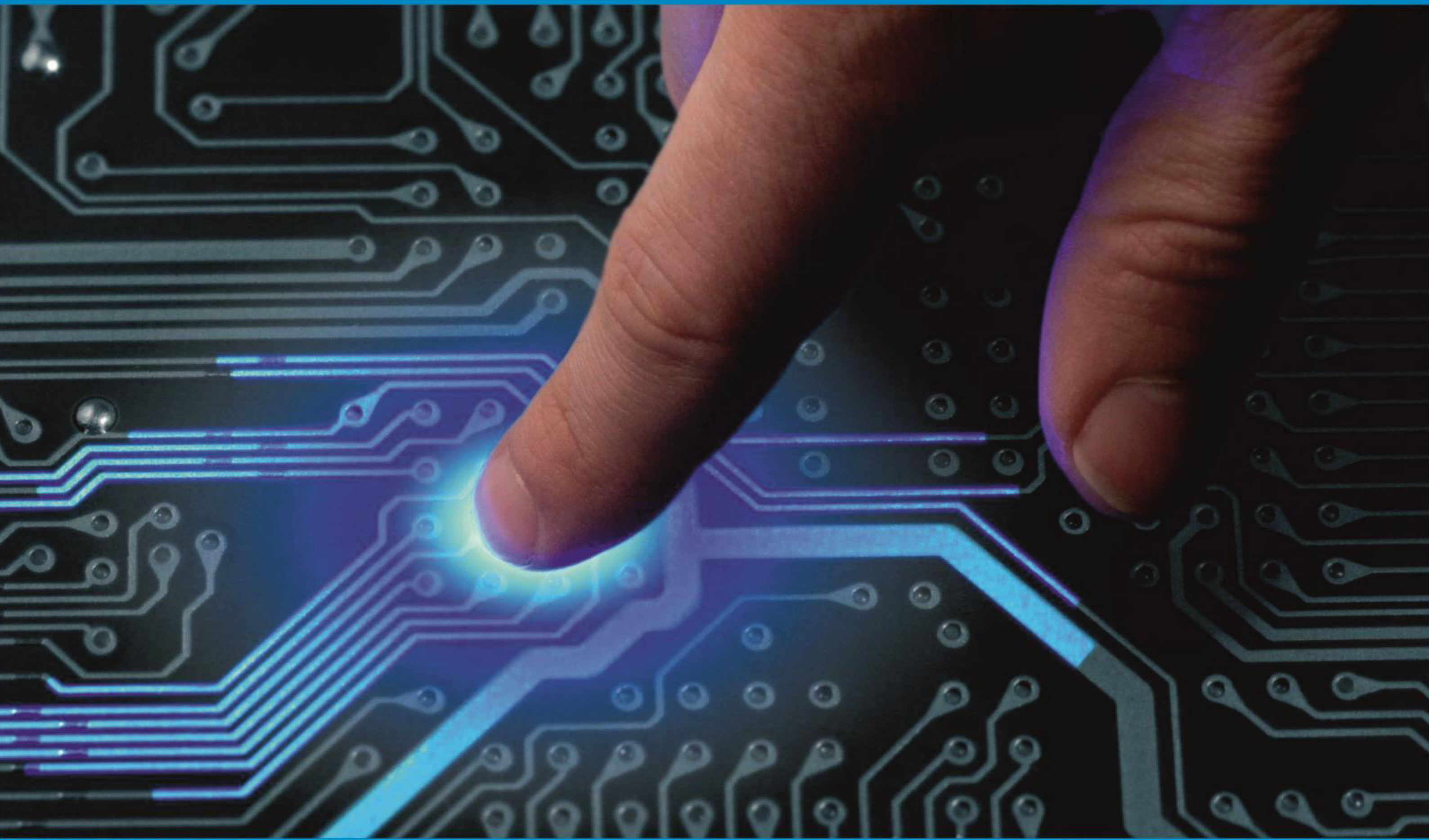
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 9, Issue 5, May 2021

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 7.488

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.488 |

|| Volume 9, Issue 5, May 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0905261 |

Review of Brain Tumor Diagnosis Techniques from MRI Images

Ashish Bhatt[1], Dr. Vineeta Saxena Nigam[2]

Research Scholar, Dept. of E.C.E., University Institute of Technology, RGPV, Bhopal, India[1]

Professor & Head, Dept. of E.C.E., University Institute of Technology, RGPV, Bhopal, India[2]

ABSTRACT: The successful early diagnosis of brain tumors plays a major role in improving the treatment outcomes and thus improving patient survival. Manually evaluating the numerous magnetic resonance imaging (MRI) images produced routinely in the clinic is a difficult process. Thus, there is a crucial need for computer-aided methods with better accuracy for early tumor diagnosis. The past works of many researchers under medical image processing and soft computing have made noteworthy review analysis on artificial intelligence (AI) based brain tumor detection techniques focusing segmentation as well as classification and their combinations. In the manuscript, various brain tumor detection techniques for MR images are reviewed along with the strengths and difficulties encountered in each to detect various brain tumor types.

