Automatic Brain Tumor Segmentation and Detection with Histogram Equalization of Morphological Image Processing

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Abstract. Nowadays, one of the primary causes of increasing adult and kids death rate is brain tumors. Most worldwide research has found that throughout the previous few decades, the number of people suffering from and dying from brain tumours has increased to 300 each year. Early brain tumour detection is still a difficult problem. An uncontrollably growing mass of cells is called a brain tumour. Malignant or cancerous tumours and benign tumours are the two primary categories of tumours. When diagnosing brain tumours, medical imaging is essential. Medical image data gathered from many biomedical devices is an essential component of medical diagnosis. This information was gathered using a number of imaging methods, including CT (Computed Tomography), Magnetic resonance imaging (MRI) and X-rays. Tumour segmentation is a difficult process that medical experts carry out using data from MRI. Segmenting brain tumours from complex MRI brain images is an important way to extract information. In this system, a tumour in a brain MRI is segmented using a new FCM formulation technique (Fuzzy C Means algorithm). Therefore, by using this system brain tumour is detected at initially and accurately. Hence, automatic segmentation and detection of brain tumours using histogram equalization in morphological image processing provides better results in terms of F1-score, precision and accuracy.

Keywords: FCM (Fuzzy C-Means algorithm), Brain Tumour, Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Histogram Equalization.

1 Introduction

A "brain tumor" is an abnormal development produced by an excessive amount of brain cell division. Brain tumors may present as benign or cancerous. In addition to being benign, brain tumors are usually malignant. A collection of cells with expanded nuclei that have developed in the brain made up primary brain tumors. The brain is the only place in the body where expansion of cells can occurring. In a benign brain tumor, there are no malignant cells present [1]. Since the tumor's development is still in its early

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stages, surgical excision remains a possibility. The impact of a lesion on a specific brain region represents significant challenges, with the survival prognosis varying significantly based on the location of the tumor.

A tumor can develop as a disease known as cancer when brain cells expand out of control. Many cancers are primarily caused by uncontrolled expansion of cells and disruption of the body's normal cycle of cell death. Brain tumors that are both primary and metastatic are not only possible but also rather frequent [2]. A benign tumor does not pose a threat to the around healthy brain tissue and does not spread to other brain regions. This Malignant tumor will grow and spread to other parts of the brain quickly. Malignant tumors (often referred to as cancerous ones) impact surrounding tissue and organs, although benign tumors do not. Sometimes benign brain tumors can be shown to have normal-appearing cells when viewed under a microscope. These tumors form a protective capsule due to their distinct boundaries, this stops them from spreading to different brain regions [3].

Though they are extremely uncommon and frequently limited to the brain, malignant brain tumors carry a significant risk of metastasizing, or spreading to other bodily areas. But the brain is where malignant tumors are almost exclusively found. Malignant tumors of this type always present a serious threat to life since they have the ability to infiltrate and destroy adjacent healthy cells, it shows how fast or slowly they advance [4]. It is challenging to remove malignant brain tumors from the spine and brain without causing harm to healthy brain tissue.

Digitalized medical images are become essential for the detection of many diseases. It can also be used in research and training. Electronic medical images are becoming increasingly necessary; between 12,000 and 15,000 images are produced everyday by the radiology department of the university hospital of Geneva in 2002 [5]. Medical image research and report generation require an accurate and efficient computer-aided diagnosis system. It is inaccurate, time-taking and chances for human errors are traditional manual approach to evaluating medical imaging. Now United States (U.S) considers brain tumours are the main reason that causes death, accounting for 10 percent of all medical diseases [6]. According to reports, there are 700,000 people with 80% of benign and 20% of malignant brain tumor. As of 2021, 78,980 people have been diagnosed with brain tumours, according to predictions from the American Cancer Society, there were 24,530 malignant tumours (13,840 men and 10,690 women) and 55,150 noncancerous tumours. Worldwide, according to the studies, brain tumours leads to cause cancer-related deaths in adults as well as children.

Unregulated development of brain cells is the characteristics of most common type of brain disease, known as a brain tumour. There are two categories for brain

tumours: primary and secondary. However, it begins as cancer in the body before moving to brain [7]. Malignant as well as benign tumours are the two types of tumours. Throughout the body, a malignant tumour is the most aggressively spreading tumour.

