Section A-Research paper
ISSN 2063-5346

MRI BRAIN TUMOR DETECTION USING FUZZY C MEANS CLUSTERING ALGORITHM

Ms. A.Anbu Rani[1],
[1] M.E-Communication Systems, PSN College of Engineering and Technology, Melathediyoor, Tirunelveli, Tamilnadu,
lovelyqueen2604@gmail.com
Dr. T. Rajesh[2]
[2] Professor and Head, Dept. of Electronics and Communication Engineering, PSN College of Engineering and Technology, Melathediyoor, Tirunelveli, Tamilnadu,
tnanjilrajesh@gmail.com
Dr. C.Mariyal[3]
[2] Associate Professor, Dept. of Electronics and Communication Engineering, PSN College of Engineering and Technology, Melathediyoor, Tirunelveli, Tamilnadu,
mariyalwatson@gmail.com
Mrs.S.Indhumathi[4]
[2] Assistant Professor, Dept. of Electrical and Electronics Engineering, PSN College of Engineering and Technology, Melathediyoor, Tirunelveli, Tamilnadu,
indhumathi1241997@gmail.com

Abstract -Many people around the world suffer from Brain tumor. It is not only affect the old age people but also affect the early age people. We can early identify the brain tumor using image processing. Medical image processing is the most advanced field today. Many scientist and researchers are working in the brain tumor detection process for improving the results .It plays a vital role. Brain tumor detection is helpful for the doctors to identify the early stages of tumor. The complex architecture of the brain makes it difficult to detect brain tumors using MRI imaging. This study uses a MATLAB GUI (Graphical User tool) tool to detect brain tumors from MRI images. Various image segmentation techniques can be used to process the MRI picture, segment the brain tumor, and segment the brain tumor. Pre-processing, picture segmentation, feature extraction, and image detection are the four categories into which the process of detecting brain cancers by MRI can be divided. In order to save time and labor, a method for removing brain tumors from magnetic resonance brain pictures was proposed in this article.

Keywords: MRI Image, Image processing, Image segmentation, Feature extraction and Tumor detection

1. Introduction

Magnetic resonance imaging (MRI) is the finest biomedical technology for identifying and classifying brain cancers, which provides information on anatomical structures and aberrant tissues that are crucial for treatment planning and patient follow-up. In addition to its potential value for the creation of pathological brains, brain tumor segmentation may also prove very useful. With the types of feasible shapes, areas, and image intensities, it is a very challenging medical image processing process, and there are a number of types of tumors involved. There may also be edema or necrosis associated with them, which alters the depth of imaging around the tumor in addition to deforming the surrounding structures. In order to increase automation and accuracy, current approaches department large rooms. With the use of modern medical image processing, it is possible to identify every aspect of a brain tumor in order to save a patient's life today. The purpose of this project is to extend the detection of brain tumors in order to save the young and old age people in starting stage of the tumor. Since the brain is separated into two distinct regions, segmenting images is necessary for the purpose of identifying brain tumors. It is regarded as one of the most crucial but challenging steps in the process of finding a brain tumor. The MRI pictures must be accurately segmented for this reason before requesting the computer to provide a precise diagnosis. In the past, numerous algorithms for segmenting MR images have been created utilizing various instruments and strategies. Another definition of image segmentation is the grouping of all the pixels or picture elements in an image into distinct groups that have similar characteristics. In order to segment an image, it must be divided into homogeneous groups of pixels. Each and every distinct group must be diverse, and no two groups may intersect. Segments are the names for the groups. Image segmentation is thought to be the best general strategy for conclusive analysis and interpretation of an acquired image. One of the most challenging problems in image processing, it is an important and fundamental part of an image analysis and pattern recognition system, which decides how well the segmentation is done in the end. Researchers have extensively researched on this fundamental issue and offered several image segmentation techniques. Cancerous tumors and benign tumors are two types classified by brain tumor. One of the most popular methods for finding brain tumors is magnetic resonance imaging (MRI), which provides precise pictures of the brain. For more accurate brain tumor detection, growth rate forecasting, and treatment preparation, brain tumor segmentation using MRI is beneficial. It is also essential for tracking tumor development or shrinkage in patients during therapy. Additionally, it is crucial for arranging radiation treatments or surgeries. In these situations, the tumor must be defined, and the healthy tissues nearby are equally important for subsequent processing and therapy. The size and appearance of the brain tumor make diagnosis challenging. We can quickly detect the tumors and its stage by segmenting the MRI picture using our image processing technique. Both interactive segmentation and automatic segmentation are examples of previous methods for segmenting brain tumors. No matter how much training data there is, interactive segmentation still works. It needs input from the user, such as naming the object of interest or inserting seeds indicating that the labels of some pixels belong to a particular class. The interactive segmentation also enables users to assess the outcomes. If the segmentation results are unsatisfactory, users can then update and improve the results by adding more seeds. Until no additional alteration is required, the interactive segmentation process can be repeated. Even though interactive segmentation can produce good segmentation results, trained professionals must still put up a lot of effort until they receive satisfactory results. In order to automatically get tumor segmentations. Its goal is to research automatic brain tumor segmentation. This thesis makes use of an interactive and previously successful brain segmentation system, although it does not ask for human input. This thesis demonstrates how to automatically segment the tumor for the entire slice.

