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A DETAILED STUDY ON MRI BRAIN TUMOR DETECTION AND SEGMENTATION TECHNIQUES

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Abstract

In recent days, brain tumor is a serious cause for increasing humanity among people. During the past few decades, the number of people suffering and fading from brain tumors has been increased to 300 per year. Detecting and classifying the tumor in Magnetic Resonance Imaging (MRI) is a critical and challenging task in medical image processing. Because, the MRI provides the detailed information related to anatomical structures and potential abnormal tissues. So, the detection and segmentation of brain tumor plays an essential role in medical imaging and it helps to find the exact size and location of the tumor. For this purpose, different image processing techniques are proposed in the existing works. This paper reviews some of the existing research works related to brain tumor detection and segmentation. The stages involved in the brain tumor segmentation system are as follows: preprocessing, feature extraction, classification and segmentation. The preprocessing is an initial stage in any medical image processing applications. In this stage, the unwanted and irrelevant noise in the given image are eliminated. After that, the features of the filtered image are extracted to detect the edges. Hence, the classification technique is employed to determine whether the given image is normal or abnormal. If it is an abnormal image, the segmentation technique is applied to segment the exact portion of the tumor.

Keywords: Brain Tumor, Magnetic Resonance Imaging (MRI), Benign, Malignant, Computer Vision, Filtering, Tumor Detection, Segmentation and Classification

1. INTRODUCTION

Brain Tumor is an abnormal growth of cells in the skull that grows from the cells of brain, blood vessels and nerves. Brain is an important part in the human body that contains different parts such as, Gray Matter (GM), White Matter (WM), Cerebrospinal Fluid (CSF) and background. Generally, the cells in the human body has the property to multiply, due to this property, the overall operations of the brain is in a controlled manner. When the multiplicity of the cells gets out of control, the growth cells became abnormal and known as a brain tumor. In which, the cells grow, multiply uncontrollably and controls the normal cells. Then, it is classified into the following categories: Benign and Malignant.

Benign is a type of tumor that does not grow in an immediate way and it does not affect its adjacent healthy tissues. Malignant is a very severe stage that grows worse with the way of time and it results in the death of a person. For the early detection of brain tumors, various imaging techniques such as Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), and Computed Tomography (CT) are used. Among them, Magnetic Resonance Imaging (MRI) is high-quality medical imaging technique that enables reliable and rapid detection of brain tumor. This is due to less harmful radiation, high contrast of soft tissues and high spatial resolution.

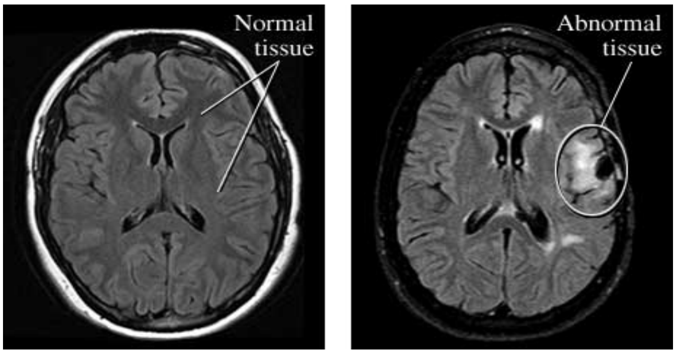

Figure1. Normal and abnormal MRI brain images

MRI is a famous tool in medical imaging that is used to detect and visualize the details in the internal structure of the brain. Moreover, it provides the detailed information about the brain anatomy, vascular supply and cellular structure. So, it is an important tool for effective tumor monitoring, diagnosis and treatment. It is a non-invasive medical test that uses a powerful magnetic field, radio frequency pulses and a computer to produce the detailed view of organs, soft tissues and bone. It does not use any ionizing radiations and allows the physicians to evaluate various parts of the body to determine the presence of tumor. It is also used to find the problems such as, bleeding, injury and blood vessel infection. Segmenting the tumor portions in the MRI has become an interesting and emerging research area in the field of medical imaging.