This benign tumour will develop slowly and nearby tissues are not damaged. A brain tumour is categorized by the World Health Organization (WHO) as I–IV. Tumours classified as slow-growing belong in categories I and II, but tumours classified as malignant and in worse condition are in categories III and IV.

Many imaging modalities have been developed in recent decades, such as the MRI, Positron emission tomography (PET), Single-photon emission computed tomography (SPECT), Electroencephalography (EEG), Magnetoencephalography (MEG), Ultrasonography, X-rays, and Computed tomography (CT). These imaging modalities not only highlight the complicated information and entirety on brain tumours, but also help medical specialists in accurately identifying the tumour and selecting the most effective method of treatment [8]. It is thought that MRI used often in imaging technique for detecting brain cancers. The size, location and form brain tumors can all be determined with an MRI, non-invasive soft tissue contrast imaging method that protects patients from unnecessary ionizing radiation treatment.

The diagnosis of a brain tumor is an intensive procedure that depends mainly on the radiology specialist's knowledge. The amount of data that has to be examined the growth in patients has resulted in a significant increase, making traditional procedures expensive and incorrect [9]. Challenges relate to the significant differences in size, shape, and variations of brain tumours of the same type, comparability of different disease characteristics. A brain tumour's misdiagnosis can have serious consequences and lower the patient's chance of survival. Finding automated image processing solutions to get around the disadvantages of human diagnosis and other related applications are becoming more and more popular. Brain tumours can now be automatically diagnosed with a number of Computer-aided diagnosis (CAD) systems that have been created recently [10].

Following is the arrangement of the remaining content in the document: In section II, the literature survey is displayed, section III presents automatic brain tumor segmentation and detection with histogram equalization of morphological image processing; section IV explains result analysis; section V concludes the paper and references are in VI.

2 Literature Survey

To increase the speed and precision of brain tumor detection a new two-module automated method. Three ML and imaging methods are used in first module, called Image Enhancement Technique, uses: neural networks, adaptive Wiener filtering as well as independent component analysis to normalize images. It solves issues such as noise and fluctuating low area contrast. Tumour segmentation and classification are carried out by the second module, which also makes use of support vector machines to verify results of first module. It received a Dice score (DSC) of 0.981 an accuracy with 0.989, an average sensitivity as well as specificity of 0.991 [11].

A deep neural network with convolution generation and this proposed layers, the basic Net-B0 (EfficientNet-B0 is convolutional neural network, from ImageNet database it is trained for more than a million images) model is enhanced to accurately identify and categorize images of brain tumors. Several filters are applied as part of image enhancement procedures to enhance quality of the images. As detection and classification accuracy is overall 98.87%, the results representing by achieving better values classification accuracy, recall, area under the curve and precision,, compared to earlier Convolutional Neural Network (CNN) models, [12].

A novel brain-tumor detection as well as segmentation scheme using active contouring with texture-based decision metric for MRI images is proposed. In this proposed new scheme, the active contouring mechanism is first employed to automatically find one or more suspected regions (image segments). Using the well-known Brain-Tumour MRI dataset, they further evaluate the efficiency for thid suggested new scheme. The Area-under-curve (AUC) and average accurate segmentation area ratio is develop due to our new approach are 0.9244 and 0.8019, this is significantly better to the current active-contour and deep-learning based brain tumor detection techniques [13].

The genetic algorithm-based edge detection method that has been optimized. Both the optimal thresholding procedure and the optimum filter coefficients are found using a basic images and the optimal edge features that correspond to training dataset. Performance studies, both quantitative and qualitative, are examined using a number of well-known indicators. To the fractional-order edge detection filters, classical edge detection technique is compared with proposed genetic algorithm-based cost minimization technique to evaluate performance, and threshold-optimized fractional-order filters [14]

Detection of brain tumors, the YOLOv3 (You Only Look Once, Version 3) deep neural network(DNN) method in portable Electromagnetic (EM) imaging system is presented. As a leading object detection model, high accuracy and enhanced processing speed characterize YOLOv3. The scattering parameters are first obtained from the nine-antenna array setup by using tissue-mimicking head phantom. The transmitter is represented by one antenna and receivers are served by other eight antennas. After post-processing the scattering parameters, to reconstruct the images, the updated delay-multiply-and-sum method is used, which have 416 x 416 pixels. With the EM imaging technology, from the different head areas, fifty sample images are collected. Investigated is the detection performance using various image data sets. The F1 score is 94.50%, and the obtained detection accuracy is 95.62% [15].