KEYWORDS: Brain Tumor, MRI, AI, Machine Learning, Deep Learning.

I. INTRODUCTION

Segmentation/classification of MR images needs to be very efficient for proper analysis of brain tumor. A range of works have utilized the capabilities of image segmentation techniques to extract the meaningful content from medical images (i.e., tumor) which thus helps in proper analysis of brain tumor. But, the variability of tumor shapes and the presence of cerebrospinal fluid (CSF) particularly make a difficult brain tumor detection task more complex. Irrespective of the superiority of segmentation technique employed, quality of segmentation depends greatly on contrast of medical images, amount of noise, and lastly incomplete boundaries. Particularly, in medical images good contrast supersedes all other basic requirements, as an abnormal structure is identified completely on the basis of certain contrast characteristics. Contrast is a function of tissue density in MR images. In other words, good image contrast is a native property of brain MR images and thus their generation does not need any kind of contrast enhancing agents.

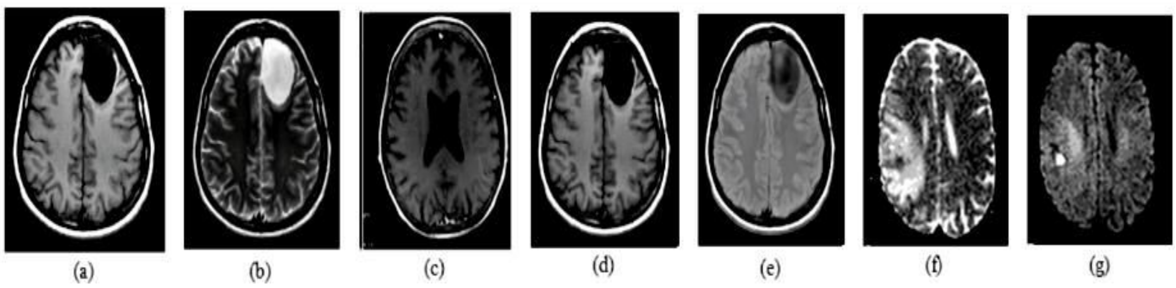


Figure 1: Types of MRI Images

The starting module is collection and acquisition of images which are to be analyzed in later phases. Standard brain tumor databases, namely BRATS, Harvard medical school, Brain Web, and Internet Brain Segmentation Repository (IBSR), are commonly used by the researchers. Moreover, studies have validated their approaches on data repositories collected from various clinical and pathology labs.

The pre-processing module is meant to improve image visual quality by filtering all the high noise levels. Presence of such disturbances makes abnormal/normal tissue discrimination relatively difficult and thus the precise interpretations. Next is the segmentation module that highlights region of interest and guides all the proceeding modules, especially analysis. Although segmentation is important but it may not be present sometimes when direct

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.488 |

|| Volume 9, Issue 5, May 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0905261 |

classification supersedes other objectives. The feature extraction module follows segmentation. A variety of standard texture features along with other information like intensity and edge, are commonly used. Robust learning models are built by picking a sub-class of relevant features and exempting the irrelevant ones. This is successfully achieved by utilizing standard dimension reduction techniques such as principle component analysis (PCA), independent component analysis (ICA), canonical correlation analysis (CCA), etc.

II. RELATED WORK

K. Hu et al., presents a novel brain tumor segmentation method based on multi-cascaded convolution neural network (MCCNN) and fully connected conditional random fields (CRFs). The segmentation process mainly includes the following two steps. First, design multi-cascaded network architecture by combining the intermediate results of several connected components to take the local dependencies of labels into account and make use of multi-scale features for the coarse segmentation [1].

Y. Ding et al., presents Deep Residual Dilate Network with Middle Supervision (RDM-Net), which combines the residual network with dilated convolution. It can solve the problem of vanishing gradient and increase the receptive field without reducing the resolution. It evaluates the relationship between this single pixel and its adjacent region to obtain the spatial structure information of brain tumors. [2].

C. Han et al., presents the Generative Adversarial Networks (GANs) can synthesize realistic/diverse additional training images to fill the data lack in the real image distribution; researchers have improved classification by augmenting data with noise-to-image (e.g., random noise samples to diverse pathological images) or image-to-image GANs (e.g., a benign image to a malignant one) [3].

