

**TUMOR DETECTION AND COMPARATIVE ANALYSIS****¹Dr. Sudha Mishra, ²Dr. Meesala Sudhir Kumar,****³Pankaj Chandra, ⁴Dr. Santosh Soni, ⁵Dr. Devendra Kumar Singh, ⁶Akanksha Gupta, ⁷Bindu Tiger**¹Assistant Professor, JKIE, Bilaspur C.G.²Professor, Department of Computer Science & Engineering, SOCSE, SANDIP University, Nashik (MH)^{3,6,7} Assistant Professor, Department of Information Technology, Guru Ghasidas Vishwavidyalaya, Bilaspur (Chhattisgarh)⁴Associate Professor, Department of Information Technology, Guru Ghasidas Vishwavidyalaya, Bilaspur (Chhattisgarh)⁵ Assistant Professor, Department of Computer Science, Guru Ghasidas Vishwavidyalaya, Bilaspur (Chhattisgarh)**DOI: 10.48047/ecb/2023.12.si13.115****Abstract:**

Manual analysis of image is a time-consuming operation that uses a step-by-step methodology and is very skill-dependent. In contrast, computer system analysis of the resulting magnet and radiography image enables professionals to make quick decisions, produces repeatable results and an electronic patient record, enhances the diagnosis process, and aids in patient treatment.

Unsupervised learning and computer-aided diagnosis of brain tumours are the subjects of this study. This paper first describes the state-of-the-art methods for segmenting brain tumours, then explains why soft computing is preferable.

Keywords: Brain tumor, Segmentation, Clustering, Member function, K-Means, C-Means, Soft Computing.

I. INTRODUCTION

Image processing is a technique developed by CS/IT professionals. Magnetic resonance imaging (MRI), range imaging, and optical (light intensity) images are only a few examples of the various image types available. In this research, we examine how image processing can be used in conjunction with MRI segmentation to detect brain tumours.

Early detection of a brain tumour improves a patient's prognosis and lengthens their expected lifespan. Experts can use imaging technologies like MRI and CT scans to spot brain tumours in photos. Medical practitioners carefully study brain imaging patterns of grey matter, white matter, and cerebrospinal fluid for abnormalities.

The brain is a unique organ of the body that regulates memory and learning, senses and emotion, as well as the body's overall regulatory process. The brain also manages and controls the body's other systems, such as the muscles, organs, blood vessels, and nerve network that are interconnected with them. Cancer cells start to proliferate uncontrollably in the tissues of the brain in a condition known as a brain tumor.

Radiologists, radiation oncologists, and other medical professionals segment medical images to look for any anomalies.

An enhanced method for learning about the examination of human brain tissue is magnetic resonance imaging (MRI). Identification of the tissue's concealed features is the aim of magnetic resonance imaging. It takes a long time to manually name brain tumors in MRI scans, and there is a big difference in the labels made by various experts.



Figure 1.1 shows an MRI image of brain affected with tumor.

1.1 Brain Tumor

Brain tumors are uncommon lumps in or on the brain that may be caused by unchecked cell growth and failure to properly dispose of dead cells. Primary and secondary tumors are the two categories of tumors. A brain tumor is a serious condition that can affect people. Resolving the issue with this hazardous disease is crucial. The central nervous system, which controls all of the body's major processes, is mostly composed of the brain.

The brain is a sophisticated bodily organ with a vast network of billions of neurons. A brain tumor is an abnormal growth of mass of tissue in the brain, commonly referred to as an intracranial neoplasm. The complexity of treating brain tumors is increased by the fact that they can have a variety of shapes and sizes and can develop in any area of the brain. The tumor's size and location also affect its stage. Recovery from diseases is a difficult but crucial work for doctors.

Primary tumors resemble brain cells more so. The nervous system of the body is supported by all primary brain tumors. tumors of the central nervous system can range from benign, slowly-proliferating injuries to cancers that can be fatal. Regarding their discovery and treatment, each of these tumors is unique.

The location of the tumor is crucial to the diagnosis. The MRI technology, which is used to take brain pictures, is unable to accurately distinguish between various tumor kinds. However, some degree of distinction can be anticipated when the tumor's information is combined with its location. Actually, they are cancer cells that have migrated into the brain. They are easily diagnosable and may be surgically removed.

Children typically develop brain tumors in their early stages. It is a mass that takes up space in the brain and is referred to as a space-occupying lesion (SOL). Both cancers and tumors are not the same thing.

It could be both a mass and a malignancy, a brain mass and a brain malignancy. K-Means is sufficient to extract information from the brain if there is brain mass. It is vital to clean up the image if there is noise. An uncontrolled development of tissue, or tumor, can occur anywhere on the body. There are various sorts of tumors, and each one responds differently to treatment.

1.1.1 Benign Tumors:

Cancer cells do not exist in benign brain tumors. The benign tumors are easily removed, and they don't usually come back. Benign tumor cells do not spread to other parts of the body or infect the tissues around them. By suppressing the brain's sensitive regions, these tumors have the potential to cause major issues. They very seldom grow cancerous and pose a threat to life.

1.1.2 Malignant Tumors:

Brain tumors that are malignant pose a greater risk to life than benign tumors do. It may be a primary or secondary type of tumor, developing from brain tissue or spreading to other parts of the body as a metastasis from another tumor. They can multiply quickly and damage healthy brain tissues close by. Rarely, cancer cells

from a malignant brain tumor may separate and spread to other regions of the brain and spinal cord as well as to other body organs.

Computed tomography (CT) scanning is another method, however MRI is more accurate in detecting brain tumors than CT. Multiplanar imaging offers accurate tumor localization in addition to information on the fundamental characteristics of the tissue. It is effective in selecting spherical cysts with sharp borders. MRI can also identify hemorrhage due to the goods' paramagnetic characteristics. The conventional method of tumor detection is carried out in MRI images, which is a manual task that provides variations in the results when analyzed by different experts and gives different results in different times. As a result, it has some limitations of the manual analysis of MRI, so there is a requirement for an automated system using soft computing technique that can produce globally acceptable and accurate results.

MRI able to give different view of images that is sagittal, axial and coronal view.

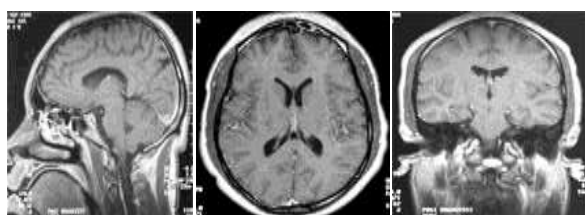


Figure 1.2 (a) Sagittal view, (b) Axial view and (c) Coronal view

An image is a two-dimensional function, $f(x, y)$, where x and y coordinates in a plane, and the value of f at coordinates (x, y) is intensity level or gray level of the image. In digital image values of x, y, f is finite and discrete. A digital image includes finite number of pixels with a definite location and value.

With the development of technology, computer-based diagnostics has largely supplanted manual detection and diagnosis. But when it comes to its computer-based counterpart, manual diagnostics is always necessary.

The goal of this work is to provide a reliable segmentation method for brain imaging modalities that can identify tumor tissue. The most important and widely studied topic of research has always been image segmentation. It is widely utilized in medical image processing to examine picture modalities that are now easily created by CT scan or MRI. Technology advancements have made it possible to create images of inside organs in a variety of dimensions.

1.2 Objective

One of the most efficient methods is segmentation processing, which may be used to extract information from complicated medical images with widespread applications in the medical industry.

Risk analysis involves finding the brain region that is affected. The goal of this research is to use a soft computing strategy to reduce the risk associated with unsupervised learning approaches. Three unsupervised segmentation approaches are used in this study. In the beginning, we use soft computing to analyze, compare, and process them.

The division of an image into segments is the primary goal of image segmentation. Segmentation is the division of an area into smaller areas where each area of interest is spatially contiguous and the pixels are homogeneous in terms of a predetermined criterion.

Segmentation is employed in many works together with their color, range, surface normal's, and surface curvatures. Unsupervised learning methods K-Means and C-Means are used to resolve the well-known clustering issue.