A Gaussian convolutional neural network (GCNN) is used to classify tumors into three categories: pituitary, glioma, and meningioma. This method is utilized to identify unique BT types on two datasets. Grade-two, Grade-three, and Grade-four gliomas are divided by the other one. For both datasets, proposed technique provides accuracy values of 99.8% as well as 97.14% [16].

The proposed approach for BT multi-class categorization is shown to be To fill the data gaps in the distribution of real images, Generative Adversarial Networks (GANs) can provide a number of realistic training images. the GAN combinations DA effect is maximized, based on GANs two-step DA is suggested. To produce high-resolution MR pictures Progressive Growing of GANs (PGGANs) are used, to enhance the texture and shape of PGGAN-generated images utilized Multimodal UNsupervised Image-to-image Translation (MUNIT). Significantly improves performance in tumor identification and other medical imaging applications regular DA is combined with two-step GAN-based DA [17].

For automated brain disorder diagnosis, a Multi-level dynamic graph learning (MDGL) framework to extract multi-level spatiotemporal dynamic representations of Resting-state functional Magnetic Resonance Imaging (rs-fMRI)data. There are three parts of the MDGL framework: multiple brain atlases uses the multi-scale dynamic Functional Connectivity Networks (FCNs)construction, in functional Magnetic Resonance Imaging (fMRI) data, multi-scale dynamic graph representation learning, multi-scale feature fusion, and classification are used to obtain the supplied spatiotemporal information. According to the results of experiments, MDGL works better than other state-of-the-art techniques [18].

Hybrid probabilistic wiener filters (HPWF) are used for preprocessing medical images. Detect edges and slopes of source images are used to Robust edge analysis (REA) features were combined with MRI and CT images using a Deep learning convolutional neural network (DLCNN). Then, the disease-affected region of the fused image is segmented using Hybrid fuzzy C-means integrated K-means (HFCMIK) clustering. Finally, Deep learning based probabilistic neural networks (DLPNN) are used to classify benign and malignant tumours. The segmentation accuracy and classification accuracy 99.21% and 99.46%, respectively [19].

A brain tumor is a dangerous disorder that is brought on by a group of abnormal cells that eat away at healthy cells. Early assessment of patients is important a reliable and cost-effective system for tumour detection from Computed Tomography (CT) scan images is needed. Tumor extraction, morphological operation, prewitt edge detection filter, segmentation, and pre-processing are some of the phases in the methodology. Prewitt is an edge detection filter that uses gradient to identify significant changes in image intensity. The system also uses a dilation operation to fill small holes in the images for tumor extraction. Experimental results show improved accuracy compared to existing systems [20].

The complicated tumor intensities are segmented using a hybrid technique. This approach creates a possible cluster by combining three different unsupervised learning strategies. The tumour area is divided using the hybrid cluster approach. Through the testing parameters such as mean squared error, peak signal to noise ratio, Jaccard and Tanimoto coefficient index, Dice overlap index, accuracy and efficiency of suggseted hybrid algorithm are explained. 18db decibel (dB) is represented as Peak signal to noise ratio, 98% is represented as the Dice overlap index, 0.06 is represented as the mean squared error and 96% is represented as the Jaccard index. Other state-of-the-art algorithms performances are compared with the recommended algorithm [21].

To present, excellent results have been demonstrated by Deep Neural Networks (DNN) in segmentation and classification applications. Taking this concept into consideration, Deep wavelet autoencoder (DWA) technique for image compression is described. This method combines wavelet transform's image decomposition property with the basic feature reduction function of an autoencoder. A DWA-DNN image classifier was suggested, and it was considered [22].

