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Brain Tumor Segmentation using Deep Learning in Medical Image Processing: A review

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Abstract— **In the medical image processing area, brain tumor segmentation is a very crucial task. Early identification of brain tumors enhances treatment options and increases the likelihood that the patient will survive. Tumor segmentation from MRI images for diagnosis purposes is a difficult and time is taken process. Image segmentation of brain tumors must be done automatically. This study aims to represent an overview of MRI-based tumor segmentation techniques. Deep learning approaches for automatic segmentation have rapidly acquired popularity since they produce cutting-edge results and are better suited to this task than previous methods. Deep learning methods can also be used to efficiently process and objectively evaluate vast amounts of MRI-based image data; however, in this study, we have focused on deep learning approaches which are used in the medical field. First, a brief overview of brain tumors and strategies for segmenting them is provided. Lastly, we have concluded that the deep learning approach is the most promising technique for tumor segmentation.**

Keywords— Brain tumor, CNN, Deep Learning, image segmentation, MRI.

I. Introduction

In the human brain, a tumor is a group or expansion of irregular cells. In the human brain, there are various types of tumors may exist. Some tumors are cancerous (malignant) while others are noncancerous (benign). The malignant brain tumor is the main cause behind the increasing death found in adults and children. In humans, cancer or tumor may initiate within the brain (primary brain tumors) or may spread from other body parts to the human brain (metastatic brain tumor). The growth rate of a brain tumor, as well as its location, defines how it will influence our nervous system's function. The type of tumor as well as its size and location specify the treatment options for brain tumors [20]. MR imaging is critical for detecting brain cancers at an early stage and providing suitable treatment. Accurate MR imaging segmentation necessitates a large number of records for speedy examination of a brain tumor, as well as verified top-notch benefits in scientific image analysis. To diagnose a tumor, an MRI is obtained and analysed by a specialist to discover abnormalities. But this technique is more time-consuming and varies from person to person. In recent years, several automated and moderately methods have been presented to aid practitioners in making decisions on how to solve these difficulties. The vast development in the area of machine learning and its subset deep Learning provides medical practitioners facility for medical image analysis [19]. In the medical field, image processing especially brain tumor image segmentation is a significant activity. In the early stage of the disease diagnosis of brain tumors increases treatment options and increases the likelihood that the patient will survive. It takes time and effort to segregate brain tumors from a huge collection of MRI imaging. To overcome the complexity of the process an automatic brain tumor image segmentation method is required. Deep learning techniques for automatic tumor segmentation have increasingly acquired popularity since they produce cutting-edge output and most suitable than previous approaches. This technique can also be used to analyse and objectively evaluate massive amounts of MRI-based image data [18]. DL is most commonly used for brain tumor study in a variety of situations, including as categorization and segmentation of regular and irregular cerebrum tumors. In deep learning, CNN is a well-known structure that is commonly used to characterise and segment brain tumor images [1]. Processing of medical images can be done in four phases. The initial step is to acquire images from the sufferers who will be examined. The next step is to improve the image quality by using various image enhancement techniques. Image segmentation methods are used in the third step. In the final step experts, extract the necessary characteristics from segmented and improved images, which provide critical information about the images [9]. There are several image segmentation methods available, each with its own set of benefits and drawbacks.

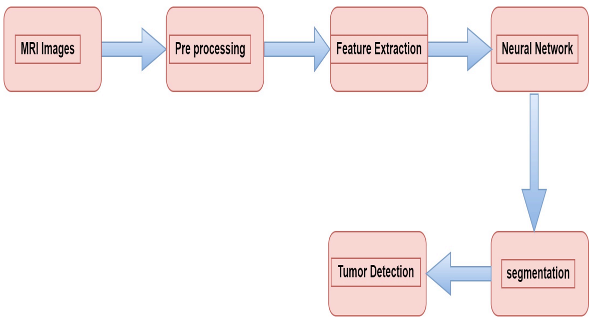

Fig 1. Block diagram of the tumor detection

II. Background

A. *Classification of Brain Tumor Image Segmentation Methods -*

Brain tumor segmentation methods can be classed as manual, semi-automated, or fully automatic based on the extent of human engagement necessary.

- Manual Segmentation - Medical practitioners must employ the multi-modality information provided by the MRI scans, as well as anatomical and physiological knowledge earned via training and experience, to perform manual segmentation. The radiologist examines many slices of photos slice by slice, diagnosing the tumor and meticulously sketching the tumor regions manually.
- Semi-Automatic Segmentation Methods - In this method user must involve in three main purposes:

initialization, intervention and evaluation. To use this method, the user must sketch the tumor's maximal diameter on the input MRI images. Although these methods take less time and produce more accurate findings than manual approaches, they are nevertheless subject to intra and inter-user variability. As a result, the majority of current research is focused on fully automated methods.