For accurate detection and segmentation of tumor, various techniques have been in the existing works. The existing image segmentation approaches are thresholding, region and edge based segmentation, supervised and unsupervised classification, Artificial Neural Network (ANN) and hybrid techniques. Heterogeneity of tissue causes the potential rise in the uncertainty of the segmentation task. Moreover, presence of redundant and noisy features increases the computational complexity and degrades the performance of clustering. This paper surveys various image processing techniques for accurate tumor detection and classification. Here, the advantages and disadvantages are also stated for selecting the best technique. The techniques are analyzed for the following stages: preprocessing, feature extraction, classification and segmentation.

2. RELATED WORK

This section presents some of the existing works related to MRI brain tumor detection and segmentation.*Devi, et al* [1] presented a new Vector Quantization (VQ) based segmentation method for detecting the tumor from MRIs. The vector quantization was a traditional quantization technique that permits the modeling of probability density functions by the distribution of prototype vectors. Moreover, it is mainly used to compress the data by dividing a large set of points. *Kannade and Gumaste*[2] suggested a Fuzzy C-Means (FCM) technique to detect and classify the stages of tumors from the MRI. In this paper, the MRI brain images were used to detect the tumor portion. The authors of this paper surveyed various Neural Network (NN) based techniques for segmentation and classification. From this analysis, it was observed that the NN algorithms requires extensive supervision and training for classification. *Gupta and Gupta* [3] proposed a new Fuzzy based Window Detection and Median (FWDM) filter correlation technique for reducing the impulse in the image. It is a hybridization of adaptive median and fuzzy switching median filter. It increases the size of filtering window based on the incoming local density to filter the salt and pepper noise. This filtering technique contains two stages such as, detection stage and filtering stage.In the first stage, it filters the noise before identifying the actual location of noise pixel. Once it detects the noise pixel, it will go to filtering stage. *Mehta and Dhull*[4] proposed an enhanced fuzzy based median filtering technique for gray scale images. *Zulpe and Pawar*[5] recommended a Feed Forward Neural Network (FFNN) technique for brain tumor classification. In this work, the four different classes of tumor were classified such as,

- Astrocytoma
- Meningioma
- Metastatic bronchogenic carcinoma
- Sarcoma

Here, the proposed FFNN technique was integrated with the LevenbergMarquart (LM) technique for providing high recognition rate.*Jain* [6]suggested a Gray Level Co-occurrence Matrix (GLCM) based feature extraction technique for brain cancer classification. This work includes the following stages:

- Noise removal
- Morphological operations
- Region isolation
- GLCM based feature extraction
- Back Propagation learning Network (BPN) based classification

John [7] suggested a wavelet and texture based Neural Network technique for brain tumor classification. This work includes the following stages:

- Wavelet decomposition
- Textural feature extraction
- Classification

The proposed technique provides the better classification results for MR images. *Sangeetha*[8]developed a Probabilistic Neural Network (PNN) based classification technique to accurately classify the types of brain tumors such as, benign and malignant. In this work, the Discrete Cosine Transformation (DCT) technique was utilized for feature selection. This system includes the following stages:

- Image decomposition

- Feature extraction and selection for region identification

Prajapti and Jadhav[9] proposed a Non-Negative Matrix Factorization (NMF) technique for brain tumor detection and segmentation. This work includes the following processes were performed:

- Histogram equalization
- High pass filtering
- Median filtering
- Threshold based segmentation
- Morphological operations
- Image subtraction