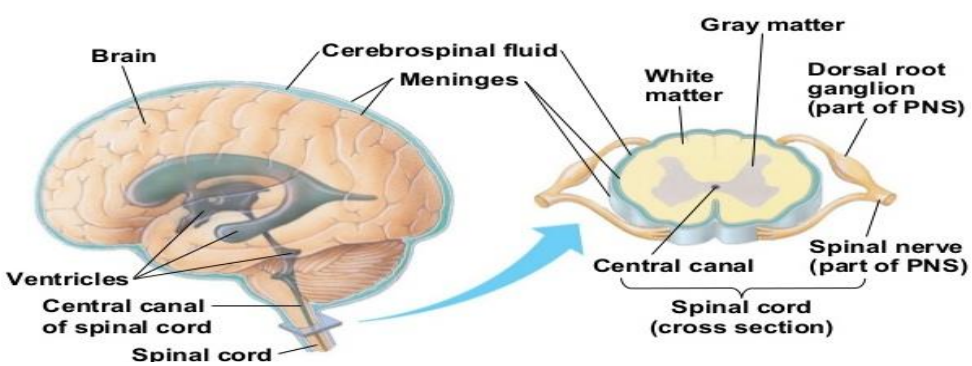


Fig1.1 Anatomy of brain

The above Fig 1.1 is the normal anatomy of brain. Image data from an MRI is used in this study. A magnetic resonance imaging (MRI) scan our strong and week tissues with image format using magnetism, radio waves, and computers. MRI can detect minute changes in the human body's structure and offer a very complete depiction of the organs. Doctors can assess different body sections and check for the presence of certain disorders using detailed MRI. A signal in two dimensions is all that an image is. The mathematical function f (x, y), which takes the two co-ordinates x and y as inputs, defines it. The pixel value of a picture at every position is given by the value of f (x, y) at that location. In a digital image, a two-dimensional image is represented as a finite set of values called picture elements or pixels. A set of points in 2- or 3-dimensional space can be an image. An image's amplitude or intensity is defined as every point at every (x, y) coordinate. It is a digital image when the amplitude and the x, y coordinates are discrete. We refer to it as an analogue image if the values are continuous. Utilizing sampling and quantization, an analogue image can be transformed into a digital image. A digital image's primary building block is a pixel, and all of its 2-d function's coordinates and associated values are finite. Every value that is present at every position is regarded as a pixel. Alternatively put, a pixel is the smallest component of an image. A digital image can be viewed as a two-dimensional collection of pixels. Every pixel has a certain intensity value, known as a grey level.

