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A Brief Survey on MRI Brain Image Segmentation Using Image Processing Techniques

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ABSTRACT

This article introduces the effectiveness of biological and medical imaging. The distribution of brain tumors consists in the separation of various tumor tissues from normal brain tissue. In brain tumor studies, the existence of abnormal tissue can be easily detected. In the past, many researchers in the field of medical science and soft computation have made important studies in the field of brain tumor MRI, a non-invasive imaging technology that produces detailed three-dimensional anatomical images without damaging radiation. A brain tumor or central nerve cell occurs when abnormal cells leave the brain. This article provides an overview of the most appropriate brain tumor classification approaches after imaging. Given the benefits of magnetic resonance over other imaging diagnostic studies, this study focused on MRI brain tumor classification.

Key words : Brain tumor, Classification, Magnetic Resonance Imaging, Segmentation.

1. INTRODUCTION

The brain is the center of the human central nervous system. The brain is a complex organ because it contains 50-100 billion neurons that make up giant networks. Brain tumor is an abnormal growth of a group of cells growing inside or around the brain. The types of brain tumors are benign and malignant. Benign tumors are non-cancerous tumors. Many benign tumors are localized and do not spread to other parts of the body. Most benign tumors respond well to treatment. Benign tumors are less dangerous than malignant tumors. Malignant tumors are cancerous growths. They are often resistant to treatment and can spread to other parts of the body. Malignant tumors are classified as primary and secondary tumors. Malignant tumors spread rapidly, invading other tissues of the brain, progressively worsening the condition and leading to death.

Detecting brain tumors is the most difficult problem due to complex brain structures [20] - [23]. Magnetic resonance imaging is used in medical imaging to provide details on the internal tissue of the image. The exact positioning is important in diagnosing brain tumors, which helps you understand the shape and size of the tumor. In the brain tumor detection technique, image segmentation plays an important role, there are several imaging methods used to extract the tumor from the endoscopy of the brain.

Brain tumor classification is one of the competing tasks for analyzing tumor characteristics when planning medical treatment. Medically, brain tumors, called neoplasm in the brain, are caused by a special development of brain tissue. There are two types of brain tumors: primary brain tumors and metastatic cancers. The former develops in the brain and the remainder, then begins to develop cancer elsewhere in the body and spread to the brain. Mortality of brain tumors has increased, and studies show that approximately 90% of benign tumors are found within 20 years [24]. Brain tumors vary depending on their individual components, such as location, shape, size, and intensity of the image.

While segmentation provides details on soft brain tissue such as gray matter (WS), white matter (WM), cerebrospinal fluid (CSF). Etc. There are two types of divisions, including manual division and automatic segmentation. The technique of manual separation depends on the experience or technical skill and use of human time, but reduces the efficiency of computation. While autocorrelation involves histograms. Which is based only on pixel intensity. This study introduces existing image classification techniques to detect and detect brain tumors from MRI images, e.g. [25] [29]. Automated tumor detection and classification study by doing survey have some objectives

• Use a complete automated automation method to segment brain tumor.

• Provides software (computer code) to detect the size and location of brain tissue according to the method. This confirms a good rating of segmenting brain tumor.

• Provides early and accurate tumor detection.

This document provides an overview of various techniques and algorithms for detecting brain tumors using MRI contrast decomposition. Semi-automatic and automated methods are applicable for brain tumor classification because in this case the error is lower than the manual separation method. The outline of this document is as follows: Part II deals with literary studies. Section 3 presents a summary of the methods of brain tumor classification. Section IV looks at the techniques of the method already presented. Section V concludes the report.

2. LITERATURE SURVEY

The next section deals with existing methods for detecting brain tumors from brain MRI images. Parven and Amritpal Singh [3] proposed a hybrid technique for the detection of brain tumorsusing Support Vector Machine (SVM) and Fuzzy C-Means Clustering (FCM). Real data were determined for 120 patients with NMR. MRI images were converted into a two-dimensional array (using MATLAB) to enhance the image. Prior to the distribution of MRI images using Fuzzy C-Means, the enhanced images were strips the skull using Double Thresholding, Erosion, and Region Filling methods. The segmented image is a function derived from the Gray Level Run Length Matrix (GLRLM) for better understanding. In addition, by training SVM classifiers on 96 brain images, the remaining 24 brain images were used for the assay to identify tumors in brain imaging.