From this paper, it was observed that the morphological operations were very useful in various image extraction and filtering applications. *Mustaqeem, et al* [10] suggested a watershed and threshold based segmentation techniques for brain tumor detection. *Njeh, et al* [11] developed a graph cut distribution matching approach for MRI brain tumor segmentation. Here, a non-parametric model was estimated to characterize the normal regions in the current data. In this analysis, the global similarity between the distributions was evaluated and, the isolated regions in the image were eliminated. *Demirhan, et al* [12] designed a new algorithm for stripping the skull before segmentation. Here, the Self Organizing Map (SOM) technique was utilized for segmentation and the Learning Vector Quantization (LVQ) technique was employed for fine tuning. *Kong, et al* [13] suggested an Information Theoretic Discriminative Segmentation (ITDS) for clustering the super voxels in the brain. The main intention of this paper was to simultaneously select the informative feature and to eliminate the uncertainties of super voxel assignment. *Galimzianova, et al* [14] proposed a new robust mixture model for outlier detection. Here, the robustness was attained by selecting the outliers based on the component wise confidence level. *Roy, et al* [15]studied various automated brain tumor detection and segmentation techniques for the MRI brain images. Here, different types of filtering techniques were reviewed such as,

- Min max median filter
- Center weighted median filter
- Adaptive median filter
- Progressive switching median filter

In this work, the advantages and disadvantages of these techniques were also discussed.

3. PROPOSED METHOD

This section presents the descriptions for some of the image processing techniques used to detect and classify the brain tumors. The investigation is done for the following stages:

- Preprocessing
- Feature Extraction
- Classification
- Segmentation

Fig 2 shows the overall flow of the brain tumor detection and segmentation system.

3.1Preprocessing

Preprocessing is an initial and important step in any image processing applications.It removes the noise and smoothens the given image by filtering the images. Hence, it stabilizing the intensity of the specific particle images, eliminating reflections and masking some portions of the image. For image preprocessing, various techniques are used:

- Mean Filter
- Median Filter
- Hybrid Median Filter
- Adaptive Median Filter
- Fuzzy based Median Filter

3.1.1 Mean Filter

The mean filter [16]is a basic smoothening filter that is mainly used to eliminate the Gaussian noise, small detail, blurring and bringing gaps in the image. Normally, this filter is worked based on the convolution operation known as mask, which is moved across the image until cover the every pixel in the image. The smoothening process of this filter is equivalent to the operation of low pass filtering. It also removes the edges and regions of the image by replacing the center pixel by the neighborhood average.

3.1.2Median Filter

The median filtering [17]is one of the non-linear technique that eliminates the noise from the given image. It effectively removes the noise, where the impulse noise is mixed with the signal. When compared to the mean filter, it provides better results by preserving some useful details in the image. This filter belongs to the non-linear filters that preserves the edges by smoothening the image. During smoothing, it preserves the small and sharp details. Moreover, it is one of the main building block in image processing applications that adequately removes the salt and pepper noises by moving through the image pixel by pixel.