Using a computer, digital images can be edited using digital image processing. It is a division of signals and systems with a focus on images. DIP's main objective is the development of an image-processing computer system. This system take input as digital format images, it will proceed to some of the algorithm and output is an image format. Any Photoshop is used for illustration. This is one of the most used apps for modifying digital photographs. In imaging science, a subfield of signal processing, a picture is the input data. Image processing entails converting a physical image into a digital one and using a variety of methods to enhance or remove critical elements. At that time result of a image or video outline will be an image, a set of properties, a set of parameters related to the image, etc. In image processing frameworks, which regard them as two-dimensional signals, standard signal processing algorithms are frequently used to images. Enhancing pictorial information for human interpretation and processing image data for storage, transmission, and representation for autonomous machine perception are the two main goals of digital image processing. There is some debate about the boundaries between image processing and disciplines such as image analysis and computer vision. Ability to categorize processes on the continuum from image processing to computer vision into low-, medium-, and high-level categories. The input image is a requirement for image processing. In order to determine the quality of an image, performance metrics are analysed for tumour and non-tumor images after discussing the principles of image processing.

2. Field of study

A method that recognizes and using thresholding and watershed techniques, segment the brain image. was presented by Roshan G. Selka and M. N. Thakare. This process consists of three steps. They initially improved the input scanned image before applying morphological operators.

Mohammed Sabbih Hamoud Al-Tamimi and Ghazali Sulong assessed the ability to detect tumors in the brain using MR images. They gave a thorough analysis of the methods and processes in this study used in image segmentation to find the brain tumor. The discussion of these future directions for brain image segmentation and tumor detection research served as the report's short conclusion. A method for segmenting brain images using the modified fuzzy c-means (FCM) clustering algorithm has been presented by Indah Soesanti et al.

An innovative method for the automatic segmentation of brain tumors in MRI images was developed by Saeid Fazli and Parisa Nadirkhanlou. After the extraneous sections of the MRI images which exist tissue an isotropic diffusion filter with a photos are processed with an 8-connected neighborhood to eliminate noise. Fast Bounding Box (FBB) method, by the MRI image the tumor area is displayed, and the core region is selected as a set of sample points for an SVM classifier.

Mark Schmidt et al. suggested a method for segmenting images of brain tumors using alignment-based criteria. The performance of four distinct Alignment-Based (AB) feature types for storing spatial data for supervised pixel classification is statistically evaluated in this work. For the first time, several AB feature types are compared, ways to integrating different AB feature types are investigated, and blending AB feature types with textural characteristics in a learning framework is investigated. When applied to scenarios where prior approaches failed, we discovered that combining textural and AB characteristics significantly improves performance and produces segmentations that nearly resemble expert annotations.

Mohamed Abdel-Basse, Qiu, Ahmed E. Fakhry and Arun Kumar Sangaiah developed a combined approach in registration of medical images. It presents an improved version of Mutual Information (MI) as a metric for

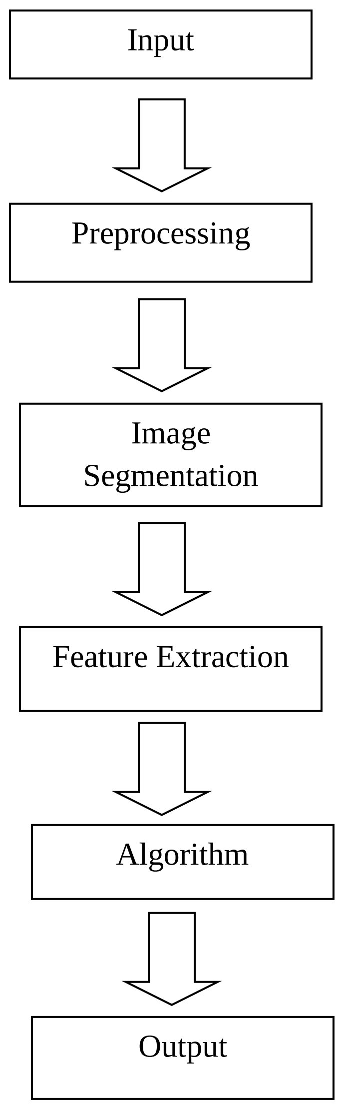
ISSN 2063-5346

similarity and Particle Swarm Optimization (PSO) technique. In this procedure, arithmetical and spatial data of the picture is get added to the procedure. Enhancement of the altered s information gets affected utilizing the adaptable Particle Swarm Optimization which can be effortlessly created by modifying few parameters. The modified approach was tested and checked effectively on various images from database

A 3D brain tumor segmentation method has been proposed by Hassan Khotanlou et al to segment an MRI picture. Initialization and refinement are the two stages of this project; in the initialization stage, the brain picture is segmented, and in the refinement stage, morphological procedures are used to segment the correct tumor part.