In the field of medical imaging, to generate segmentation masks for brain tumours especially to perform image segmentation tasks if present in brain MRI scans, Two new CNN-based models have been proposed by them: first, S-Net; then SA-Net (An attention mechanism in S-Net). For the data set related to High-Grade Glioma (HGG) and Low-Grade Glioma (LGG), the models were given presented Dice similarity coefficient (DSC) values of 0.78 and 0.81 [23]

This study develops the Brain Tumor Classification technique, which uses Ensemble Learning Driven Computer-Aided Diagnosis Model for Brain Tumor Classification (ELCAD-BTC) for Brain Tumor Classification on MRI scans. The proposal that is being given aims to detect and classify various Brain Tumors (BT) processes. In order to lower noise and enhance MRI images quality, system under discussion utilizes Gabor filtering (GF) technique. Finally, Deep Learning methods hyperparameters were adjusted using the Social spider optimization algorithm (SSOA) [24].

This research presents a novel approach that combines preoperative MRI and Magnetic Resonance Spectroscopic Imaging (MRSI) images to detect and localize brain tumors with high-grade gliomas. While MRSI maintains biochemical information, MRI allows for the differentiation of soft tissues. Accurate tumor detection is achieved by combining these two techniques. According to the experiment's results, random forest classifier performs better than other classifiers, achieving 83% accuracy. The suggested approach locates the tumorous tissues using a texton map once the tumor has been identified. From the smallest to the largest size, every distributed tumor tissue has a specific location [25].

3 The Proposed Framework For Automatic Brain Tumor Segmentation And Detection With Histogram Equalization Of Morphological Image Processing

In this section, Figure 1 demonstrates the architecture for automatic brain tumour segmentation and detection using histogram equalization in morphological image processing.

Insert the brain MRI images as input, then the input images are tested by bias field correction. Then the data is filtered by Anisotropic Diffusion Filtering, and the filtered images are sharped by Unsharp Masking. The apply histogram equalization for the images, then thresholding is applied that images. Finally the images are segmented by using Fuzzy C-Means and it is labeled. Then tumor images are extracted and area of the tumor also calculated for determinng the tumor

Brain MRI images are utilized as the input; these pictures include information about diseased and non-infected regions. However, brain imaging methods are not limited to diagnosing diseases. Additionally, they are able to differentiate between certain changes in the brain associated with mental health issues like anxiety disorders, early-stage psychosis, and schizophrenia.

The process known as "bias field correction"reduces the bias field's negative impacts, which are an undesirable in the majority of MRI images, particularly older ones. An extremely smooth, low-frequency signal known as the bias field signal affects MRI images, particularly those created by old MRI (Magnetic Resonance Imaging) machines.

This is possible to eliminate noise from digital images using anisotropic diffusion without causing edge blurring. The heat equation can be obtained using the anisotropic diffusion equations, it is same as Gaussian blurring with a constant diffusion coefficient. This blurs boundaries indiscriminately and is enhance for eliminating noise. These approaches have advantages and disadvantages. For example, Anisotropic Diffusion Filtering (ADF) reduces noise in the smallest MR image features while maintaining edge details. However, this method requires parameter number of iterations.