The tabulated performance of SVM Classifier shows that the accuracy of linear kernel function is approximately 91.66%. However, the authors conclude that a hybrid SVM algorithm can be applied to improve the level of accuracy by reducing the error rate. Karthik, Menaka and Chellamuthu's method [4] effectively detected brain tumors from MRI images by combining characteristic of Curvelet and Gray Level Co-occurrence Method (GLCM) features using Support Vector Machine (SVM) classifier. Regardless of the technique, pre-processing of MRI images becomes necessary for brain removal from MRI images. Skull removal was used to process MRI images in advance.

Pre-processed images are subdivided by watershed transformation to capture areas of interest. The statistical characteristics and size and texture characteristics of MRI images are stored as feature vectors. These vectors are used to train SVM classifiers. The algorithm is evaluated on the Brainweb and IBSR datasets. The study compares different classifiers based on their level of accuracy. Comparison of levels of efficacy and RoC graphs for different classifiers suggests that the combination of SVM with curvelet and GLCM outperformed other methods in tumor detection. The authors claim that they are expanding studies to classify images for different pathological conditions and diseases..

Dina, Samy, and Selim proposed a modified Probabilistic Neural Network (PNN) model based on Learning Vector Quantization (LVQ) to perform automatic brain tumor classification [5]. The performance of the modified PCN model is measured on the effect of training, classification accuracy, and computational time. The sample was tested on a 64-MRI data scan, a grayscale image with a resolutionof 220 x 220 pixels each. Out of the 64 images, the NN image group. Eighteen random groups were used as the test set and the remainder were used as the dataset. The simulation results show that the proposed system classifies the MRI image with 100% success. The modified PPN method reduced 79% of processing time compared to previous systems [6].

The method requires further exploration into the network structure to facilitate the process. Vishnukumar, Syed and Suthar have proposed an automatic contrast enhancement scheme for mammals [7]. The detection process involves several steps, such as soothing, edge detection, histogram modifications and color mixing. The noise elimination and edge reinforcement were performed using the Gabor Algorithm and Fast Fourier Transform, while the separation was performed by the Marker-Controlled Watershed Algorithm (MCWA) method. his method was tested on breast X-ray mammograms. Experimental results have shown improved visibility for identifying valuable information for identifying breast cancer. Although this method resulted in improved visibility of the tumor area, it did not confirm with the standard dataset.

Anant and Siddu [8] proposed a method for classification of medical images without human verification. The proposed technique uses Principal Component Analysis (PCA) to extract the features and applied Adaptive Neuro-Fuzzy Inference System (ANFIS) tool for training. The ANFIS classifier found the tumor to be 90% accurate. The statistical results show that the ANFIS method is over 90% better than the PNN method for the same dataset. However, there is no clarity in the data set used to evaluate the proposed method.

Vishal Paramane, LalitaAdmuthe, VinayakSutar proposed a method [9] for detecting brain tumors and their classification of MRI brain images using computer-aided design (CAD). The CAD system includes step-by-step procedures for classifying tumors, such as, (i) MRI image pre-processing (ii) Determination of ROI (iii) Edge Detection of brain skull (iv) Tumor Segmentation and (v) Classification of tumor stage. To classify brain tumors, feature extraction was performed using the localized segmentation method and Back Propagation Neural (BPN) Network with Levenberg-Marquardt(LM) algorithm. Although this method was not tested on special data sets, six images were used randomly for the study. Since the binary mask is applied to the original image for 100 repetitions, the result is correct with a regression value of R = 0.99. The best validation is obtained in the 23rd epoch.

In addition to identifying and segmenting brain tumors, the CAD method also determines the rate of tumor growth. Nithyapriya and Sasikumar [10] proposed a modified

AdaBoost Support Vector Machine (AdaBoost SVM) to detect and differentiate brain tumors from the MRI images. MRI tumor images were classified as subtypes or blocks. The features were extracted from the sub-image using the multi-fractional Brownian motion (mBm) method. On application of AdaBoost SVM algorithm, the features are analyzed in detail to detect the tumor area(s). When applying the AdaBoost algorithm, the SVM characteristics are analyzed in detail to identify tumor regions. Although the algorithm can detect the presence of tumors in MRI images of the brain. The hybrid approach, implemented by Dipali and Patil [11] is a combination of Support Vector Machine (SVM) and Fuzzy CMeans in predicting brain tumors effectively. Images were preprocessed to map and highlight skulls. Fuzzy clusters were used to detect regions of interest (RoI) from brain MRI images. Feature extracts allow identification of tumors and non-tumor areas of the ROI.