The clustering process uses a specific number of clusters to categorize a given data set in a straightforward

and straightforward manner. In this study, we developed a hybrid segmentation method that combines fuzzy K-Means and fuzzy C-Means with threshold clustering. We then compared the computing performance of all three methods simultaneously using the MATLAB GUI TOOLBOX and Soft Computing.

These three strategies aim to lessen the manual process analysis and the time complexity. K-Means has been improved and extended by fuzzy C-Means clustering. C-Means performs fuzzy data analysis more effectively.

1.3 Problem Statement

Digital image processing is the manipulation of an image. It has wide variety of application in medical field. MRI is a Magnetic Resonance computerizes Technique to identify the disease of body parts. To find out the disease area in brain is a typical task. To analyze soft tissue is challenging task it is done by experts only. In this research only we overcome the computation of segmentation techniques. It is the partition of an image into region and specific features of pixel. Recognition of damaged part of brain tissue is a problem statement. It is observed by MRI technique but which part of tissue is damaged area is done by segmentation techniques. Restoration of input image after process and removing noise is also a time taking and challenging task. In this research three types of segmentation techniques are used and compared their execution time. We need to improve the computation time using soft computing approach with GUI MATLAB TOOL, it is toolkit in which can change feature and component of image.

II. LITERATURE REVIEW

Brain tumor segmentation has been the subject of a number of recent studies in the field of medical imaging technology. The load on doctors is reduced by automatic segmentation, but only quantitative measurements allow for accurate tracking and illness modelling.

It is extremely difficult to distinguish tumors from natural scenes in MR pictures. The tumors vary in size and placement. Additionally, they can overlap in intensity with healthy brain tissue, have a range of shapes and appearances, and frequently injure surrounding brain structures by changing the geometry of good tissue. Because of this, it is typically challenging to partition a tumor using just unsupervised thresholding. Unsupervised learning techniques were proposed by a number of scholars, but they operated differently. In this section various latest techniques for BrainTumor Detection techniques are studied.

Basak et al. (2018) The author presented a number of significant strategies for image segmentation in this survey work. Author is an example of a hybrid approach that combines two or more strategies. The hybrid technique will be the most effective way to address the picture segmentation issue.

Sharma et al. (2018) This essay discusses the fundamental ideas underlying image segmentation techniques. Author suggested that the photos be segmented, and this study uses approaches for detecting borders, thresholds, the expansion of regions, and grouping based on those techniques. Segmentation is based on two pixel characteristics: similarity and discontinuity. This article focuses on the many segmentation techniques that are frequently employed to segment the image.

Devi, N. et al. (2018) Author suggests utilising different GLCM (Gray-Level Co-occurrence Matrix) settings to train an ANN to look for the existence of a tumor.

Rajam et al. (2017) This study computes picture similarity measures, including Jaccard, Dice, false positive rate, false negative rate, sensitivity, specificity, accuracy, and precision, to verify the proposed work. On the dataset under consideration, the experimental outcome provides better results.

Banchpalliwar, R. A. et al. (2016) This review article uses algorithms for mri brain image segmentation. The comparison of the various segmentation approaches is the goal of this study. In this essay, the author contrasts the clustering and segmentation algorithms K-means with Fuzzy C-means. Following investigation, it was discovered that precision was more crucial than timing in medical analysis, with FCM's execution time being longer than K-means. In order to improve this segmentation accuracy, FCM is more accurate than K-Means. It may make advantage of the optimisation method.

Baraiya et al. (2016) The goal of this work is to implement various segmented methods using MATLAB and to compare their accuracy. Preprocessing has been suggested as being necessary for improved segmentation. It is the first step in the process, after which noise is eliminated using filtering techniques and segmentation accuracy is increased.

On the basis of these literature reviews challenges are being listed out in next section and problem statement and objective of this research work are defined.

III. RESEARCH METHODOLOGY

This work is based on analysis and implementation of Unsupervised Learning Techniques. On studying different types of work, it is found that segmentation of brain tumor is difficult due to under listed reasons, which are required to be addressed and eradicated:

As edema appears around the tumor in white matter regions, it is sometimes difficult to differentiate tumor and edema because of gradual transition in intensity of these structures.

Non-tumor structures hamper proper segmentation of tumor region.

Results obtained by clustering techniques, which are utilized in the reference work, are not giving sharp boundary of tumor. It is always required to get precise area of tumor.

3.1 Image Processing

The aim of image processing can be achieved through a variety of methods. The technique of applying computer algorithms to a picture on a digital system is known as digital image processing. The act of performing an operation on an image is referred to as image processing. We can improve an image or use it to gather some insightful data.

Digital image processing can be used to extract the portion of an image that corresponds to size, scales, the number of items or region, improve image quality, eliminate noise, and convert signals from an image sensor into digital images. Image processing involves a number of phases, including image pre-processing, image segmentation, feature extraction, and classification. A signal is represented in two dimensions by a picture.

It is defined by mathematical function $f(x, y)$. Where x and y are two co-ordinates horizontally and vertically. The value of $f(x, y)$ at any point x and y of an image.

Various picture segmentation techniques are described in this article. Numerous industries, including mathematics, computer vision, remote sensing, digital entry, face detection, finger print, face identification, and the medical industry, heavily rely on image processing.

3.2 Image Segmentation

The process of segmenting an image involves dividing it into different segments. Analysing and identifying human body diseases is crucial. Image segmentation is the process of analysing and interpreting input data that has been provided. picture segmentation is the examination of a picture in which information can be extracted according to purposes. Segmentation's primary objective is to divide a picture into smaller, more meaningful, and/or simpler regions for easier analysis. In pictures, it is used to identify objects and boundaries (such as a line, curve, region, etc.).

3.3 Types of Segmentation

Segmentation techniques come in many different forms.

Region based, Thresholding based, Edge based, Feature based, Model based, Clustering based, Watershed based segmentation, Partial differential equation, ANN based, Statistical based, Compression, Histogram based, Graph based and Density based segmentation. Types of segmentations are as follows:

3.3.1 Region based segmentation:

This method is based on recurring patterns in the intensity values of a group of nearby pixels. It has a

comparable intensity value for type. The segmentation process aims to categorise regions based on their anatomical behaviour or functional responsibilities, with the cluster being referred to as the tiny region. In terms of time and memory, it is an expensive method.

3.3.2 Thresholding based:

The simplest method of segmentation is through thresholding, which is utilised in many fields of image processing. A strong manual method for segmenting photos with luminous objects that have pixel values on dark backgrounds is thresholding. The process of dividing an image into foreground and background based on intensity value is straightforward and efficient. It transforms binary images from grey scale images. The binary image's intensity values form the basis of the histogram. While an MRI image only contains primary colours (RGB content), a grayscale image only contains grey scale values.

3.3.3 Edge based segmentation:

These methods rely on differences in picture values across various regions, and the segmentation algorithm's objective is to precisely define the border dividing these parts. It is inappropriate for people who are weak or have a lot of edges.

3.3.4 Feature based segmentation:

It locates the boundaries of image based on intensity value of binary image.

3.3.5 Model based segmentation/knowledge-based segmentation:

This method uses deformable templates, active contours, and active shape and appearance of training models. Active form models and active appearance models are included.

3.3.6 Clustering:

There are numerous clustering methods available. Fuzzy K-means and C-means are unsupervised learning methods based on fuzzy theory. The process of grouping a set of data objects into clusters is known as clustering. Two sub categories can be used to classify clustering. Hard clustering and soft clustering are two examples. Fuzzy logic desegregation using data mining techniques has emerged as one of the fundamental pillars of the soft computing movement to address problems brought on by massive natural data collections. The fuzzy clustering technique allows the clusters to evolve into their organic shapes by assigning the data points to their membership values for each cluster.

3.3.7 Watershed:

It is based on interpretation of topology. Although its results are more consistent and the border is continuously identified, the gradient calculation is complicated.

3.3.8 Partial Differential Equation:

It is the differential equation-based method that is fastest. It requires more complicated processing.

3.3.9 ANN based:

Synthetic neural network based on intelligence system to make decisions. It wastes extra time during training.

3.3.10 Statistical approaches:

In this approach labels pixel are determined in an image by considering intensity distribution of the image. After selecting pixel label, its algorithm attempts to approximate the class label associated with it.