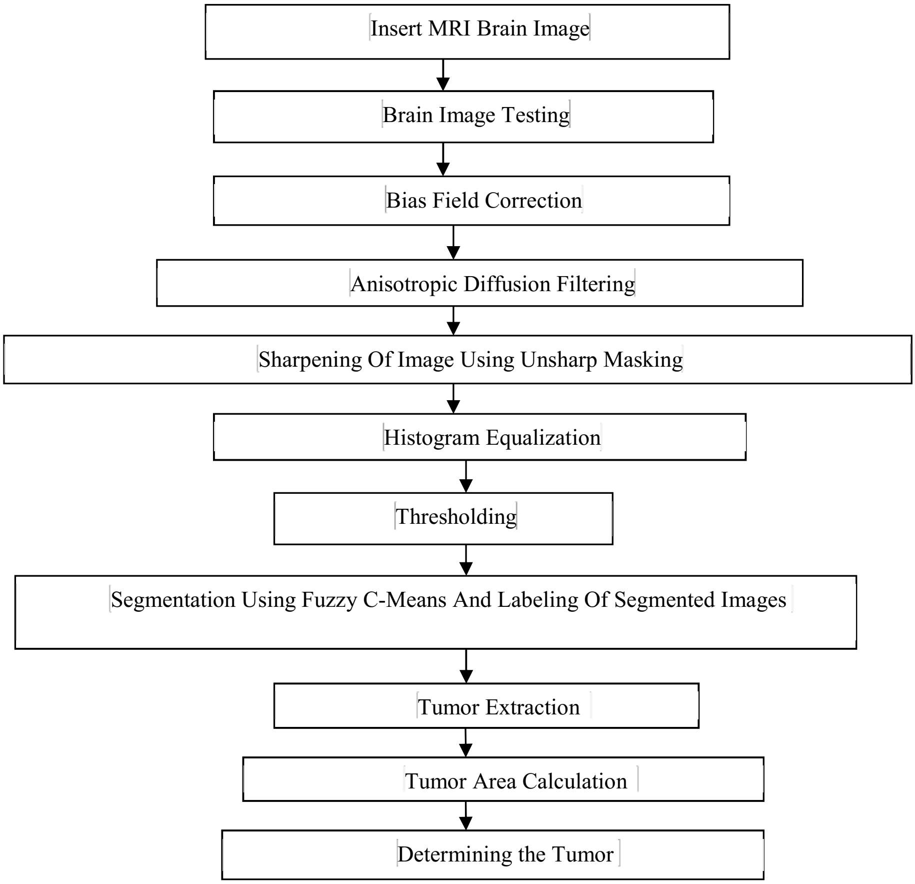

Fig.1. Framework of an Automatic Brain Tumor Segmentation and Detection With Histogram Equalization Of Morphological Image Processing

Go to Filter › Sharpen › Unsharp Mask to select the Unsharp Mask filter. To enhance edge contrast, modify edge width, and sharpen only the edges are move the Amount, Radius, and Threshold sliders. To enhance the contrast in the pixels, move the Amount slider.

Image sharpening is a process that improves an image's contrast, edges, and features to make it appear more colorful and clearer. Images that are distorted, noisy, or fuzzy due to things like compression, low resolution, or camera shake can be made more clear and understandable by sharpening them.

The process of image processing known as "histogram equalization" it uses an image's histogram to modify the contrast of the image. It expands out the image's intensity range or distributes the most common pixel intensity values to improve contrast. Histogram equalization enhances the visual appeal of images by bringing out the details and enhancing the overall appearance. It can help computer programs spot important features in images, which is handy for tasks like medical diagnosis or identifying objects.

Divide an image into foreground and background using image thresholding an simple but efficient method. By transforming images of binary as grayscale, this type of image analysis technology separates objects. Grayscale images can be used for image thresholding. It is a method for dividing grayscale image into binary image. A certain value for pixel intensity is used as the threshold for thresholding. The maximum or minimum value is applied to any pixels that are either more or less than the threshold value.

A labeled image or mask can be used to represent a collection of pixel regions that make up an image. This process is known as image segmentation. You can focus on the most crucial components of an image rather than the whole by processing it in segments. Among the popular techniques for segmenting images is fuzzy c-means clustering. One of the most popular unsupervised clustering methods in the field of medical imaging is the Fuzzy C-Means (FCM) clustering algorithm. The process of extracting recognized anatomical structures from medical photographs is known as "medical image segmentation". On the other hand, sensitivity to starting values, entrapment in local optima, and an inability to differentiate between objects with comparable color intensities. After pre-processing the image to eliminate artifacts and noise, it is segmented to identify areas of interest that may contain tumors. To determine if the brain tumor in the segmented image is benign or malignant, numerous textural and statistical features are retrieved.

The commonly used technique for estimating the volume of subcutaneous tumors is to use a caliper to measure tumor's length and width. Then, using formula for an ellipsoid, one can calculate tumor's volume assuming that the tumor has an ellipsoid shape and that its height is equal to its width. Therefore, the tumor is detected.

4 Experimental Results and Analysis

In this section, results analysis of automatic brain tumor segmentation and detection with histogram equalization of morphological image processing is observed.