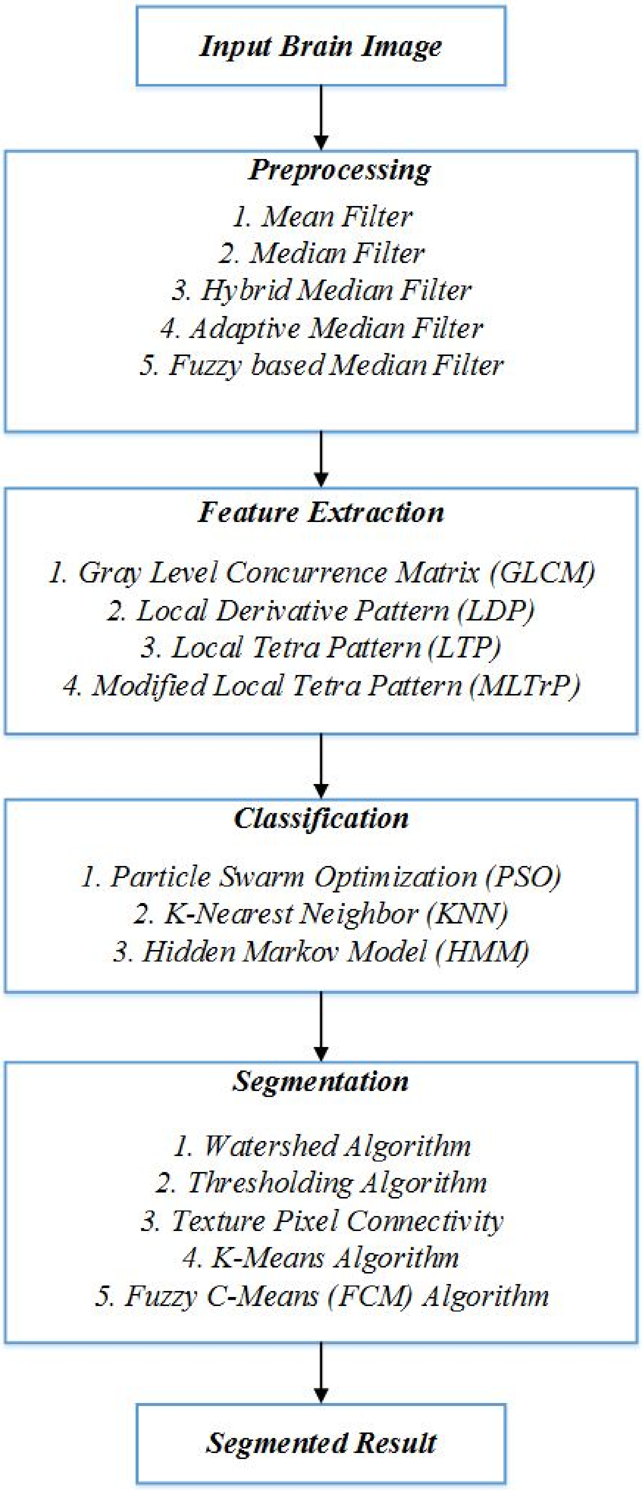

Figure 2. Brain tumor detection and segmentation system

3.1.3 Hybrid Median Filter

The hybrid median [18]is a natural extension of the non-linear rational type filter. A method for processing an image contains a foreground and background to produce a highly compressed and accurate representation of the image.

In hybrid filtering, the neighboring pixels are ranked based on the intensity and median values. Here, the median value becomes the new value for the pixel under evaluation. Moreover, it is expensive to compute than a smoothing filter.

3.1.4 Adaptive Median Filter

The adaptive median filtering[19, 20] technique performs spatial processing to determine whether the pixels in the image are affected by impulse noise such as salt and pepper. It compares each pixel with its surrounding neighbor pixels to classify the pixels as noise or not. A pixel that differs from the majority of its neighboring pixel is considered as impulse noise. Hence, the noise pixels are replaced with the mean and median value of the neighborhood pixels. The size of a window around each pixel varies corresponding to the mean and median value of the pixels in 3×3 window. If the median value is detected as an impulse noise, the size of the window is increased. Hence, it is verified whether the center pixel of the window is an impulse or not. If it is detected as noise, the new value of the center pixel in the filtered image is considered as the mean and median of the pixel in the window. If the center pixel is detected as a non-impulse, the value in the filtered image remains unchanged. Unless the considered pixel is detected as an impulse, the gray scale value of the pixel in the filtered image remains same as the gray scale value of the pixel in the input image. Thus, the filter provides dual advantage including the removal of impulse noise and reduction of distortion in the image.

3.1.5 Fuzzy based Median Filter

The fuzzy based noise filtering is an efficient noise detection scheme that filters the impulse noise without damaging the healthy pixels. This technique has high rate of impulse noise detection. Moreover, it minimize the false hit and miss hit errors and it is worked based on the following principles:

- In this technique, the rank is given for the center pixel with respect to the other pixels in the window. If the rank is high, it is identified that the pixel is corrupted by an impulse noise.
- Here, the impulse noise is considered as an outlier and the absolute deviation from the median is used to detect the outliers. Then, the absolute difference between the center pixel and the median of the pixel in the window is measured.