3.3.11 Compression based segmentation:

This technique minimizes the length of data of the data set used hence transformation bandwidth can be saved. Segments can be performed by coding and decoding to determine boundary shapes and textures. Two

compression methods are discrete cosine transform and discrete wavelet transform.

3.3.12 Histogram based segmentation:

The peak and valley points of a picture are determined using the histogram approach, and the image pixels are then grouped according to characteristics such as colour, texture, intensity, etc.

Active points can lead segmentation called video tracking. However in some kind of image, it may fails to distinguish specific peak and valley points.

3.3.13 Graph based methods:

This method finds out edges in graph. In this graph, each pixel is observed as a node. To differentiate between pixels weighted pixels are calculated. Classified pixels or nodes show the segmented portion of the image. Some methods for estimating graph are minimum spanning tree, isoperimetric partitioning, normalized cut and Random Walker method.

3.3.14 Density based approach:

In this method distance between objects is calculated. It estimates spherical cluster. Also in any arbitrary shapes, it is difficult to create cluster.

3.3.15 Unsupervised Image Segmentation Techniques

As was mentioned in the previous section, many techniques have been developed to date to segment images into non-overlapping clusters. This technique is used to extract some hidden data from images. The next section discusses a few of these methods.

Unsupervised algorithms are self-organized learning techniques in which no prior knowledge is present to produce a membership function of any class in an image. Finding unknown patterns in a data set is helpful. Finding some latent structure in an image is what unsupervised learning technique known as clustering refers to.

The objective of a supervised algorithm is to infer a function from training data. Images used as input and a desired result make up these training data. Here, training data are analyzed using a few different functions and compared to test images. For any legitimate input image, the inferred function determines the right value. A type of algorithm called unsupervised learning technique is used to infer conclusions from datasets made up of input data without labeled replies. In bioinformatics and medical science, this is utilized for genetic clustering and sequence analysis; in data mining, it is utilized for sequencing; in medical imaging, it is utilized for image segmentation; and in computer vision pattern mining, it is utilized for object identification such as face, pattern, text, and picture. When there is insufficient data to provide the desired results, unsupervised techniques are applied.

One of the difficult issues in image processing is capturing images from the body's internal organs. We looked at a number of segmentation techniques for tumor detection. Medical professionals must spend a lot of time manually processing Magnetic Resonance Imaging (MRI) data. We must introduce the soft computing approach. The MATLAB GUI TOOL, when used in soft computing, improves the features of the analyzed image. To solve mathematical problems and describe mathematical notation, MATLAB is a high-performance language. An emerging field of technology is soft computing, which combines intelligence, neurosystems, and fuzzy systems.

In this work, RGB colour images of the input MRI brain imaging are first converted to gray-scale images and then downsized to 256×256 . The Histogram Thresholding, K-Means Clustering, and Fuzzy C-Means Clustering Technique are then individually applied to this image. In histogram thresholding, a brain image is divided vertically into equal halves, and the tumor intensity in either of these two halves is determined by comparing the histograms of the two halves. K-Means clustering divides the brain image into four groups based on intensity. High tumor cluster intensity will aid in choosing this specific cluster. Similar to this, the image is split into two clusters in fuzzy C-Means clustering, and the tumor cluster is then chosen. Three unsupervised approaches' effects on the brain imaging are compared.

On the basis of problem analysis of last chapter, in this, algorithms of three different unsupervised image segmentation techniques are being proposed to detect brain tumor. So, the techniques which are going to be

implemented in this research work are:

3.3.16 Histogram Thresholding Technique.

K-Means Clustering Technique.

Fuzzy C-Means Clustering Technique.

Each sample image is initially applied with the denoising approach before the image segmentation technique is used. Real-time applications frequently result in tainted images due to sensor or electronic device noise, so these disturbances must first be eliminated. In this work, photos are inserted from outside, and denoising is done using a spatial filter. Gaussian noise will be introduced, and Weiner filter will then be applied as a spatial filter.

3.3.17 Gaussian Noise

Gaussian noise, commonly referred to as the Gaussian distribution, is statistical noise with a probability density function (PDF) equal to the normal distribution. In other words, the noise in the data is Gaussian-distributed in terms of the possible values.

$$p_G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}$$

Here, z stands for the grey level, the mean value, and the standard deviation, while p is the probability density function of a Gaussian random variable. White Gaussian noise is an exception, and it is utilised in communication channel testing and modelling approaches where it is combined with white noise to produce additive white Gaussian noise.

3.3.18 Weiner Filter

There are various filtering techniques used in signal processing systems, such as the Wiener filter, which produces an estimate of a desired or target random process by linear time-invariant (LTI) filtering of an observed noisy process under the assumption of known stationary signal and noise spectra and additive noise. The procedure for restoring images uses the Wiener filter. It reduces the mean square difference between the intended process and the estimated random process.

The filter is least squares. When an image is blurred by a known low pass filter, inverse filtering or generalised inverse filtering can be used to recover or restore the image. This is a restoration approach for deconvolution. Inverse filtering is particularly vulnerable to additive noise, though. We may create a restoration algorithm for each form of deterioration and then easily combine them thanks to the method of lowering one degradation at a time. Inverse filtering and noise smoothing are optimally balanced by the Wiener filtering. Both the blurring and the additional noise are simultaneously reversed.

The Wiener filtering has the best mean square error performance. In other words, it reduces the total mean square error during the inverse filtering and noise smoothing processes. The original image is linearly estimated by the Wiener filtering. Based on a stochastic framework, the method is used. Where $S(f_1, f_2)$, $S_{yy}(f_1, f_2)$ and $H(f_1, f_2)$ are the blurring filter and the power spectra of the original picture and additive noise, respectively. It is clear that the Wiener filter consists of two distinct components: an inverse filtering component and a noise smoothing component. In addition to deconvolution or denoising using inverse filtering (high pass filtering), noise removal via compression (low pass filtering) is also carried out.

3.3.19 Clustering

There are numerous clustering methods available. Fuzzy K-Means and C-Means are unsupervised learning methods based on fuzzy theory.

It was used to find collections of related objects in various data sets. Using clustering, it is possible to subdivide the supplied data into homogenous subsets and extract a collection of cluster prototypes for the compact representation of the dataset. A mathematical technique called clustering looks for patterns or structures in a dataset where the items inside each cluster have some characteristics.

Cluster analysis is a participatory multi-objective optimization or iterative process of knowledge discovery, not an automatic procedure. Preprocessing and parameter changes are frequently required in order to get the

desired results. Fuzzy clustering methods are among the most frequently used algorithms in clustering. A machine learning method called clustering is based on the grouping of data points. Data points that belong to the same group or a different group should have similar or dissimilar traits and/or attributes, which can be determined using a clustering method and used to categorise each data point into a particular group or similar group. Unsupervised learning is a widespread technique for statistical data analysis that is utilised in a variety of industries.

3.4 Types of clustering

To enhance the performance of clustering, numerous algorithms have been proposed. A crucial clustering method in fuzzy logic is fuzzy C means. K-Means is a significant hard clustering approach, and fuzzy C-Means (FCM) is a very common soft clustering method. A point may partially belong to more than one cluster according to the fuzzy C-Means (FCM) algorithm, which generalises the hard C-Means or K-Means clustering algorithms. Each data point in a C-Means clustering analysis can be a member of many clusters. A defined number of flat and disconnected clusters are created by K-Means clustering. The K-Means clustering algorithm is a straightforward method for segmenting a picture utilising a rudimentary understanding of cluster value. It is dependable, quick, and easy to use.

3.4.1 Clustering can be classified as:

Soft Clustering is Overlapping Clustering & Hard Clustering is Exclusive Clustering.

The overlapping clustering algorithm is called FCM. Unsupervised clustering challenges related to feature analysis, clustering, and classifier building are addressed by this approach. Agricultural engineering, astronomy, chemistry, geology, image analysis, medical diagnosis, form analysis, and target recognition are just a few fields where FCM is frequently used.

An exclusive clustering algorithm is K-Means. The execution process takes extra time. An iterative method called the K-Means algorithm is used to divide an image into K clusters.