Table 1. Performance Analysis

Performance Metrics	FCM	K means
Accuracy (%)	97.94	94.56
Precision (%)	87.71	75.52
F1-Score (%)	90.23	84.68

Table 1. Performance comparison between Fuzzy C-Means (FCM) and Kmeans is observed for tumour detection. The compared parameters are in terms of precision, accuracy, and F1-Score.

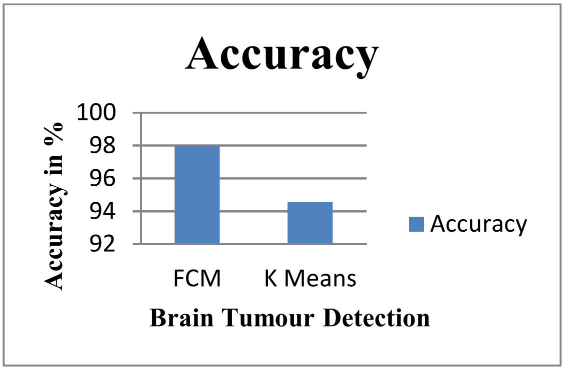

Fig. 2. Accuracy Comparison Graph

When using histogram equalization of morphological image processing for automatic brain tumour segmentation and identification, an accuracy comparison graph between FCM and K means is shown in Figure 2. When compared with K-means, FCM demonstrates high accuracy.

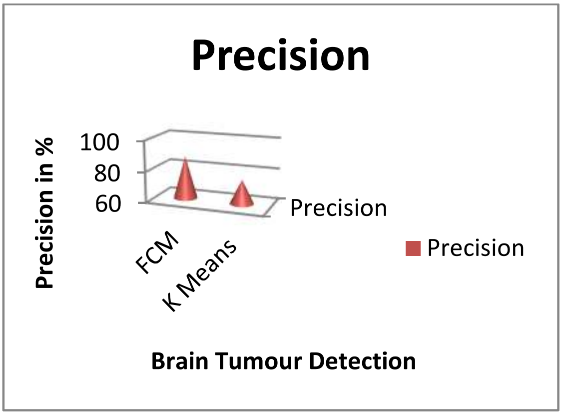

Fig. 3. Precision Comparison Graph

Figure 3 demonstrates the precision of automatic brain tumour segmentation and detection using histogram equalization of morphological image processing. K-Means performs less accurately than FCM

The comparison of F1-Score for FCM and K Means is observed in Figure.4 as graphical representation. The graphical representation of FCM shows high F1-Score for automatic brain tumor segmentation and detection with histogram equalization of morphological image processing.

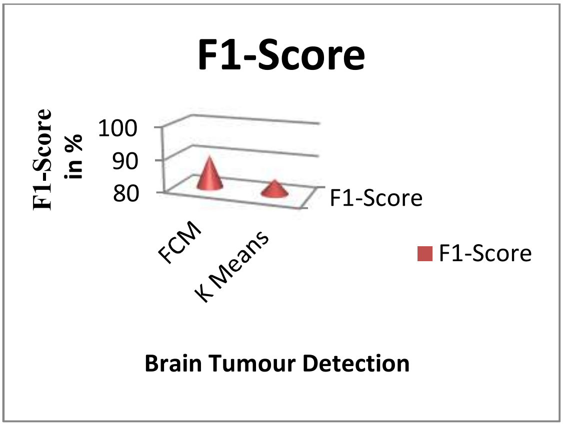

Fig. 4. F1-Score Comparison Graph

5 Conclusion

The abnormal mass of brain tissues that is mostly identified by imaging tests is called a brain tumor. As a result, this analysis includes the algorithm for automatically segmenting brain tumors from MRI images using the FCM method, calculating the variances means of the object and background pixel numbers, determining the proper segmentation points based on morphology. The procedure for improving image quality and converting Red Green Blue (RGB) to grayscale, the optimal thresholding procedure is used to automatically enlarge the images and improve the structures of the brain tumor images. Therefore, a tumour in a brain MRI is segmented using a new FCM formulation technique (Fuzzy C Means algorithm). Therefore by using this algorithm, brain tumour is detected at initially and accurately. Hence, this automatic brain tumour segmentation and detection with histogram equalization of morphological image processing achieves better results in terms of F1-Score, accuracy, precision.

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