3.2 Feature Extraction

Feature extraction is defined as the process of capturing the visual content of images for indexing and retrieval. It is a method of capturing the visual content of images for indexing and retrieval. It involves facilitating the amount of resources needed to represent a large set of data exactly. The main aim of feature extraction is to represent the raw image in its reduced form to facilitate decision making process such as pattern classification. Moreover, it is an important step to get high classification rate. This stage allows a classifier to identify the normal and abnormal pattern by extracting a set of features.There are various types of features for image classification such as, color, statistical features, shape features and transform coefficient features. Selection of feature extraction approach is usually single but more critical task in accomplishing high recognition performances.

3.2.1 Gray Level Co-occurrence Matrix (GLCM)

GLCM[6] is one of the second order statistical feature extraction technique that is mainly used to extract the texture features in the image. Generally, texture is one of the important property that is mainly used to identify the objects or regions of interest in a given image. The GLCM describes the frequency of specified spatial relationship within the area under investigation. Various statistical parameters can be extracted from the GLCM. Some of the parameters like variance and contrast have a clear textural meaning, which are related to specific first order statistical approaches. The functions of GLCM are used to indicate the texture of an image by considering how often pairs of pixel with distinct values. It contains the information about pixels having similar gray level values in an image.

3.2.2 Local Derivative Pattern (LDP)

The LDP[21] is the best and a high-order texture feature descriptor for that encodes the directional features based on the variations of derivative patterns. It captures the change of derivative directions between the local neighbors and encodes the turning point in a given direction. It is a non-directional first order local patterns, which are collected from the first order derivatives. When compared to CLBP, it contains more details about the discriminative features. Moreover, it extracts the derivative direction information based on the second order pattern information. Here, each neighboring pixel contributes to the pattern code with the direction of its derivative with respect to the derivative of the center point.

3.2.3 Local Ternary Pattern (LTP)

The LTP [22]is less sensitive to noise that encodes the small pixel difference into a separate state. Here, the ternary code is divided into two binary codes for reducing the dimensionality. But, it may result in a significant information loss. In this technique, the ternary code is derived by encoding the large pixel difference into two strong states. Then, it encodes the small pixel difference into a separate uncertain state. The ternary code is transformed back to a binary code. In this way, the ternary code in transformed back to a binary code.

3.2.4 Modified Local Tetra Pattern (MLTrP)

The MLTrP[23]technique is mainly used to build the relationship between the central pixel and the neighboring pixels by calculating the gray level difference. It encodes the input image by calculating the horizontal and vertical directions of each pixels. Then, it codes the relationship based on the directions of central and neighbor pixels.

3.3 Classification

Feature selection is a process of finding a subset of features, from the original set of features for a given data set.A solution of an optimal feature selection does not need to be unique. The general paradigm of optimal feature selection is mainly used in the classifier design.

3.3.1 Particle Swarm Optimization (PSO)

The PSO[24] is a new evolutionary computation technique that gives the potential solution with certain velocity. A population-based stochastic search algorithm is termed as the Particle Swarm Optimization (PSO), which uses swarm intelligence. Here, a particle denotes each member of the population and the swarm is the population. In the search space, every particle consists of a velocity and position. It determines the best solution to the problem under a given set of constraints.

3.3.2 K-Nearest Neighbor Classification (K-NN)

Generally, K-NN [25]is an image classifier that accurately classifies the given brain images. Moreover, it gives high accuracy and stability for MRI brain images. It identifies the type of tissues by classifying each voxel of the image. In medical imaging, the K-NN is used on various subsets, where each subset corresponds to the training data. Based on the partial information of the subset, this technique produces the classification results. Moreover, it accurately detect and classify the tumor portions from MRIs. In this technique, the learning set is created from the pre-classified voxels. Hence, the voxel of the image is added in the feature space for classifying the voxel of a new patient.