S.U.Aswathy, G.Glan Deva D has concerned on highlighting the pros and pros and cons of previous proposed techniques in classification. . This work gives a basic assessment of the research which uncovers new aspects of research. X-ray gives a ton of information about the delicate tissue in people, which helps in the treatment brain tumor. Correct parcel of MRI picture is fundamental for the examination of brain tumor by PC supported clinical instrument. The multifaceted nature in tumor emerges after segmentation of pictures that is ordered to dangerous and benevolent, because of its features like shape, measure, powers in gray level and position.

3.Proposed system



3.1. Preprocessing – Weiner filter

Image processing in the medical field is critically important due to its impact on patient care. The qualities of images collected during a health examination are more significant than when analyzing data from other fields, because they involve human life. Automated data processing is necessary when collecting biomedical images, as the vast majority of these documents are inconsistent and not standardized. Medical imaging files come from a variety of sources with varying formats, which makes it difficult to process them automatically.

To address the issue of faulty recognition, image segmentation is used. It is a crucial phase in the MRI input image's object recognition process. The primary goal is to segment the incoming brain pictures. In order to create meaningful sections of the input image, using similarity criteria, such as pixels with the same label, image segmentation simply entails labeling each pixel of the image. Specific frequencies can flow through a filter circuit while weakening other frequencies. In this approach, a filter distinguishes between signals that also contain undesired or different frequencies and those that do not. By applying linear time-invariant (LTI) filtering given a known stationary signal, known noise spectra, and additive noise to an observed noisy process, The Wiener filter is a signal processing filter that provides an approximation of a desired or target random process. Between the planned process and the anticipated random process, the mean square error is decreased. It can be used to get a statistical estimate of an unknown signal by using a related signal as an input and filtering that known signal to get the estimate as an output. At that time, combining the known signal with the unknown signal may result in a signal that may be valuable but has been distorted by additive noise. By removing the noise from the distorted signal, the relevant underlying signal estimated by wiener filter. Based on statistical principles, the Wiener filter, and the article on the minimal mean square error (MMSE) estimator provides a more statistical explanation of the theory. The typical frequency response of deterministic filters is chosen. The Wiener filter, on the other hand, uses a distinct strategy in its creation. Under the presumption that both the original signal and the noise have known spectral properties. Wiener filtering is used to reduce visual noise and provide results that are identical to the first image. The goal is to have the least amount of mean square error possible. The earlier knowledge of the noise in an image is investigated by Wiener filtering. It has the capability of wide-ranging reconstruction for locating the loud image. Wiener filters cannot be used to restore frequency components but noise that have been degraded. Additionally, items for which $H(u, v) = 0$ cannot be restored using Wiener filters. As a result, they are powerless to undo the blurring caused by band limitation of $H(u, v)$. Any picture system that is applied in real life encounters this band restriction. The Wiener filter is the MSE-optimal stationary linear filter for pictures with additive noise and blur. In order to calculate the Wiener filter (in the sense of a random process), it is necessary to presume that the processes comprising signal and noise are second-order stationary. Only noise processes with zero means will be taken into account for this description (without losing generality). Inverse filtering or generalized inverse filtering, deconvolution restoration techniques can be used to restore images blurred by known low-pass filters. However, additive noise is particularly susceptible to inverse filtering effects. Technology that reduces deterioration one by one, we can easily construct a restoration algorithm for each type of deterioration and then combine them. The Wiener filtering achieves the best possible compromise between inverse filtering and noise smoothing. The blurring and the extra noise are reversed at the same time. When it comes to mean square error, the Wiener filtering performs the best. It reduces overall mean square error in the inverse filtering and noise smoothing operations. The Wiener filtering linearly estimates the original image. The technique is based on a stochastic foundation.