Fuzzy C-Means attempts to reduce the cost function, much like the K-Means algorithm, although not being similar to it in terms of method. This approach forgoes all clusters and partition matrices for some predetermined number of finite input data points. One piece of data can belong to two or more groups using fuzzy C-Means clustering. Dunn created this technique in 1973, and Bezdek enhanced it in 1981. It is used for pattern recognition.

A cost function is iteratively decreased through fuzzy C-Means clustering. The distance between cluster centres and pixels serves as this cost function. By reducing the weighted within group sum of squared error goal function, the fuzzy clustering algorithm, an iterative clustering technique, can generate an ideal c partition.

3.4.2 Member Function

Each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1 using a curve known as a member function (MF). A function called a membership function (MF) determines how much an input belongs to a set.

3.4.3 Degree of membership-

This result of a membership function is always restricted to a value between 0 and 1. also referred to as a membership grade or value.

In the fuzzification and defuzzification phases of a FLS (fuzzy logic system), membership functions are employed to convert non-fuzzy input data into fuzzy linguistic terms and vice versa. Really, the sole prerequisite for a membership function is that it must range between 0 and 1.

There are 11 types of membership function integrated into the Fuzzy Logic Toolbox.

The degree to which x is an element of set A is represented by the membership function $A(x)$ for any element x of universe X .

The degree of membership, also known as the membership value, of element x in set A is represented by this value, which ranges from 0 to 1.

3.5 Features of Member Function

3.5.1 Support:

The portion of the universe that is distinguished by a nonzero membership in the set serves as the support of a membership function for any fuzzy set A. As a result, the universe of information's core is made up of all those elements.

The support of fuzzy set A is the set of all point $x \in X$ such that $A(x) > 0$. Mathematically, we can express

$$\text{Support}(A) = \{x, \mu_A(x) / \mu_A(x) > 0\}$$

3.5.2 Core:

The portion of the universe that is characterized by complete membership in any fuzzy set A is the core of a membership function. As a result, core is made up of all the components of the information universe that,

The core of a fuzzy set A is the set of all $x \in X$ such that $\mu_A(x) = 1$.

$$\text{core}(A) = \{x \in X \mid \mu_A(x) = 1\}$$

3.5.3 Boundary:

The part of the universe that is defined by a nonzero but incomplete membership in any fuzzy set A is the boundary of a membership function. As a result, core is made up of all the components of the information universe that,

$$\text{Boundary}(A) = \{x \in X \mid 1 > \mu_A(x) > 0\}$$

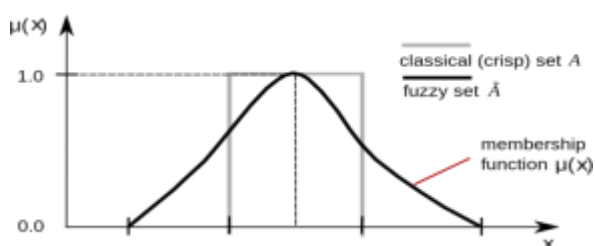


Figure 3.1 Member Function

Fuzzy logic is utilized to handle knowledge in the form of fuzzy "if-then" rules, and membership functions are used to convert images from the pixel plane to the transform plane. The process of enhancement includes fuzzy rules, fuzzy rules defuzzification, and fuzzy rules. It serves as a gauge for fuzzy logic's degree of truth.

3.5.4 Soft Computing

One of the difficult jobs in image processing is to capture images from interior body components. These reviews cover a variety of segmentation techniques for tumor detection. Medical professionals must spend a lot of time manually processing Magnetic Resonance Imaging (MRI) data. We must introduce the soft computing approach.

Utilize the tolerance for imperfection, ambiguity, partial knowledge, and approximation in order to produce unconventional solutions, tractability (the ability to be easily handled, managed, or controlled), resilience, and affordability.

Using the MATLAB GUI TOOL for soft computing, we achieve superior results over the conventional approach. It is utilized for big data. To solve mathematical problems and describe mathematical notation, MATLAB is a high-performance language.

An emerging field of technology is soft computing, which combines fuzzy, neuronal, and intelligent systems. Image segmentation is among the most vital applications.

Soft computing is used to solve problems in the real world. The phrase "soft computing approach" refers to

an algorithm's handling of the notion of natural probability in the actual world. Science and engineering are likely to benefit the most from soft computing, but eventually its impact may be felt much beyond. Imprecision, uncertainty, partial truth, and approximation are all characteristics of soft computing. It offers a wide range of solutions in a real-world setting.

Soft computing is a group of methods that aid in building a computationally intelligent system that can adapt and learn. Risk analysis involves finding the affected area. Soft computing is based on biologically inspired approaches like genetics, evolution, the behaviors of ants, particle swarming, human nerve systems, etc.

In the actual world, it resolves difficult issues. In contrast to traditional (hard) computing, soft computing is tolerant of imperfection, uncertainty, partial truth, and approximation. As a result, the human mind serves as a model for soft computing. Neural Networks, Fuzzy Logic, Evolutionary Computation, Swarm Intelligence, and Bayesian Networks are key components of soft computing.

One of the most significant characteristics of soft computing is that it should be adaptive so that any change in the environment does not influence the current process. Soft computing is a technique where we calculate solutions to the existing complicated problems, where output results are imprecise or fuzzy in nature. The properties of soft computing are as follows.

No mathematical modelling is necessary to solve any particular situation.

When we occasionally tackle a problem with a single input, it results in different solutions.

It makes use of techniques inspired by biology, including those found in genetics, evolution, particle swarming, and the human nervous system.

3.6 Proposed Approach

This Figure 3.2 shows the traditional method of image segmentation.

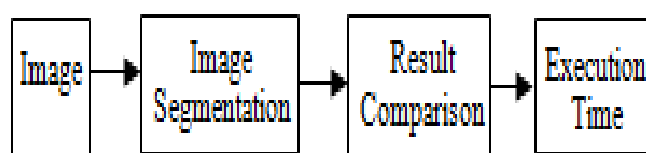


Figure 3.2 Image Segmentation

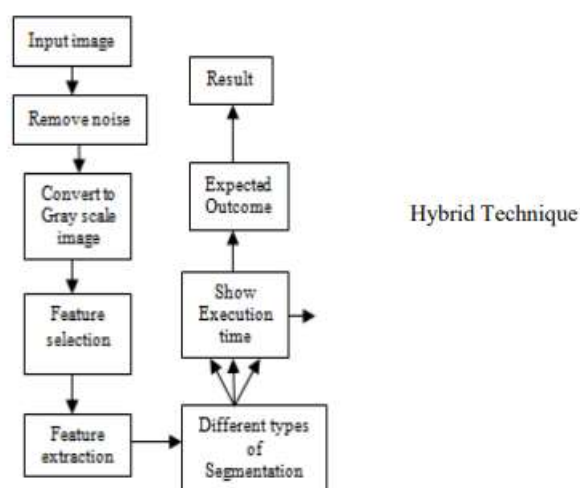


Figure 3.3 shows the Soft Computing Proposed Model using Hybrid technique.

This Figure 3.3 shows the Using a hybrid approach, the proposed model for soft computing. A hybrid clustering technique-based medical image segmentation system was created by us to accurately and quickly identify brain tumors. We contrasted the conventional approach with the suggested approach. FCM, K-Means, and Histogram thresholding are three segmentation approaches that are combined with the suggested method to further increase segmentation accuracy. As a result, this method greatly increases the accuracy of image segmentation.

Their experimental results showed that the three segmentation methods perform better when combined than when used independently. Combining three segmentation techniques results in hybrid segmentation. The main objective of combining the various algorithms is to improve segmentation accuracy and do away with the drawbacks of the three separate approaches. Many scholars proposed a novel hybrid strategy for segmentation. The MATLAB GUI Toolbox was used to complete the suggested work.

There are some major steps in the proposed approach. Input image, noise filter, Feature selection, Feature extraction and Classification.

Step 1:

It is the original image that was entered. retrieved from dataset.

Step 2:

Noise in the image must be removed. The denoising approach is initially applied to each image.

Step 3:

The input image is first read by the suggested algorithm, which then converts it to a grayscale image.

Step 4:

Variable and attribute selection are other names for feature selection.