The method was tested on tumor images collected from brain tumor warehouses and direct images from the diagnostic center. SVM techniques have been applied to classify extracted images more accurately and more effectively. The authors only used tumor imaging for the study, so the effectiveness of the proposed method was not correlated with non-tumor images. Santhoshkrishnan, Sivanarulselvan and Betty's study [12] focused on the detection and classification of brain tumors by imaging techniques. Tumor images from MRI and CT were used for the study. Images from the scanning center were initially processed for noise reduction and extraction using the Gray Level Co-occurrence Matrix (GLCM) method the features are extracted. Further, an integrated approach of both Artificial Neural Network (ANN) and Fuzzy C-Means segmentation technique were used to distinguish tumor sections of the original image. Therefore, restrictions in both methods were removed.

Finally, the ANFIS method was classified as normal or abnormal. In the event of a disorder, the type of disability is also indicated. Techniques are evaluated based on accuracy, precision, sensitivity. The results show that the proposed method is better than the existing method, but its comparison or value is not mentioned. Mariam and Zaid's work [13] focuses on images of brain tumors automatically. The proposed imaging process includes four steps for detecting a tumor: namely; (1) Pre-processing by Anisotropic diffusion filter for denoising MRI images, (2) The denoised images are masked based on symmetry, (3) SVM classifier detects brain tumorFrom masked images and (4) segmentation processes are evaluated. Dice Factor Base, where DC> 0.7 is the better part. When this algorithm was evaluated with a 40 MRI image of the brain, the accuracy of brain tumor detection was found to be 95.5%. However, the authors failed to determine the results of the algorithm with the standard dataset.

3. BRAIN SEGMENTATION METHODS

Segmentation means the separation of the image of an element or its object from the background, and is an important analytical function by which many algorithms have been developed in the field of medical imaging processing [14, 18]. In the method of automated segmentation, the computer defines tumor breakdown without human interaction. For clinical examination, the main tasks are localization, diagnostic stage, and clinical reaction monitoring [19].

The classification technique is divided into eight main classes:

- Threshold-based techniques
- Region-based techniques
- Pixel classification techniques
- Model-based techniques
- Manual segmentation
- Atlas-based methods
- Hybrid segmentation methods
- Deep Learning methods

Threshold-based, region-based and pixel classification techniques are usually applied in two-dimensional image segmentation [1]. Techniques based on Model such as parametric and level sets deformable models, are mainly applied in 3D image classification [2].

3.1Threshold methods

Segmentation methods are simple and powerful methods for separating brain tumors, where image objects are grouped by comparing their intensity with one or more intensity levels. Level values can be global or local. If the histogram image shows a 3D pattern, the object can be separated from the background of the image by a single level called the global threshold. However, if the image contains more than two types of areas that are similar to different objects, the classification must be performed using a local level. Images can be subdivided into sections by applying different levels or by using thresholding techniques. [5] The main issue in determining the threshold is the intensity and not the pixel connectivity. There is no certainty that the pixels identified by the ongoing process are continuous. Independent pixels that are not part of the required area can be easily integrated and, at times, isolated pixels within the border near the region are ignored. These effects are exacerbated by the deterioration of the noise, as pixel intensities are unlikely to represent normal intensities in the region. When using a thresholding method, sometimes too much area is lost and sometimes too many inappropriate background pixels are obtained. Shadows of objects in an image are also a problem not only where they fall on another, but when they are misplaced as part of a dark object against a light background. Another problem with global brightness is that changes due to differences in phase intensity can cause parts to be brighter (in the light) and partly darker (in the shadows) in ways that are not quite right do with image objects.