3.3.3 Hidden Markov Model (HMM)

Hidden Markov Model (HMM)[26] is a new classification technique that is defined by a stochastic processes generated by a Markov chain. In this technique, the state chain can be detected by using a sequence of observation, but it cannot be directly detected. The HMM contains two integral processes, which are listed as follows:

- It has a finite number of states, state transition probability and an initial state probability distribution.
- A set of probability functions are associated with each state probabilities.

3.4 Segmentation

Segmentation is defined as the process that divides the given image into regions with some properties such as gray level, color, texture, brightness and contrast. Automatic segmentation of medical images is a complex task in medical image processing. The main objectives of image segmentation are as follows:

- Analyze the anatomical structure
- Identify the Region of Interest (ROI) for locating tumor, lesion and other abnormalities.
- Evaluate the tissue volume for measuring the growth of tumor.

3.4.1 Watershed Segmentation

Watershed [10] is one of the most widely used segmentation technique in medical image processing. It groups the pixels in the image based on their intensities, where the pixels falling under similar intensities are grouped together. It divided the given image to separate the tumor portion from the image. Generally, watershed is defined as a mathematical operating tool that checks the output rather using the input segmentation. In this method, the following principles are used to segment the image:

- Here, the local minima is computed for the image gradient and it will be selected as a marker.
- This type of segmentation uses the markers and their positions. These positions are defined by either user or morphological tools.

3.4.2 K-Means Segmentation

Generally, k-means[27] is the supervised learning algorithm that groups the pixels in the image based on their characteristics. Here, the distance between the pixel and clusters are randomly calculated. Then, the pixel is moved to the cluster, which has the shortest distance among them. This process will be repeated until reach the center coverage.

3.4.3 Fuzzy C-Means (FCM) Algorithm

FCM[28] is defined as a clustering technique that allows the data belongs to one or more clusters in the group. The fuzzy logic is a way to process the data by giving the partial membership value to each pixel in the image. This membership value is ranges from 0 to 1 and it is a multi-valued logic allows the intermediate values. In this technique, there is no abrupt transition between the full membership and fuzzy membership. These membership functions defines the fuzziness of the image and the information contained in the image.

3.4.4 Thresholding

Thresholding [29]is one of the most widely used segmentation technique in medical imaging. It is mainly used to discriminate the foreground from the background. In this technique, the gray level image is converted into the binary image by selecting an appropriate threshold value. Then, the binary image contains all the information related to position and shape of the objects. Moreover, it reduces the segmentation complexity and simplifies the recognition process for classification.

3.4.5 Texture Pixel Connectivity (TPC)

The TPC[30] segmentation algorithm is applied to cluster out the background and tumor spot in the binary segmented output, if it is classified as an abnormal image. This segmentation process analyses the growing pattern of tumor and represents it as a binary image output. Pixel connectivity is a central concept of both edge-based and region-based approaches to the segmentation. The representation of the pixel connectivity defines the relationship between two or more pixels. To ensure the connection between two pixels, certain conditions on the brightness and spatial adjacency of the pixel are to be satisfied.

4. CONCLUSION AND FUTURE WORK

Brain tumor detection and segmentation are the challenging tasks in medical image processing. Brain tumors are a kind of intracranial mass of tissue and are caused by abnormalities and uncontrolled cell division. It is a cluster of abnormal cells growing in the brain. It may occur in any person at almost any age. So, early detection and prevention will helps to diagnose this disease. In this paper, different image processing techniques are surveyed for brain tumor detection and classification. The performance of various image segmentation techniques used for the analysis of human brain is affected by the artifacts such as random noise, intensity inhomogeneity, etc.To overcome the limitations of the existing image segmentation techniques, a novel TPC based segmentation technique and thresholding technique are presented for the efficient segmentation of brain MRI image.The proposed approach enables detection of exact location of tumor in the brain. Here, the techniques are surveyed for the following stages: preprocessing, feature extraction, classification and segmentation. The advantages and disadvantages of the paper are also discussed in this work.

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