Y. Ding et al., shows the improvement in the network structure of Unet to make it more suitable for brain tumor segmentation. propose a novel framework called Stack Multi-Connection Simple Reducing_Net(SMCSRNet) that are stacked by our basic blocks called Simple Reducing_Net(SRNet). The basic block SRNet is improved from the original Unet, which consists of four downsampling and upsampling operations during the encoding and decoding [4].

H. H. Sultan et al., Brain tumor classification is a crucial task to evaluate the tumors and make a treatment decision according to their classes. There are many imaging techniques used to detect brain tumors. However, MRI is commonly used due to its superior image quality and the fact of relying on no ionizing radiation. Deep learning (DL) is a subfield of machine learning and recently showed a remarkable performance, especially in classification and segmentation problems [5].

A. Yang et al., takes tumor images as the research object, and first perform local binary pattern feature extraction of the tumor image by rotation invariance. As the image shifts and the rotation changes, the image is stationary relative to the coordinate system. The method can accurately describe the texture features of the shallow layer of the tumor image, thereby enhancing the robustness of the image region description [6].

M. I. Razzak et al., present embed the cascade architecture into two-pathway-group CNN in which the output of a basic CNN is treated as an additional source and concatenated at the last layer. Validation of the model on BRATS2013 and BRATS2015 data sets revealed that embedding of a group CNN into a two pathway architecture improved the overall performance over the currently published state-of-the-art while computational complexity remains attractive [7].

P. Kumar Mallick et al., presents a technique for image compression using a deep wavelet autoencoder (DWA), which blends the basic feature reduction property of autoencoder along with the image decomposition property of wavelet transform is proposed. The combination of both has a tremendous effect on sinking the size of the feature set for enduring further classification task by using DNN. A brain image dataset was taken and the proposed DWA-DNN image classifier was considered [8].

P. Mohamed Shakeel et al., shows the computational multifaceted nature of neural distinguishing proof incredibly diminished when the entire framework is deteriorated into a few subsystems. The features are extracted using fractal dimension algorithm and then the most significant features are selected using multi fractal detection technique to reduce the complexity. [9].

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.488 |

|| Volume 9, Issue 5, May 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0905261 |

G. Wang et al., propose image-specific fine tuning to make a CNN model adaptive to a specific test image, which can be either unsupervised (without additional user interactions) or supervised (with additional scribbles). Also propose a weighted loss function considering network and interaction-based uncertainty for the fine tuning. [10].

Table 1: Echo and Repetition times for abnormal brain tissues for each MR image

MR Image	T1-W	T2-W	FLAIR	PD-W	DWI	ADC
TE	$< 30mm$	$> 80mm$	$> 80mm$	$< 30mm$	User dependent	User dependent
TR	$< 80mm$	$> 2000mm$	$> 3000mm$	$> 1000mm$	User dependent	User dependent
FAT	White	Medium black	Grey	Light grey	Medium black	Medium black
White matter	Medium grey	Grey	Medium grey	Medium grey	Grey	Light grey
Grey matter	Grey	Medium grey	Light grey	Light grey	Medium grey	Medium grey
CSF	Black	White	Black	Grey	Black	White
Tumor tissue	Medium black	Medium grey	White	White	White	Black

III. VARIOUS TECHNIQUES

There is various approach to predict brain tumor diagnosis, some of the conventional and advanced techniques are discussed followings-