A. Global Thresholding

Global thresholding is well implemented if the image contains objects of the same intensity or the contrast between the background and the object is high. Thresholding create a binary image from the gray level, turning the pixels below the threshold to zero and the pixels around the threshold.
It may not work with fully automatic segmentation, and may fail when two or more tissue structures have overlapping intensities. The accuracy of the area of interest (ROI) is also uncertain because it is separated from the background on the basis of thresholds, which can lead to significant statistical fluctuations. When the number of areas or the noise level increases or when the image contrast is low, selecting the level becomes more difficult.

B. LocalThresholding

Local Thresholding techniques can be applied when a threshold cannot be defined by a histogram for the whole image or a single threshold cannot give accurate segmentation results. The Local Thresholding can be used effectively when the small gradient effects correspond to the chosen size of the complement image. If the gradient is too large, the sections found in the sub-image will no longer match..

3.2Region Based Methods

The region classification method looks at pixels as images and creates bounded regions, integrating adjacent pixels with the same characteristics, based on predefined similarity criteria. These methods can be mapped in the following general ways: Let X be a subdivision into N regions, each of which is bounded by thousands, where I = 1, 2 N. The original image can be properly assembled. By putting all the regions together and there should be no overlap between the two regions, Ri and Rj for i ≠ j. Logically, the projection L (.) contains a set of rules (usually a set of homogeneity criteria) that must be satisfied by all pixels in a given region and fail in the union of two regions because of the merging of two separate regions will cause the same region..
The region growing and the watershed segmentation methods are part of a region-based approach commonly used for brain tumor classification. The following sections describe these methods and some of the applications in the brain tumor classification literature.

A. Region Growing

The simplest regional classification method is the region growing, which is used to extract regions of similar pixels from images [47]. Growth in regions begins with at least one seed belonging to the interest structure. Seed neighbors were inspected and those that met similar criteria were added to the region.

Similar criteria are determined by the pixel intensity values or other features in the image. Seeds can be manually selected or provided by the automatic seed search procedure. The procedure was repeated until there were no additional pixels in the region. The advantage of a growing region is that it can segment the regions with similar properties and create cohesive regions.

B. Watershed

The main method of watershed segmentation an be explained by comparisons based on water behavior in the landscape. When it rains, waterfalls in different areas will follow a downward landscape. The water will be at the bottom of the valley. For each valley there will be an area where all water flows into it. In other words, each valley is connected to a reservoir and each point in the landscape belongs to a single pool. Dams will be built in places with water from different tanks. When the water level reaches the highest peak in the landscape, the process stops. As a result, the landscape is divided into areas separated by dams called towns or sanctuaries. It creates a complete contour of the image and avoids the need to attach any contour.

3.3 PIXEL CLASSIFICATION METHODS

This method of classification is based on pixel classification. The pixels in the image can be represented in the size function using a pixel attribute that can include gray levels, local textures, and color components for each pixel in the image. In the case of a single channel image (or a single frame), pixel classification is usually based on gray levels, and image classification can be performed in one-dimensional space. For multifunctional or multispectral images (multimedia), segmentation can be performed in multidimensional space. Pixel classification is limited to the use of controlled or unsupported classification groups for pixel compression in spaces that have the characteristics of image separation. Grouping is the process of grouping similar objects into groups, whereas objects of different nature are grouped into different groups based on some similar criteria. The similarity is determined by the appropriate distance measure.
The unsupervised clustering methods are: Fuzzy C-Means (FCM), K-means, and statistical methods as Markov random Fields among others. The supervised methods are Artificial Neural Networks (ANN) and Bayes. FCM techniques are analyzed in this section.

A. Fuzzy C- Mean Clustering

The goal of FCM is to identify natural data groups from large datasets to create a brief representation of the system behavior. It is not easy to determine whether a pixel must belong to an area or not in many situations. This is because the same set of characteristics may not significantly change in the region. FCM bracing is the most popular technique in the field of image classification, which is not supported by pixel classification, especially in the case of brain tumor classification.