Step 5:

With feature extraction, the tumor is identified in the MR image and its precise location as well as a few other features are established. The method for locating the affected area is called feature extraction, during which the tumor is retrieved from the MR picture. Feature extraction is one type of dimensionality reduction used in image processing. The process of extracting features from a set of input data is known as feature extraction.

Step 6:

Classification: In this stage, using a soft computing method, we employ these three picture segmentation approaches to derive the Region of Interest (ROI). It is a hybrid method that combines the methods of histogram analysis, K-Means clustering, and fuzzy C-Means clustering. All techniques are conducted simultaneously using a soft computing tool. Fuzzy C-Means and Fuzzy K-Means are two clustering approaches that are evaluated using a soft computing tool. Compared to K-Means, the fuzzy C-Means clustering technique is more accurate.

Step 7:

In this step calculate execution time. It shows execution time. It is the speed of Computation.

Step 8:

At the conclusion of the process, compare all execution time to the anticipated results. Soft computing software produces results simultaneously.

Step 9: Results. Processed image after calculation. The result obtained from hybrid technique takes less time than tradition method. For comparison iteration is required.

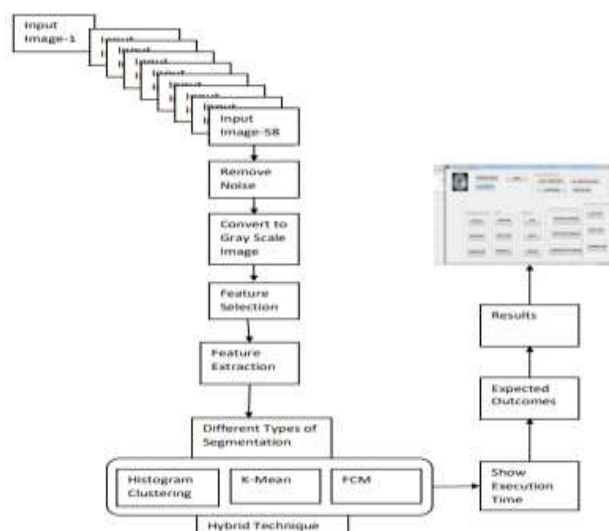


Figure 3.4 Soft Computing Proposed Model using Hybrid Technique (For different Images from 1 to 58)

Figure 3.4 shows the soft computing proposed model using hybrid technique in which the basic process of expected outcomes is in above steps. Here we used 58 different images of brain, to check the comparison of traditional method and proposed method. Iteration is required to check the better performance of segmentation. Here the data input is mri brain image for segmentation. Second step is to remove the noise from image. Each image is first applied with denoising technique. Then next step is feature selection and extraction after that different segmentation method is applied.

In this work two methods are compared existing and proposed. Individual performance of traditional method is also done by this work. Comparison, Results and analysis is given in next chapter.

Due to the limitations of manual MRI analysis, an automated system using soft computing techniques is required in order to produce results that are both accurate and widely accepted. The traditional method of tumor detection in MRI images is a manual analysis, which results in variations in results when analysed by different experts. The proposed method will execute the image more quickly. This model's goal is to evaluate and contrast various segmentation methods.

Expected outcomes can be achieved by MATLAB GUI TOOL with the help of toolbox we can perform the different features of result analysis. In this GUI feature traditional and hybrid methods are presented. This work is based on detecting brain tumor from MRI images using and interface of GUI in MATLAB. All the MATLAB programs work with GUI "MATLAB Guide". It is MATLAB interface file used to hold and process information. GUI program is easy to control and manage of segmentation. There are some push buttons. Each button has different functions. In result, we can see that using GUI program we obtained better result than traditional method for detection of tumor image. The use of GUI-based programmes enables quick and easy tumor diagnosis and enables changing programme parameters without rewriting it. Clearly, the outcomes are quicker and more precise.

3.7 Hybrid segmentation technique

In this figure 3.4, it is using a hybrid technique that combines three segmentation techniques, soft computing developed a model. Hybrid segmentation, which has been suggested to segment tumor images, combines the Histogram, K-Means, and FCM. After pre-processing, the image is turned into a grayscale version and denoised using a filtering approach. This pre-processing image is segmented in the final step utilising the combined features of these three methods.

These three segmentations are contrasted with the outcome of the hybrid segmentation. It shows various execution times and shortens the time analysis for the detection of brain tumors. In comparison to the conventional method, the hybrid segmentation methodology effectively integrates two or more methodologies.

The proposed hybrid approach's main goal is to combine these methods in a way that will extract the tumor effectively and reliably. The basic goal of hybridization is to strengthen one approach while weakening another.

IV. OBSERVATIONS AND ANALYSIS

The suggested method consists of a few significant phases. To separate the image into different segments, image segmentation is used. After segmentation, the segmented image is subjected to the fuzzy clustering algorithm. Compared to K-Means, the fuzzy C clustering technique is more accurate.

4.1 Process Analysis

4.1.1 Manual processing:

The typical approach will require more time and add to the intricacy of the timeline. It proceeds step by step, carrying out one process at a time before moving on to the next.

4.1.2 Batch processing:

The process known as a batch involves gathering a number of tasks into a batch or group. Following the execution of one procedure, another one is executed. It works in a sequential manner.

4.1.3 Soft computing:

Here, we are applying unsupervised machine learning to reduce the amount of manual image processing that must be done. This allows for the simultaneous running of many processes. Soft computing is used to solve nonlinear, time-varying, unpredictable, and very complicated problems in the real world. Soft computing, commonly referred to as computational intelligence, provides dependable, effective, and ideal solutions. Medical science, engineering, artificial intelligence, power systems, and control applications are just a few of the domains where soft computing is applied. Rich knowledge representation, acquisition, and processing are all parts of soft computing techniques, which are used to address a variety of applications. The use of soft computing in this work is to execute multiple processes at once using the MATLAB GUI TOOLBOX.

V. RESULTS AND CONCLUSION

In this chapter results are drawn, on the basis of methodologies, discussed in previous section.

Each algorithm's results are presented step-by-step before being compared, starting with the tumor outcomes.

5.1 Datasets and Results

5.2 Input Brain Images

In this work, 58 brain images are collected from open sources and hospital to check working of the brain segmentation technique which are implemented. Tumor may be different shape and size. It could be both a mass and a malignancy, a brain mass and a brain malignancy.

If there is mass in brain K-Means is enough to extract information from brain. If there is noise it is necessary to remove noise from image. C-Means is better for overlapped data set. All of these images are of different sizes and have different properties like .jpg, .bmp, .tiff, .gif. So, these images are converted into .bmp format before applying in any of the algorithm. Some of these images are being shown as below:

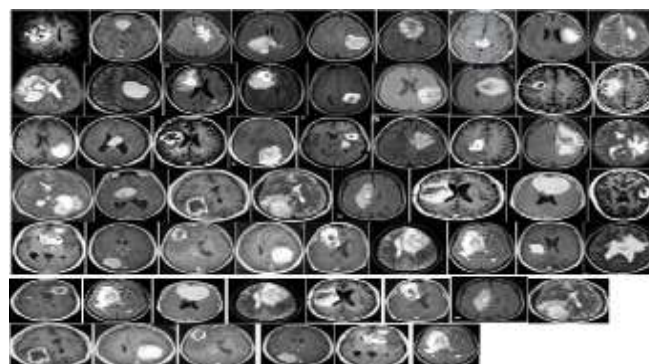


Figure 5.1 Input Brain Images

Comparison of Tumor Results by Three Unsupervised Techniques

In this section, tumor region found out after applying Histogram Thresholding, K-Means Clustering, Fuzzy C-Means Clustering Technique are compared.



Figure 5.2 GUI MATLAB TOOLBOX

5.3 Manual analysis by Histogram Clustering

In this work also we need to analyze the manual process for comparison to GUI process.

The following results for Histogram clustering are:

1. Original Image, 2. Gray scale image, 3. Segmented image of left half, 4. Segmented image of right half 5. Segmented image with border clear, 6. Tumor Region and 7. Tumor affected region of brain.

