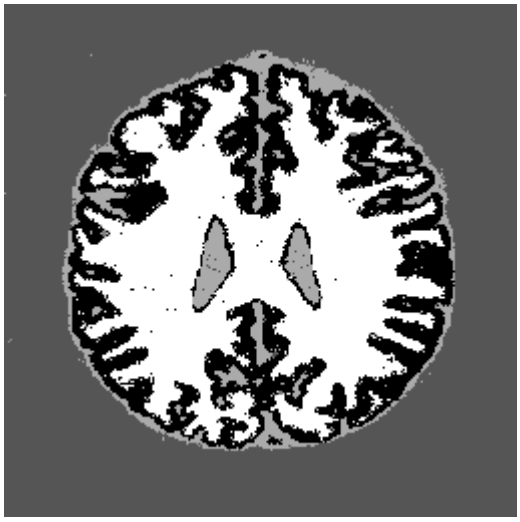
Fig1. (a) Normal Brain(T1-weighted slice 126), (b) Normal brain (noise 5%), (c) Segmented result using ACO-FCM, (d) Gray matter, (e) CSF, (f) White matter



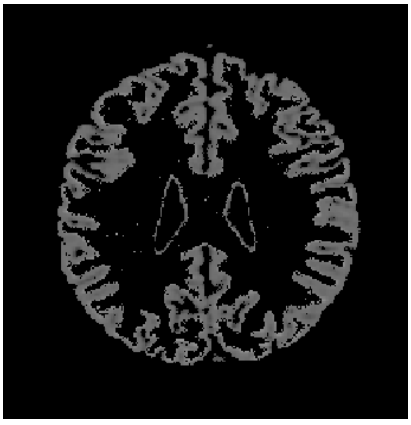
(a)



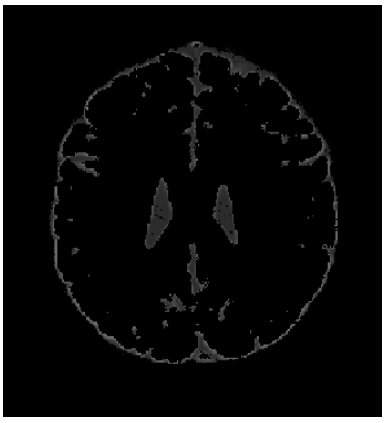
(b)



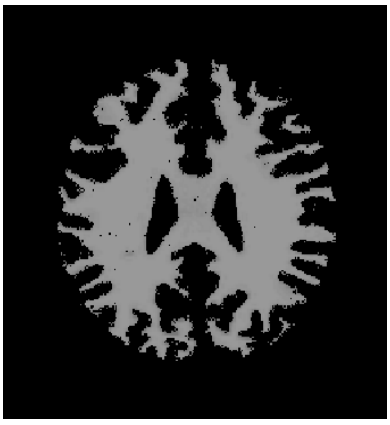
(c)



(d)



(e)



(f)

Fig4.13. (a) Normal Brain(T1-weighted slice 100), (b) Normal brain (noise 5%), (c) Segmented result using ACO-FCM, (d) Gray matter, (e) CSF, (f) White matter

Chapter 5

CONCLUSION

In the work presented, image segmentation is done using ‘Fuzzy Logic’ technique. Step by step methodology for automated brain MRI image segmentation is presented. Classification of three main tissues of brain is performed. These tissues include- gray matter, white matter and cerebrospinal fluid. The Ant Colony Optimization technique is used to obtain the results of segmentation as ACO is a meta-heuristic approach that tends to give close to optimal solution. Also inclusion of spatial information of pixels ensures better clustering as neighbouring pixels are more likely to belong to the same class/cluster. Consideration of geometrical shape of clustering classes is also taken into account. Therefore, Mahalanobis distance is included to solve the purpose. Brain MRI acquisition are also subjected to random noise. Our work ensures better classification in presence of such noise as well. The results of our work has been evaluated and validated against ground truth. Both real time database and simulated database with varying level of noise is used to test the accuracy. Significant improvement in correct classification of brain tissues can be seen as compared to standard FCM. In future, the work of thesis can be extended to further improve the accuracy and efficiency of the algorithm. Also this work dealt with noise and partial volume effect, so it can be extended to work for images with intensity inhomegenity as well.

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