B. Artificial Neural Network

Another suitable method for cluster management is the Artificial Neural Network (ANN) technique. his classifier feeds through a series of nodes where mathematical operations are performed on input nodes and a classification of the end result nodes is made. The training phase for this technique consists in determining the value of the parameters considered (or relevant) in the mathematical operation, so that the errors in the predictions made by the output nodes are minimized. Since no parametric distribution (such as a

Gaussian distribution) is assumed for the data, ANN approaches are non-parametric techniques. Moreover, the use of “hidden” layers of nodes allows the modeling of non-linear dependencies in the features. Although ANN training is complex, the ability to model non-trivial distributions offers clear practical advantages. This is noteworthy in the case of tumor segmentation since assuming the data follow a simple Gaussian distribution may not be appropriate for segmenting heterogeneous tumors.

C. Color Information

In this strategy, the restrictions are based on the position of the number plate using the attributes of the shadow plate. The information is an RGB color image. Four colors are considered here: white, blue, red and green. The following edge identification is performed by looking at four colors. Currently, RGB shadow sizes are being converted to HSI. Candidate area of the plate was detected using the color information above, then it was compared with the ratio of height, foreground and background color with the current plate standard and split into areas Which are not bowls and non-bowl areas.

D. Texture Features

Texture is a feature that helps image sections in areas of interest and classifies them. Provides information about the color sequence of colors or intensities in the image. Strategies for Chinese number plates are given. Limits are the number of focus edges, the length of the allowable area of the tab, and the amount of line of focus each. The mural information was preprocessed from the middle channel, and from that time using Sobel's edge detection, edge focus was mapped. An autopsy of the resulting image was performed to reduce inaccurate and unwanted fragmentation in the image. The span between the number of end focuses and the length of the number plate is 3.9 to 13. The circumference, segment, and level of the columns are positioned and centered around the number of edges focusing the length of the section. etc. Rough endurance is centered around the base and most focused on the edges.

3.4 MODEL BASED SEGMENTATION

Segmentation of 3D imaging data is a difficult procedure that is mainly reached by segmentation-based models such as geometric deformable models and geometric or level sets. deformation models. In the model classification, a connected and continuous model was developed for a particular anatomical structure, including a preliminary knowledge of the object in the form, position, and orientation. Some of the models include preliminary statistical information drawn from a series of training data sets. Separating medical imaging structures and reconstructing the compact geometric representation of these structures is difficult due to the large size of the data distortion and the complexity and variability of the anatomic shape of interest. The challenge is to extract boundary elements belonging to a single structure and integrate these into a coherent and consistent model of the structure. The perturbation model involves the creation of propagation interfaces (closed curves in 2D and closed surfaces in 3D) that move under the velocity function defined by local, global and independent properties. Degradable models can be divided into two types: parametric and geometric methods.

A. Parametric Deformable Models

Parallel deformable models clearly represent curves and surfaces in their model. The power of the parasitic deformable pattern, also known as the active contour pattern, or the snake stems. The ability to distinguish, match, and track images of anatomical structures using constraints obtained from image data along with prior knowledge of the location, size, and shape of these structures. Parallel deformed models can often adapt to significant variations in biological structure over time and across individuals. In addition, these models maintain a highly interactive interaction mechanism that allows medical scientists and practitioners to apply their expertise to perform imaging-based assessment tasks when necessary. Deformable models is a theoretically defined curve or surface that moves under the influence of weight forces composed of two components, called internal and external forces. The internal force is used to satisfy the smoothness of the model during the deformation process, while the external force is set to push / pull the model to the boundary of the structure.

B. Geometric Deformable Models or Level Sets

Geometric Deformable Models or Level Sets using a model that can split models into 3D images, it is difficult to deal naturally with changes in the physics of separation and mixing of contours. This problem is solved by introducing the use of deformed or constrained geometry. In the method of thresholding, the object is separated from the image using the evolution of the curve. The decoupled object is started with a closed curve. An important component of the thresholding method is the actual representation of the interface. If the interface is given by Γ, Γ is represented as the zero level set $\{\phi = 0\}$ of a level set function ϕ.

The geometric contour with the image gradient method improved the onset of the active contour, with the original symmetry contour being placed symmetrically with respect to the boundaries of local interest. Not related to the object in the right shape.

3.5 MANUAL SEGMENTATION

In manual segmentation, the tumor area is manually placed on all adjacent slices where the tumor is thought to exist, but it is expensive and time-consuming work. In addition, it is subject to manual modifications that increase the ability for different observers to draw different conclusions about the presence or absence of a tumor, or even if the same observer draws different conclusions on different occasions. Clearly, the need for automatic brain tumor resection.