3.2. Image segmentation – Fuzzy C means

To address the issue of faulty recognition, image segmentation is used. It is a crucial phase in the MRI input image's object recognition process. The primary goal is to segment the incoming brain pictures. In order to create meaningful sections of the input image, image segmentation simply involves assigning labels to each pixel of the image based on similarity criteria, such as pixels with the same label.

When utilizing fuzzy clustering, sometimes referred to as soft clustering or soft k-means, each data point might belong to multiple groups. The practice of allotting data to cluster in a way that makes things within one grouping as similar as is practical and those within another cluster as dissimilar as is practical is known as clustering or cluster analysis. Clusters are discovered using similarity measures. Some of these similarity measurements include distance, connectivity, and intensity. Depending on the data or the application, different similarity measures may be selected. The K means and a spatial fuzzy-c means algorithm are combined in the suggested method to increase the accuracy of tumor detection and decrease the processing time needed for segmentation. Clustering is one of the appropriate methods for segmentation, according to a thorough examination of the literature. K means is chosen among other clustering techniques for the reasons listed below. K denotes practically sound even when some presumptions are incorrect It is basic and straightforward to use. The clustering results are simple to interpret. Quick and cost-effective in terms of computation. The accurate selection of the k value is a crucial parameter in the computation of the tumor area in the k means algorithm. But it yields subpar segmentation results in the presence of noise and artifacts. The approach cannot be implemented for big data sets and only provides a partial segmentation for the type of malignant tumor. The other system is fuzzy C-means segmentation, which has access to more pertinent data from the original image to help find cancerous tumors. However, the process takes a long time to finish. When detecting tumors and categorizing textures, FCM does not employ spatial information. However, with K-means, the pixel that belongs to any one of the clusters, as opposed to SFCM, where the pixel can move to any cluster. To achieve clustering, SFCM ties all of the spatial data to the membership function. The value of the membership function added together for each pixel under consideration's neighborhood is known as the spatial function. The approach that best handles overlapping grey scale intensities is SFCM.

Non-fuzzy clustering, commonly referred to as hard clustering, is a data sorting technique where cluster consist of each data. In fuzzy clustering, data points might be a part of more than one cluster. For example, an apple comes in both red and green kinds (fuzzy clustering), but can only be either red or green (hard clustering). In this case, the apple may be partially red and partially green.

3.3. Feature extraction - GLCM

Based on the image histogram, the texture filter functions offer a statistical analysis of texture. While these functions can be helpful in revealing an image's texture, they are unable to reveal its structure, or the spatial relationships between its pixels. Utilizing the GLCM method, features are extracted. A statistical study of texture is provided by the texture filter functions using the image histogram. The texture of an image can be shown by using these functions, but the structure or the spatial relationships between the pixels cannot be revealed. The texture feature is defined in this module using a matrix of the co-occurrence of grey levels (GLCM). The segmentation step begins with the creation of the grayscale image from the color image, and then the image co-occurrence matrix is generated. The features of an image or item are its stated characteristics. These features should be extracted using various feature extraction methods that maximize within-class similarity and reduce between-type similarity. The GLCM feature extraction is employed in this work. Extraction of the key traits for identifying brain tumors is the task at hand. The extracted features provide the texture's property, and they are stored in a knowledge base where they are later compared to the features of unidentified example images to help with categorization. As a result, textural characteristics are employed to distinguish between regular and irregular brain tumors. One of the main characteristics of texture is autocorrelation.

The Gray Level Co-occurrence Matrix (GLCM) and associated texture feature estimates are two techniques used in image analysis. Given an image created with an intensity of pixels each (a different grey level), the GLCM is a tabulation of the frequency with which various combinations of grey levels appear together in a picture or image section. To calculate the texture features and provide an intensity variation measurement, the GLCM data is employed. Commonly referred to as picture texture, at the pixel of interest. The Echo View's GLCM Texture Feature operator generates a virtual variable that represents a specific texture calculation on a single beam echogram. The second-order statistical texture analysis method is referred to as GLCM. It analyzes the spatial relationships between pixels in an image and makes an estimation of how frequently a group of pixels will occur beside one another at a specific distance and direction. Statistical texture features of the second order can be extracted using the Level Co-occurrence Matrix (GLCM) approach. The method has been applied in a number of circumstances. In textures of the third order and higher, the relationships between three or more pixels are considered.