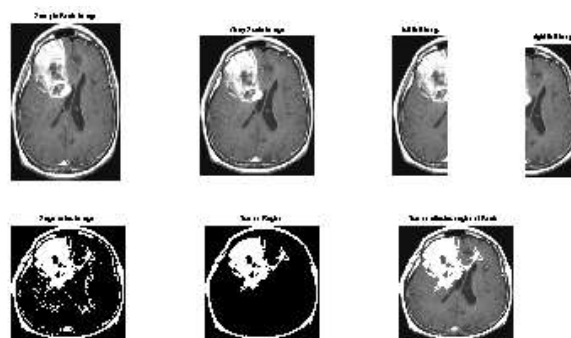


Figure 5.3 Manual analysis by Histogram Clustering

5.4 Manual analysis by K-Means Clustering

In this work also we need to analyze the manual process for comparison to GUI process.

The following results for K-Means clustering are:

1. Original image, 2. Gray scale image, 3. Cluster no. 1, 4. Cluster no. 2, Cluster no. 3, 6. Cluster no. 4, 7. Segmented Cluster with high intensity pixel, 8. Segmented image with farthest pixel point, 9. Segmented image with border clear, 10. Segmented image with all holes filled, 11. Tumor region and 12. Tumor effected region of brain.

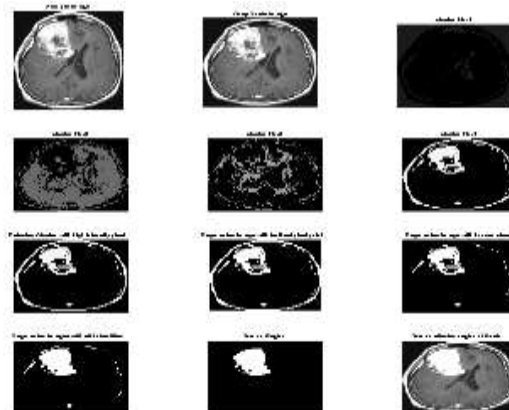


Figure 5.4 Manual analysis by K-Means Clustering

5.5 Manual analysis by FCM Clustering

These are the tradition method of image process that is performed step by step. It is time consuming, follow one by one step. Manual analysis is the process of segmentation in which we can apply segmentation technique one by one.

The following results are for FCM clustering:

1. Original image, 2. Grayscale image, 3. Cluster after Segmentation, 4. Segmented image with farthest pixel, 5. Segmented image with border clear, 6. Segmented image with all holes filled, 7. Tumor region and 8. Tumor affected region of brain.

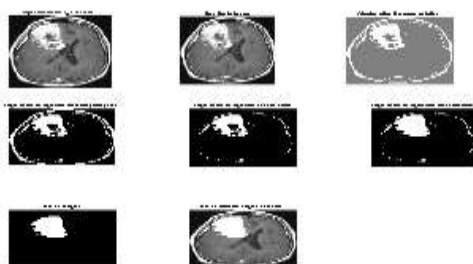


Figure 5.5 Manual analysis by FCM Clustering

5.6 Comparison by Histogram

It is part of traditional method to perform with or without filtering techniques in an image. This program took 7.288259 seconds to run.

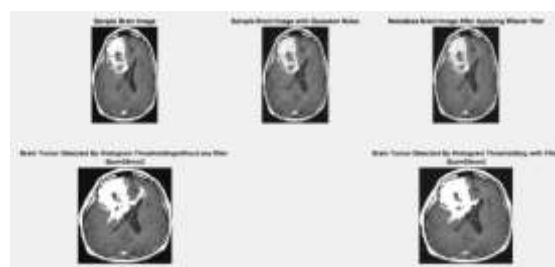


Figure 5.6 Comparison by Histogram Clustering

5.7 Comparison by K-Means

It is part of traditional method to perform with or without filtering techniques in an image. This program took 12.731474 seconds to run image.

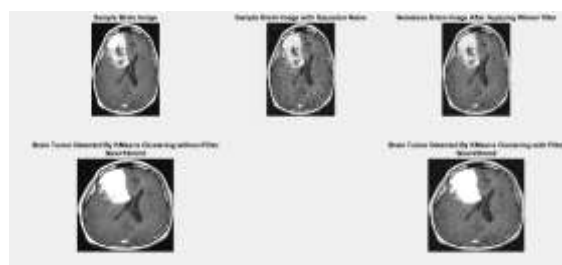


Figure 5.7 Comparison by K-Means Clustering

5.8 Comparison by FCM

It is part of traditional method to perform with or without filtering techniques in an image. This program took 9.525325 seconds to run.

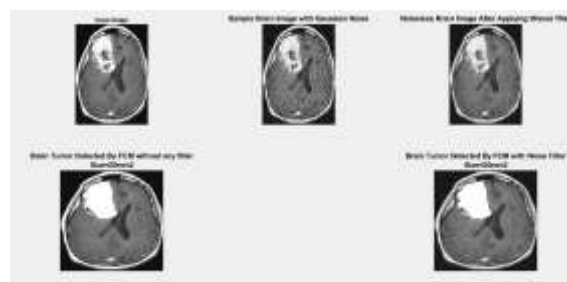


Figure 5.8 Comparison by FCM Clustering.

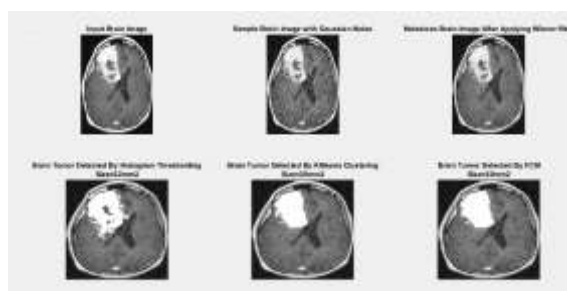
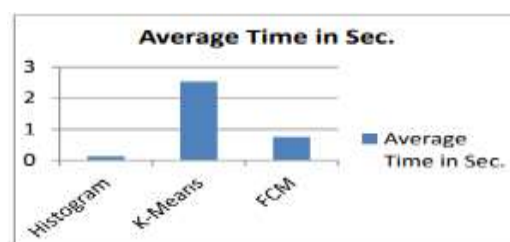


Figure 5.9 Comparison of Tumor Results with Soft computing approach using hybrid techniques (Reduction of time complexity).

Manual analysis by us is given in table is clearly shows the execution time is greater than analysis of proposed approach.

Table No. 5.1 - Comparison of Tumor Results with three techniques.

Method	Average Time in Sec.
Histogram	0.13
K-Means	2.54
FCM	0.76



Graph 5.1 Comparison of Tumor Results with three techniques.

Result is shown below comparisons among all these three methods with filtering technique. After execution, this program took 11.081672 seconds to run.

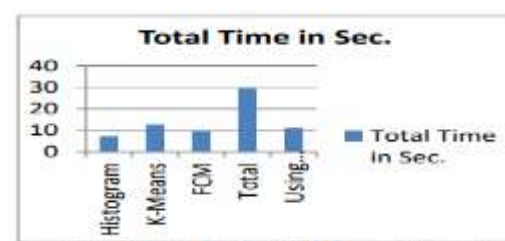
Table No. 5.2 Existing Method and (automatic process) Proposed Method done by MATLAB GUI TOOLBOX.

Method	Total Time in Sec.
Histogram	7.288259
K-Means	12.731474
FCM	9.525325
Total	29.545058
Using Soft computing approach, based on hybrid technique	11.081672

The following chart represents the result of execution time of comparison between manual and automatic process done by MATLAB GUI TOOLBOX.

The system model is based on combined approach that is achieved by hybrid technique. In which we can run these three techniques simultaneously at a time and gives results. It shows the less execution time than manual approach.

The following chart represents the accuracy of comparison between (manual) Existing Method and (automatic process) Proposed Method done by MATLAB GUI TOOLBOX.



Graph 5.2 Time Calculation and Comparison between Manual analysis and Soft Computing with GUI (Existing method and Proposed method)

In this chapter results of three unsupervised techniques viz. Histogram Thresholding, K- Means Clustering and Fuzzy C-Means Clustering techniques are shown and discussed. Results are tried to improve from previous result by using morphological operations. It can be observed that Histogram and Fuzzy C-Means clustering is giving good results all the time as compared with K-Means works in some brain images.