3.6 ATLAS-BASED METHODS

Proper visual segmentation can be a difficult task as large tumors or lesions occupied by space change the shape and location of brain structures and sub-structures. The comparative advantage of Atlas-based classification over previous segmentation methods is the ability to image images without a clear relationship between the intensity of the region and the pixel. This usually occurs when objects with the same structure are segmented (i.e., the same texture) and information about the differences between these objects is linked in the space relations between them. other objects or within their morphometric characteristics.

It is important to note that MRI scans of the atlas-based brain have become a research stimulus in recent years. MRI classification of fetal brain tissue is more complicated than that of adults due to the complex anatomy of the developing brain and poor MRI quality. Therefore, the astrophysics of the fetal brain, with varying degrees of tissue structure, is used to distinguish different brain tissues such as myelinated, nonmyelinated white matter and brain cortex. Therefore, it is imperative to establish dynamic, probabilistic atlas for each stage of fetal brain development (for the age of 29 to 44 weeks).

3.7 HYBRID SEGMENTATION METHODS

Problems focusing on applications with brain MRI scans have long been established, and new techniques are being developed and demonstrated regularly [30 - 33]. Then, choosing the most appropriate technique for a particular program is usually a challenge. Therefore, a combination of different techniques may be required to achieve segmentation goals. Therefore, hybrid or combined decomposition methods have been used exclusively in many applications for MRI brain segmentation [34, 35] and have improved classification accuracy. Kapur et al. [36] Allocating different brain regions to adults with 2D MRI by fusing expectation maximization segmentation, binary mathematical morphology, and active contours models. Masutani et al. [37] An area based on a unified model grows with morphological information localized to parts of the blood vessels. Warfield et al. [40] developed an integrated three-dimensional algorithm for MRI brain classification, which is repeated between classification steps for tissue detection and slow matching steps to align patterns of normal brain structure with tissue. Classify. Hybrid segmentation methods are also used for segmenting the brain of newborns. For example, Despotovic et al. [42] presented a hybrid method for segmentation of the neonatal brain using TL, weighted T1 and T2, incorporating the following strategies; thresholding, active contours, FCM clustering, and morphological operations. Akselrod-Ballin et al. [39] implemented a hybrid technique by combining mass distributions by weighted aggregation (SWA) and classified on the basis of a support vector machine (SVM). Another hybrid method, such as wavelet fusion and for classification of abnormal and normal brain images, was used by Chaplot et al. [41] This approach indicates that the SVM hybrid is superior to the Kohonen neural network in terms of performance measures. The main disadvantages of using a hybrid segmentation method are the lower computation time and the greater number of parameters one would want to set for a particular application. Therefore, the method of hybridization must be carefully and logically planned to ensure efficient and high quality distribution.

3.8 DEEP LEARNING METHODS

Recent advances in deep learning methods, particularly in the convolutional neural networks (CNNs) in recognition of objects and the challenges of segmentation of biological images [43] have heightened the appreciation of researchers. These methods require large datasets as well as powerful training process. CNNs take the input image and return the resulting tag or segmentation mask as output between them is a complex network of hidden layers. These can be convolutional, pooling, activation or activation, or layers that are fully coupled with a large amount to be adjusted during training. CNN explores the connection between the pixels of an input image by exploiting the representational features using a compact and integrated operation. The features found on each layer using the learned kernel vary, with the first layer extracting simple features such as edges and the latter, extracting complex and advanced features. Urban et al. [44] proposed a 3D CNN architecture for the multimodal MRI glioma segmentation application, while high dimensional processing can represent 3D scaffolds of biological structures but also increase network load. Shen et al. [45] first put the fully convolutional network (FCN) for multidimensional segments of brain tumors with single-layer connections lost at different levels, and the authors also introduced brain symmetry inputs to FCN to further improve the segmentation performance. In contrast to the dimensional approach, Zikic et al. [46]eveloped an analytical method for reconstructing 4D data so that standard 2D-CNN architectures could be used to deal with brain tumor distribution functions. This eliminates the stress of designing high-dimensional CNN design while maximizing computational efficiency. A more recent method uses the cascaded two-pathway CNN architecture by Havaei et al. [47]. This technique involves extracting smaller and larger patches. In addition, the output of the first one is used as an input to the second network. They also perform a post-treatment step that separates the dots near the skull based on the connected components. In addition, this technique takes three minutes to divide the whole brain using GPU-based deployment. One of the current methods of CNN is to determine the efficacy of brain tumor resection using a more deeper CNN architectures [48]. This method is understood by applying small 3×3 filters in the convolutional layers. In such cases, a more complex layer should be added to the architecture, without prejudice to the useful field of perception of the larger filter.