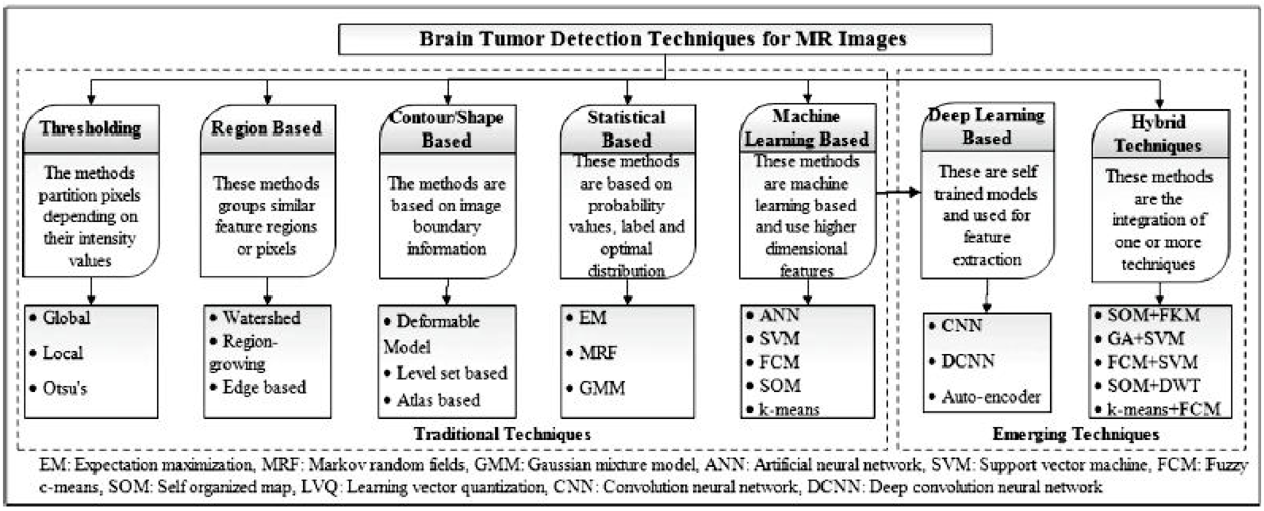


Figure 2: Classification of brain tumor detection techniques used in MR images

Thresholding is a simple and aged procedure for image segmentation, based on the images with different intensities. In this method image is partitioned into different regions by comparing their intensities with one or more predefined intensity value(s). These intensity values are known as threshold, which actually separates the image into different classes. Threshold values are generally estimated by prior knowledge related to local statistical properties like mean intensities.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.488 |

|| Volume 9, Issue 5, May 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0905261 |

Region based methods search for group of pixels having similar features to get connected regions. These methods are simple and also resistant to noise. An effective seed pixel based region-growing segmentation uses similarity criteria to verify and add neighboring pixels to a region. The process iterates till no further pixel satisfies the criteria. On the other hand, seed-based segmentation considers a set of seeds denoting the objects to be segmented. A pixel is assigned to a region whose mean is the closest to pixel's intensity. Systematic watershed segmentation is eminent in identifying background and foreground of an image. The seed point selection is really difficult in such methods but several iterations lead to the attainment of minimum values for foreground and background locations.

Statistical based segmentation is simpler to implement and further, the associated statistical probabilities make acceptance of such methods in medical image processing quite natural. These methods work with parameters like mean, median, standard deviation, probability distribution, and amplitudes to statistically describe an image. They are mainly classified into three, namely Markov random field (MRF), Gaussian mixture model (GMM) and expectation maximization (EM). MRF is non-deterministic and considers spatial information via dependency concepts of neighbors and cliques. One can embed prior knowledge into MRF through clique possibilities. GMM in comparison has effortless implementation and requires few parameters. Lastly, EM uses other methods, like k-means for initialization of matrices such as mean and covariance.

Applicability of machine learning techniques in the domain of automatic brain tumor detection is extensively explored to efficiently proceed with analysis and diagnosis phases. It is observed that the introduction of such learning techniques eases work at the end of radiologists as well as experts in medical practice. These techniques understand relationship depth of patterns and complex data more accurately. They are broadly categorized as supervised (classification) and unsupervised (clustering). A few studies that have utilized learning for brain tumor identification are fuzzy c-means (FCM), self-organized maps (SOM), k-means, support vector machine (SVM), learning vector quantization (LVQ), artificial neural networks (ANN) etc. Subsequent sections detail utilization of such approaches. Supervised techniques derive functional relationship between features and labels during training by utilizing the labeled information. Then in testing, labels are generated for unlabeled information based on the estimated feature.

A range of well-known classifiers is used in several studies for the identification of brain tumor. A distance and voting function based k-nearest neighbor (KNN) is the simplest of all the classification techniques. It is known to achieve higher accuracy and stability for MR image data but is observed to take large running time. Artificial neural network (ANN) maps an image to network of neurons which are considered as pixels. ANN considers detection as an energy minimization problem and tries to establish not only the connection but weights between nodes too while training. Weights are modified by means of an error factor computed by comparing observed and desired output for the given input. One can extract features as well using ANN. Next is support vector machine (SVM) which uses the concept of hyper planes to train itself in appropriately selecting margins and thus distinguishing between or among classes. SVM helps in overcoming issues related to local minima and neurons overhead as compared to ANN.