The tumor image that is very clearly displayed by FCM is even impossible to construct using Histogram Thresholding and K-Means clustering. FCM outperforms K-Means.

K-Means is fast, robust and simple to implement. But, in our analysis found that execution time is less in FCM clustering. Also, we need to more improvements, performance and accuracy in these segmentation techniques. This will be achieved by using Soft Computing MATLAB TOOLBOX found that Soft Computing approach can reduce the execution time rather than manual execution.

5.9 Result analysis using Fuzzy Logic Toolbox

We can also design your own membership functions using Fuzzy Logic Toolbox. Utilize the Fuzzy logic Designer's custom functions to create a fuzzy inference system. You can substitute your own membership functions, inference functions, or both when creating a fuzzy inference system, as explained in the Fuzzy Inference procedure.

In this section, you learn how to build a fuzzy inference system using custom functions in the **Fuzzy Logic Designer** app.

Utilizing unique functions in the Fuzzy Logic Designer software to construct a fuzzy inference system. After entering this command, open the Fuzzy Logic Designer programme and type fuzzy Logic Designer there. An editor for fuzzy logic appears. As per Fuzzy Logic Designer's instructions, provide the fuzzy system's number of inputs and outputs. As stated in specify custom membership function, create custom membership functions and replace the built-in membership functions with them.

Membership functions define how each point in the input space is mapped to a membership value between 0 and 1. Create rules using the Rule Editor, as described in the Rule Editor. Rules define the logical relationship between the inputs and the outputs. We can create custom membership functions and use them in the fuzzy inference process. The values of these functions must lie between 0 and 1.

Fuzzy Logic Designer opens with the default FIS name, Untitled, and contains one input, **input1**, and one output, **output1**.

In **Fuzzy Logic Designer**, select **Edit >Membership Functions** to open the Membership Function Editor. By default, three triangular-shaped membership functions for input1 are shown.

To add a custom function to the Membership Function and replace the default membership function Editor.

Select **Edit >Remove All MFs** to remove the default membership functions for **input1**.

Select **Edit >Add Custom MF** to open the Custom Membership Function dialog box.

FIS editor window is shown in figure 5.10 for process analysis. In this section observation and analysis, process and result analysis is discussed.

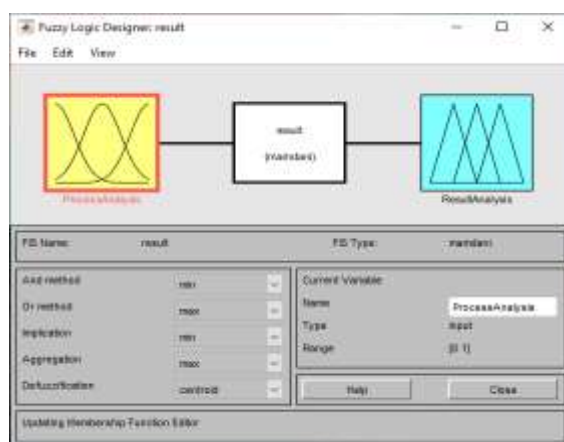


Figure 5.10 Process and Result analysis

5.10 Process Analysis

For the complete fuzzy inference system, the Membership Function Editor is the tool that allows you to view and edit all of the membership functions connected to all of the input and output variables.

In Member Function Editor set the input output variables and different range of the variables below figure is showing the member function editor window. The main graph shows the membership functions from the current variable.

In this we set the membership values of the function are as shown below.

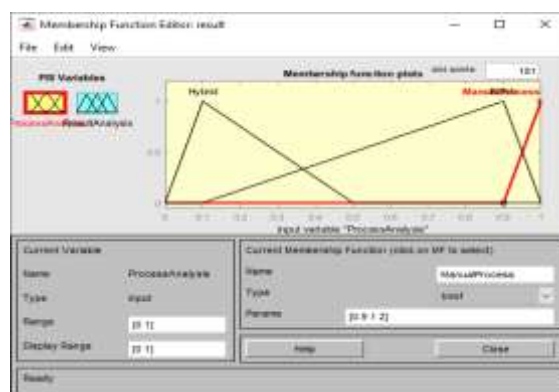


Figure 5.11 Member function of process analysis

5.11 Result Analysis

In result analysis output variable depends upon the input variable.

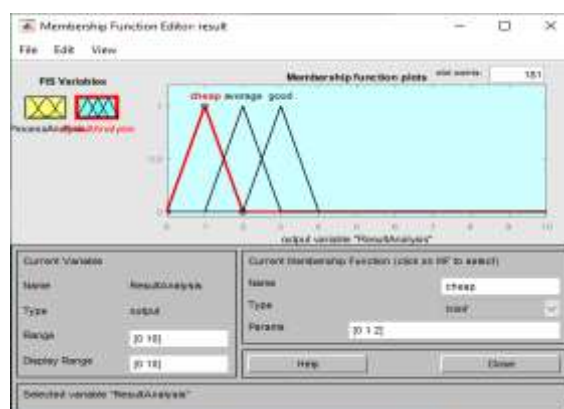


Figure 5.12 Member function of result analysis

5.12 Rule Editor

The description of the input and output variables is the foundation of the rule editor. It allows us to create rules by selecting an item for each input and setting a variable box for the output. The Rule Viewer now has a custom membership function that may be used to add rules for the fuzzy inference procedure. Select Edit >Rules in the Membership Function Editor or the Fuzzy Logic Designer to view the custom function in the Rule Viewer.

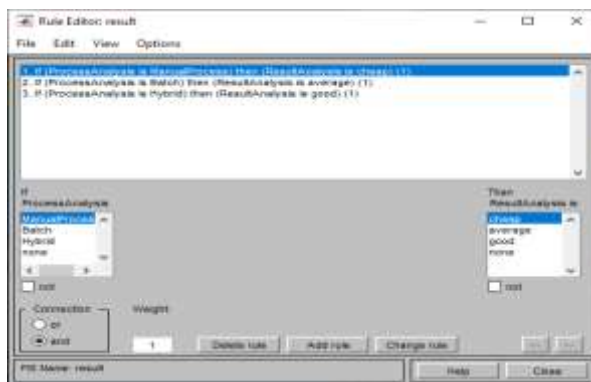


Figure 5.13 Rule Editor of process and result analysis

5.13 Rule Viewer

In Rule Viewer Window, it depends upon the rule editor. Output will vary according to the input variables. The fuzzy inference diagram is shown here. Use this viewer to perform diagnostics, such as determining which rules are in effect or the effects of different membership function shapes on the outcomes.

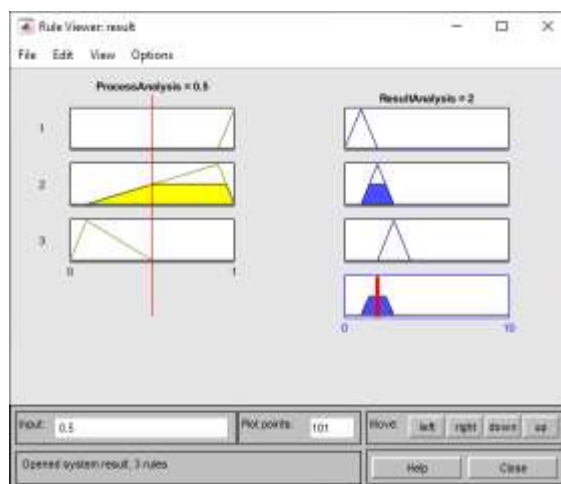


Figure 5.14 Rule viewer window

In this work we used different types of method and its execution time is different taken by algorithms. In this work three different methods are used. In Chapter 5, GUI Processing MATLAB Toolbox using Soft Computing is discussed, here comparison between three techniques and hybrid technique.

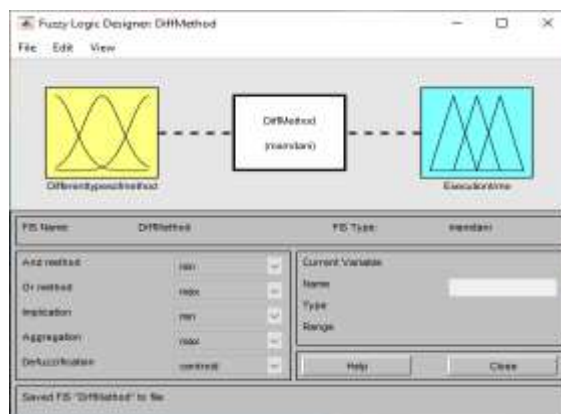


Figure 5.15 Different types of method and their execution time

5.14 Member Function Editor for different types of method

This editor has 2 FIS variables input and output. The comparison of different types of method and their execution time is given in Table no. 4.2 in chapter 4, observations and analysis.