4. DISCUSSION

The threshold-based technique is the presence of simple and fast segments when good light values are determined. Despite the limitations, these techniques were used as the first step in the segmentation process (Table 1). Region-based techniques have been used as a refinement step to delineate the associated tumors [9] have reported the most accurate results in tumor classification, but in general these methods are limited to semi-automated [16]. The pixel segmentation technique for brain tumor classification is limited to grouping, whereas it is commonly used for brain tumor segmentation. The unsupervised FCM techniques, one of the most popular for medical imaging [15], produce the most accurate results in a tumor. The unsupervised method of MRF provide a way to incorporate information related to cluster size, reducing cluster overlap and the effect of noise on the output [17]. Model-based techniques are widely used for their sensitivity when exploring the boundaries of brain tumors. Segregation of the tumor using a model approach that can be deformed geometrically or level sets enable the most accurate and automatic method of segmentation. Even with these methods, they are still highly computationally expensive [16].

Table 1: Comparison of different Methods

Methods	Advantages	Disadvantages
Thresholding	The threshold is an important task for any type of segment and is useful in image orientation	Due to the high sensitivity of the surface intensity and background image intensity, this algorithm does not work properly for all MRI brain images.
Region growing	methods can properly divide the area, which is exactly what we describe	Very sensitive to noise, resulting in extracted regions having holes or even being excluded
Watershed	The best technique for grouping pixels per image is based on their intensity	A major problem of watershed transform is its sensitivity to differences in production intensity that occur when images are subdivided into a large number of irrational regions.
k-means clustering	The algorithm also runs so fast that real-time image segmentation can be completed with the k-means algorithm	Incorrect selection of k can also lead to bad and incorrect results
FCM clustering	This is an unsupervised algorithm. It also sets the level of data membership for each class, thus allowing for a soft group	Calculation time is very high and is tolerated by local trap problems
Markov random fields fields	It is likely to decide whether abnormality is present in the image or not	Calculation time is very high
MRF-EM framework	The spatial information in the image is encoded at the context level of the adjacent pixel	This applies only to homogeneous tissues to classify normal tissue groups, so is usually not applicable to hereditary tissue compartments and allows identification of tumor structures with normal but too thick anatomical features.
k-nearest neighbor	It can be simplified by including other methods with respect to both field bias assessment and tissue classification	This model can approach the wrong border in case of heredity inhomogeneity
Artificial neural networks	Neural networks work well on non-linear domains, multifunctional problems, such as tumor distribution, where it is difficult to use decision trees or rule-based systems. They also perform slightly larger on the noisy field	Collection of training models is not easy, and the training phase is mainly slow, using gradient training

5. CONCLUSION

Medical imaging analysis should solve real-world problems beyond the field of computer vision. Image classification and feature extraction techniques are widely used in biological imaging and are important for the study of anatomical structures, tissue volume calculations, non-invasive diagnoses, pathology, treatment plans, and Computer Surgery. These practices are performed on the basis of characteristics that allow for the differentiation of abnormal tissues from normal tissues. This article explores automated and semi-automated classification, methods for brain extraction, and tissue classification using MRI. The advantages and disadvantages of various automation techniques for identifying brain lesions are also analyzed in detail. The basic idea is to determine the most viable method for future development of better and more efficient segmentation techniques that will enable radiologists to perform a thorough brain examination at a given time. Reduce. The ultimate goal is to develop new imaging techniques and focus on future medical and medical imaging developments. There are several future directions that could further improve the existing MR brain imaging system: (1) access to large databases from different institutions with varying image quality for clinical evaluation and improvement of new methods; (2) improve classification accuracy by citing effective functions and enhancing the training database; (3) use other machine learning techniques and integrate them into a single hybrid system.

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