Another emerging domain of machine learning is deep learning. It's multiple layer architecture represents data with manifold layers of abstraction which helps to overcome several challenges that occur in traditional machine learning approaches. Additionally, it's generalization and self-learning characteristics enable better quantitative analysis of imaging features and thus better detection of neurological disorders. As a result deep learning based segmentation/classification techniques are gaining acceptance in the field of medical imaging process. CAD systems designed with deep learning techniques are frequently observed in medical image analysis ranging from breast lesions and pulmonary nodules, chest and pulmonary tuberculosis to brain tumors. Several deep learning techniques, namely deep neural networks (DNN), convolutional neural networks (CNNs), deep convolutional neural networks (DCNNs), auto-encoders, stacked auto-encoders, are developed for efficient brain tumor detection, segmentation, and classification using MR images. Researches in great pace continue to dig more and more deep learning approaches to achieve the best performance.

IV. CONCLUSION

Brain tumor identification, extraction, segmentation, and classification are some of the challenging tasks for physicians and radiologists. Automation of these modules thus occupies a major proportion of research in the domain of medical imaging. Several existing detection techniques are shown to achieve good performance on different tumor datasets. Irrespective of the accuracy percentages reported by any automatic tumor detection system using the best

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.488 |

|| Volume 9, Issue 5, May 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0905261 |

performing segmentation approach, a second opinion is still required for better diagnosis in any of the case. MR image contrast is a significant factor as it highly influences the process of brain tumor detection. AI best techniques are very effective to identify the brain tumor deceases.

REFERENCES

1. K. Hu et al., "Brain Tumor Segmentation Using Multi-Cascaded Convolutional Neural Networks and Conditional Random Field," in IEEE Access, vol. 7, pp. 92615-92629, 2019, doi: 10.1109/ACCESS.2019.2927433.
2. Y. Ding, C. Li, Q. Yang, Z. Qin and Z. Qin, "How to Improve the Deep Residual Network to Segment Multi-Modal Brain Tumor Images," in IEEE Access, vol. 7, pp. 152821-152831, 2019, doi: 10.1109/ACCESS.2019.2948120.
3. C. Han et al., "Combining Noise-to-Image and Image-to-Image GANs: Brain MR Image Augmentation for Tumor Detection," in IEEE Access, vol. 7, pp. 156966-156977, 2019, doi: 10.1109/ACCESS.2019.2947606.
4. Y. Ding, F. Chen, Y. Zhao, Z. Wu, C. Zhang and D. Wu, "A Stacked Multi-Connection Simple Reducing Net for Brain Tumor Segmentation," in IEEE Access, vol. 7, pp. 104011-104024, 2019, doi: 10.1109/ACCESS.2019.2926448.
5. H. H. Sultan, N. M. Salem and W. Al-Atabany, "Multi-Classification of Brain Tumor Images Using Deep Neural Network," in IEEE Access, vol. 7, pp. 69215-69225, 2019, doi: 10.1109/ACCESS.2019.2919122.
6. A. Yang, X. Yang, W. Wu, H. Liu and Y. Zhuansun, "Research on Feature Extraction of Tumor Image Based on Convolutional Neural Network," in IEEE Access, vol. 7, pp. 24204-24213, 2019, doi: 10.1109/ACCESS.2019.2897131.
7. M. I. Razzak, M. Imran and G. Xu, "Efficient Brain Tumor Segmentation With Multiscale Two-Pathway-Group Conventional Neural Networks," in IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 5, pp. 1911-1919, Sept. 2019, doi: 10.1109/JBHI.2018.2874033.
8. P. Kumar Mallick, S. H. Ryu, S. K. Satapathy, S. Mishra, G. N. Nguyen and P. Tiwari, "Brain MRI Image Classification for Cancer Detection Using Deep Wavelet Autoencoder-Based Deep Neural Network," in IEEE Access, vol. 7, pp. 46278-46287, 2019, doi: 10.1109/ACCESS.2019.2902252.
9. P. Mohamed Shakeel, T. E. E. Tobely, H. Al-Feel, G. Manogaran and S. Baskar, "Neural Network Based Brain Tumor Detection Using Wireless Infrared Imaging Sensor," in IEEE Access, vol. 7, pp. 5577-5588, 2019, doi: 10.1109/ACCESS.2018.2883957.
10. G. Wang et al., "Interactive Medical Image Segmentation Using Deep Learning With Image-Specific Fine Tuning," in IEEE Transactions on Medical Imaging, vol. 37, no. 7, pp. 1562-1573, July 2018, doi: 10.1109/TMI.2018.2791721.

INNO SPACE

SJIF Scientific Journal Impact Factor

Impact Factor:
7.488

ISSN INTERNATIONAL STANDARD SERIAL NUMBER INDIA

निस्केयर
NISCAIR

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462 6381 907 438 ijircce@gmail.com

Scan to save the contact details