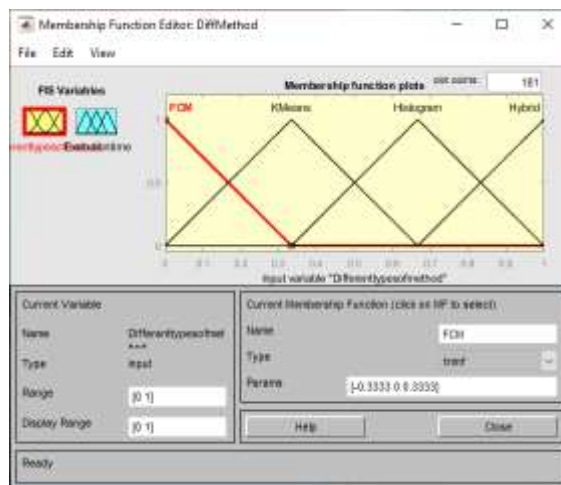


Figure 5.16 Member function of different types of method (FIS input variable) Member Function Editor for different types of method and their execution time

Below figure is FIS output variables



Figure 5.17 Member function of different types of method (FIS output variable).

5.16 Rule editor for different types of method

The Rule Editor enables you to automatically create the rule statements based on the descriptions of the input and output variables provided with Fuzzy Logic Designer. We can edit, save, delete, and alter the input and output variable based on the UI control tool. The system's behaviour changes as input and output variables are modified.

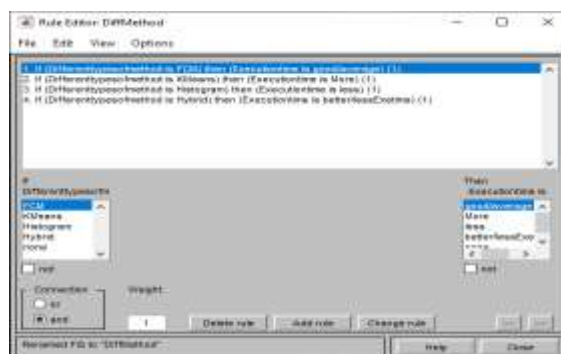


Figure 5.18 Rule editor for different types of method

5.17 Rule Viewer for different types of method

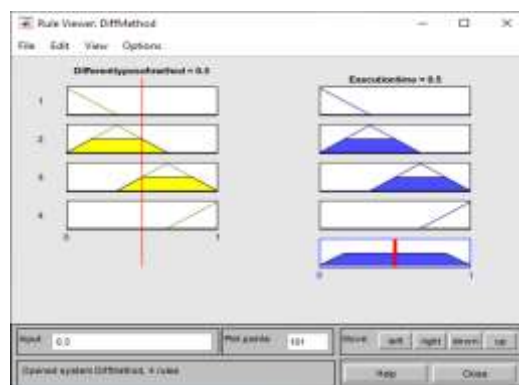


Figure 5.19 is showing the rule viewer window.

In this window, we can increase and decrease the range of input level by this changing output will also be change.

Rule Viewer, which is used to view the inference process for the fuzzy system.

5.18 Experimental Result

Each step of the process has a number of research publications available. The experimental findings of the suggested work are presented in this section.

Here number of research paper available that proposed the work with Histogram, K-Means and C-Means. The existing system proposed the method of Histogram, K-Means and C-Means that is manual analysis takes more time for process. Also, it has demerit that is author worked with only one image. In the proposed system worked with more than one images for analysis of clustering technique. In this work we used 58 and above images.

The existing system output is not represented by GUI and proposed system worked with MATLAB GUI TOOLBOX that is user friendly. In proposed work FCM algorithm is used and it compared with another two Histogram and K-Means. Using analysis and observation, it was discovered that Histogram and C-Means has less execution time and K-Means is higher than other two. It is the manual analysis by us that is higher than automatic analysis using Soft Computing with GUI.

The present work is based on hybrid technique in which we proposed the combine approach that is Histogram, K-Means and C-Means. The following table shows the result of execution time of comparison between manual and automatic process done by MATLAB GUI TOOLBOX. It minimizes the 50% load of data. Manual analysis by us on the basis of observation and analysis is given by following table. It represented the comparison between existing system and proposed system.

The hybrid approach uses the benefits of both approaches while addressing their respective drawbacks. Using the combined features of these three algorithms, we suggested a hybrid approach-based picture segmentation in this work. Segmentation is carried out using the K-means clustering algorithm, the Fuzzy C algorithm, and the histogram. As a result, it provides an accurate tumor segmentation result. In these situations, using a combinational approach is advantageous.

In comparison to segmentation algorithms functioning alone, the hybrid segmentation technique effectively combines two or more techniques. The effectiveness of this proposed hybrid strategy depends on the method's implementation and similarity metrics. The MRI brain tumor pictures are segmented using the hybrid segmentation technique.

The primary goal of this proposed hybrid clustering technique is to quickly and accurately identify a brain tumor. The accuracy and shortest execution time were taken into consideration at each stage, which allowed the suggested hybrid technique to effectively address the major issues.

According to the experimental findings, the over segmentation and under segmentation issues were resolved,

and the number of iterations and calculation time were both decreased.

5.19 Expected Outcomes

Brain tumor detection using segmentation with unsupervised learning technique is proposed. Working with risk analysis we can improve the segmentation techniques. Using hybrid technique, it will give better result; it reduces the time complexity of given comparative method. On the basis of the result that FCM clustering algorithm is less time consuming than K-means algorithm.

VI Conclusion

Three alternative unsupervised image segmentation techniques have been developed and implemented in this work using Soft Computing in the MATLAB GUI TOOLBOX to identify tumor regions in brain MRI data.

A hybrid solution for image segmentation that combines these three techniques is the best method, according to a literature review that found manual brain image analysis for brain tumor identification to be a time-consuming task.

Also brain tumor segmentation is challenging and time consuming task and it is because of unclear boundaries or edges of gray and white color intensity of different tissues in MRI brain images. Researchers have proposed many methods MRI brain segmentation. For each steps there are numbers of method available.

Improve the quality of MRI pictures to achieve better quality images from hybrid techniques and accuracy will be obtained in the final outcome depends on handing out of each phase. It is necessary to detect and identify that cell has been injured in the human body and remove that problem. There are several approaches that can be used for each phase.

Enhance the quality of MRI images to obtain higher-quality images using hybrid approaches, and accuracy will be attained in the final result depending on how each phase is carried out. In order to solve the issue, it is crucial to find and recognize the damaged cells in the human body. Each phase can be approached in a variety of ways.

To find a method of soft computing, we looked into all of these techniques. With the use of soft computing in MATLAB TOOLBOX, which can deliver exceptional accuracy, choose the best medical photos, and have the potential to enhance the diagnosis.

It will reduce the time complexity of execution of segmentation techniques. It has robustness and low cost. It has the advantages of many applications in different area. Soft Computing minimize the computation complexity and gives usable solution for complex problem.

It will make using segmentation techniques less time-consuming. It is affordable and strong. It offers the benefits of several applications in various fields. Soft computing reduces computation complexity and offers practical solutions to challenging issues.

Accuracy cannot be achieved using the conventional methods. The capacity to improve the error-free image and demand less time for an accurate result are two advantages of this comprehensive evaluation of the methodologies and techniques used to detect brain tumors by MRI image segmentation.

The suggested method can deliver superior results even in environments with a lot of noise. The algorithm is easy to use and quick. This algorithm offers improved segmentation quality and is more resistant to noise.

Therefore, it is required to eliminate image noise and decrease the temporal complexity of the given data's execution speed. The Fuzzy C-Means clustering technique consistently outperforms other techniques in our results, it has been discovered.

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