Determine the chosen feature. Only the values from the GLCM are used in this calculation.

Energy,

$$\sum_{i,j=0}^{N-1} (P\,ij)^2$$

Entropy,

$$\sum_{i,j=0}^{N-1} -\ln\,(P_{ij})P_{ij}$$

Contrast,

$$\sum_{i,j=0}^{N-1} Pij(i-j)^2$$

3.4. Classification algorithm - ANN

Artificial neural networks (ANN) have been effectively applied to image processing in a number of industries, including geotechnics, civil engineering, mechanics, industrial surveillance, the defense industry, automatics, and transportation. Back propagation networks were employed in this study to analyze MRI pictures, and a feed-forward neural network was used to show that ANNs can classify MRI images as normal or pathological. Artificial neural networks (ANNs), a type of statistical learning technique, are inspired by characteristics of biological neural networks. They are used for many different purposes, such as speech recognition, computer vision, and very simple categorization problems. ANNs are effective data-driven modeling tools that are frequently utilized for the identification and dynamic simulation of nonlinear systems because to their flexible structure and capacity to mimic any complex nonlinear behavior. When signals are occasionally changed at the synapses that receive them, the processing unit adds the weighted inputs. If it crosses the threshold, input from one neuron is sent to another (or output is sent to the outside world), and the cycle is repeated. The first step was to create a three-layer BP network with a hidden input layer, an output layer, and training using a sigmoid transfer function.

There are three or more interconnected layers in a neural network consisting of artificial neurons. Neurons in the input layer make up the first layer. These neurons connect with the lower layers, which then send the information for the top layer's output to the lower layers. The components that make up the inner layers, all of which are concealed, convey data from layer to layer. Since each layer functions as both an input and an output layer, the ANN can comprehend more complicated concepts. Each of these inner layers put together is referred to as a "neural layer". The neural layer's units try to learn about the data by comparing the collected information to the ANN's internal logic. Artificial neural networks (ANN) come in a wide variety of forms, and they all do tasks in a way that is comparable to how human brain neuron and network function. The bulk of artificial neural networks are quite good at what they are supposed to do and have some characteristics in common with a more complicated biological counterpart in tasks like segmentation or categorization.

An artificial neural network is composed of at least three interconnected layers. These neurons communicate with deeper layers, which subsequently communicate with the final output layer to transmit the information for the final output. Information is transmitted from layer to layer and adaptively transformed by the units that make up the inner layers, which are all hidden. The ANN can understand increasingly complex things thanks to each layer's dual roles as input and output layers. The neural layer is the aggregate name for these inner layers. By weighing the gathered data in accordance with the fundamental logic of the ANN, the units in the neural layer attempt to learn about the information. Units are able to provide transformed results using these guidelines, which are subsequently output to the layer beneath. Back propagation is a technique used by an additional set of learning instructions that enables the ANN to correct its output results by taking errors into account. Each time the output is identified as an error during the supervised training phase, the data is propagated backward. Each weight is changed based on how much it contributed to the error. The error is used to modify the weight of the unit connections on the ANN to account for the mismatch between the expected outcome and the actual one. The ANN will eventually have the ability to lessen the risk of errors and undesirable consequences. An artificial neural network can only be trained using a set of approved models and related methodologies. The ability of ANNs to learn effectively from observing data sets is one of their most well-known advantages. There are numerous other advantages of using an ANN. These tools can be utilized to estimate the most ideal and cost-effective strategies to arrive at solutions while defining computing functions or distributions. ANN employs data samples rather than entire data sets to identify solutions, which saves time and money. ANNs are viewed as relatively simple mathematical models to advance the state-of-the-art in data analysis. Applications for these include email spam detection, Chabot natural language processing, business intelligence predictive analysis, and many more. The fig 1.a Preprocessed image is the output of Preprocessing. The fig 1.b segmented image is the output of segmentation. The fig 1.c Extracted image is the output of feature extraction. The fig 1.d classified image is the output of classification.

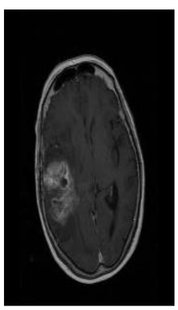


Fig 1.a.Preprocessed image

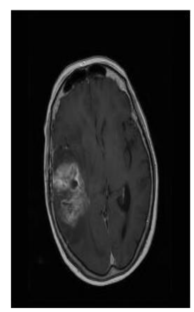


Fig 1.b.Segmented image

Fig 1.c.Extracted image

Fig 1.d.Classified image

4. Conclusion

The ideal medical solution for identifying and classifying brain cancers is MRI image processing techniques. Using MRI pictures, the medical staff can more easily recognise and categorise brain cancers. The Support Vector Machine is the best method for classifying brain tumours based on MRI images supported by some pre-processing, as can be shown from the existing methodology. In order to read MRI pictures for the detection and classification of brain cancers, it is envisaged that in the future MRI image processing will be able to combine different existing image processing techniques. In the brain, brain tumour cells proliferate. A band of tissue from the human body known as a tumor or lump is produced by the uncontrollable development and division of tumorous cells. Tumors have an impact on the entire metabolic process of the human body. A medical expert could inspire the general populace to live in wonderful health. Additionally, a tumour is defined as the formation of malignant cells that are supported and promoted by brain tumour cells. Benign brain tumours do not include active cancer cells, and diverse malignant tumours have never been examined with active cancer cells. It is feasible to determine whether there are tumor cells in the tissue sample under study by using automated machine learning procedures and medical imaging techniques. After accurate tumour cell detection, the procedure of finding the tumour using magnetic resonance imaging (MRI) is well-known in the field of tumour analysis. This investigation suggests that the existing automated interaction model should be improved because using MRI scans to forecast the affected area is a time-consuming and error-prone method. The healthcare practitioners are assisted in identifying the tumour affected location by machine learning algorithms. The systems' ability to forecast outcomes is unaffected by variations in tumour cell bulk and shape. With the aid of feature vector retrieval, search space reduction, and less exactness value in tumour identification, the region of interest is precisely extracted, including the position of infected tumors and the white and grey matter of the brain tissues. Significant significance in medical examinations for health conditions is driven by information-based visualisation approaches. Magnetic Resonance Images (MRI) are important in clinical sectors to identify distinct tissue levels since they may detect the presence of abnormalities and produce multidimensional rooted resolution reports.

In the brain, brain tumour cells proliferate. A band of tissue from the human body known as a tumor or lump is produced by the uncontrollable development and division of tumorous cells. Tumors have an impact on the entire metabolic process of the human body. A medical expert could inspire the general populace to live in wonderful health. Additionally, a tumour is defined as the formation of malignant cells that are supported and promoted by brain tumour cells. Benign brain tumours do not include active cancer cells, and diverse malignant tumours have never been examined with active cancer cells. In order to trace with the aid of medical technology, imaging methods combined using machine learning procedures can be used to rule out the presence of tumor cells in the section of tissue being studied.

References

[1] Gopal, N.N., and Karnan, (2010) Computational Intelligence and Computing Research (ICCIC), IEEE International Conference on, 28–Dec. M., "Diagnose brain tumour by MRI employing image processing clustering algorithms using Fuzzy C Means combined with intelligent optimization approaches."

[2] Gajanand Gupta, (2011) Improved Median Filter Algorithm and Mean, Median, and Improved Median Filter Comparison for Image Processing, International Journal of Soft Computing and Engineering, Volume 1, Issue 5,

[3] Mostafizur Rahman, Muzameel AIndah Soesanti, Adhi Susanto, Thomas Sri Widodo, and Maesadji Tjokronagorohmed, (2011 "Optimized Fuzzy Logic Application for MRI Brain Images Segmentation.") International Journal of Computer Science & Information Technology, Volume 3, Issue 5, October,

[4] A.Rajendran, R. Dhanasekaran, . (2011) International Conference on Communication Technology and System Design, "Fuzzy Clustering and Deformable Model for Tumor Segmentation on MRI Brain Image: A Combined Approach," pp. 327–333

[5] Rajesh C. Patil and Dr. A.S. Bhalchandra, (2012) International Journal of Electronics, Communication & Soft Computing Science and Engineering, , "Brain Tumour Extraction from MRI Images." ISSN: 2277-9477, Volume 2, Issue 1, April

[6] Arthanari Rajendran, Raghavan Dhanasekaran, (2012) ‘Brain Tumor Segmentation on MRI Brain Images with Fuzzy Clustering and GVF Snake Model’, International Journal of Computers, Communications, vol.7, pp 530-539.

[7] P. Mohanaiah, P. Sathyanarayana, and L. GuruKumar. (2013)"Image Texture Feature Extraction Using GLCM Approach," International Journal of Scientific and Research Publications, Volume 3, Issue 5,

[8] Saeid Fazli and Parisa Nadirkhanlou, arxiv.org, (2013) A Novel Method for Automatic Segmentation of Brain Tumors in MRI Images

[9] Roshan G. Selkar and M. N. Thakare, (2014) "Brain Tumor Detection And Segmentation By Using Thresholding Algorith.", IJAICT, Volume 1, Issue 3, July.

[10] Mohammed Sabbih Hamoud Al-Tamimi and Ghazali Sulong, (2014) "Tumor Brain Detection via MR Images: A Review of Literature," Journal of Theoretical and Applied Information Technology, Volume 62, Issue 2,

[11] NCI.2014-04-14. National Cancer Institute. "Information About Adult Brain Tumors." obtained on June 8, (2014)

[12] Anupurba Nandi, (2015) 'Detection of Human Brain Tumour Using MRI Image Segmentation and morphological operators', IEEE International Conference on Computer Graphics, Vision and Information Security, vol.1, pp 4673-7437.

[13] Arati Kothari, Dr. B. Indira, (2016) 'An Overview on Automated Brain Tumor Segmentation Techniques', International Journal of Computer Trends and Technology, vol.40, pp 2231-2830.

[14] Abd El Kader Isselmou, Shuai Zhang, Guizhi Xu 'A Novel Approach for Brain Tumor Detection Using MRI Images', Journal of Biomedical Science and Engineering, vol.9, pp 44-52

[15] Anitha V., and Murugavalli S. . (2016) IET, "Brain tumour classification utilising two-tier classifier with adaptive segmentation technique." Computing. Vis, vol. 1, pp. 9–17

[16] Alfonse, M., and Salem, A B. M (2016) 'An automatic classification of brain tumors through MRI using support vector machine', Computer Science Journal, vol.3, ISSN: 1110–586.

[17] Amruta Pramod Hebli, Sudha Gupta, (2016) 'Brain Tumor Detection Using Image Processing: A Survey', Proceedings of 65th IRF International Conference, pp. 978-93.

[18] Abdel-Basset, M., Fakhry, A. E., El-henawy, I., Qiu, T., and Sangaiah, A. K, (2017) 'Feature and intensity based medical image registration using particle swarm optimization', Journal of Medical Systems, vol.41, pp. 197-210.

[19] Anjali Gupta, Gunjan Pahuja, (2017) 'Hybrid Clustering And Boundary Value Refinement for Tumor Segmentation using Brain MRI', International Conference on Materials, Alloys and Experimental Mechanics, pp 225-238.

[20] Afsana Islam, Md Foisal Hossain, Chandan Saha, (2017) 'A New Hybrid Approach for Brain Tumor Classification Using BWT-KSVM', International Conference on Advances in Electrical Engineering, vol.1, pp 5386-0869.

[21] Bahadure, N B Ray, A. K, and Thethi, H. P. (2017) 'Image analysis for MRI based brain tumor detection and feature extraction using biologically inspired BWT and SVM', International journal in Biomedical Imaging.