- Fully Automatic Segmentation Methods- Systems for entirely automatic brain tumor segmentation do not require human intervention. Prior knowledge and AI are generally combined to solve the tumor segmentation challenge.
- Deep Learning Methods – In deep learning methods, especially CNN, have gained prominence in recent years due to their success in a variety of object recognition and image classification challenges. CNNs learn themselves and represent complicated characteristics from the data, in contrast to standard classification algorithms that rely on manually created features. This characteristic causes research on CNN-based brain tumor segmentation to concentrate more. CNN's use picture patches as inputs and local subsampling and trainable convolutional filters to extract a hierarchy of increasingly more complex features. In several domains, deep learning techniques have attained state-of-the-art performance. Recently, a lot of academics have applied deep learning to medical image analysis tasks such as chest x-ray image analysis and breast image analysis. Two well-known deep learning strategies are CNN and RNN. We will focus the review on CNN-based brain tumor segmentation methods due to their cutting-edge performance, despite their rarity in comparison to other conventional brain tumor segmentation approaches.

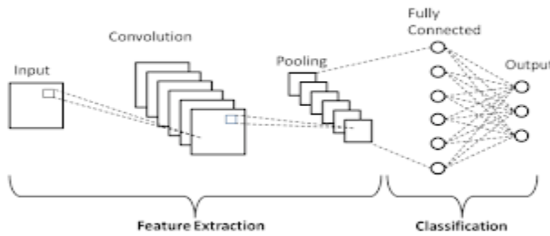

Fig 2. Convolutional Neural Network

B. Research Challenges –

Despite tremendous advances in brain tumor segmentation techniques, deep learning-based algorithms continue to produce unsatisfactory results, posing several challenges. The following are the issues linked with brain tumor segmentation.

- Location Uncertainty - High-Grade Glioma (HGG) or Low-Grade Glioma (LGG) can develop anywhere in the brain due to the extensive spatial distribution of gluey supporting cells.
- Morphological Uncertainty - The shape and size of brain tumors in different patients might differ tremendously. The oedema tissues, or outer layer of a brain tumor, reveal various fluid forms that scarcely provide any prior information for characterising tumor geometries. The shape and size of a tumor's subregions can also vary.
- Diffusion and Low Contrast - Image information is likely to be more abundant in high-resolution images with multi-modality channels (such as T1 and T2 in MRI) and high contrast. The sliced images are frequent of low quality due to the image projection and tomography technique, with the majority in diffusion and low contrast. The distinction between biological tissues is sometimes hazy and difficult to discern. It's difficult to classify cells near the boundary. This makes it difficult for automated algorithms to retrieve enough data for further processing.
- Annotation Bias - Manual annotation is heavily reliant on personal experience, which might lead to annotation bias when categorising datasets. Some annotations tend to connect all the small regions into a broad region, whereas others tend to mark the voxels separately, resulting in sparse ground truth annotation. Annotation biases have a significant impact on the detection method, which can be thrown off by biases during learning and processing.
- Imbalanced Issue - In distinct tumor regions, the number of voxels is uneven. The unbalanced issue might also impair the learning process, since large tumor patches may dominate the retrieved features.

III. Literature Review

In today's diagnostic laboratories, a large number of image data are created that are challenging to segment in a reasonable amount of time. Manual image review is also demanding, exhausting, and time-consuming. Computer-assisted tumor segmentation and classification methods have proven to be more successful and desirable.

The primary goal, according to [1] is to create a mechanism for clearly differentiating the cancer-affected tissues. The proposed method is used to create a segmented tumor region that is clear enough for a medical practitioner to see and provides additional information about the tumor in their diagnosis. Morphological procedures, pixel subtraction, threshold-based segmentation, and image filtering techniques are used in the suggested method. The proposed method relies on the acquisition of clear images of the skull, brain, and tumor.

When compared to the other strategy, the recommended approach produced a better result. In this investigation, images from The Cancer Imaging Archive (TCIA) were used. On images containing a tumor, the suggested method has a recognition rate of 94.28 per cent, while on images without a tumor, it has a recognition rate of 100 per cent. Our system has a 96 per cent overall success rate, which is higher than the industry average.

According to authors in [2] states that This research has developed an automatic brain tumor detection approach that improves accuracy and reduces diagnosis time, therefore replacing traditional invasive and time-consuming techniques including biopsy, lumbar puncture, and spinal tap. The objective is to divide tumors into two categories: healthy and cancerous. The following steps are included in this method: (i) Wavelet Decomposition (db4) (ii) Feature extraction (iii) Classification (iv) Segmentation. This approach was tested on real MR images, and the classification accuracy utilising PNN as a classifier was found to be approximately 100 per cent. To improve the accuracy and speed of diagnosis, Method introduced an automatic brain tumor detection method. In the future, PNN will be a complex classifier to acquire. Diverse images can be used to test the system. It is necessary to employ a big amount of patient data to improve the system's accuracy. Standard methods are used to measure performance validation, with an accuracy of 96.66 per cent. The goal is to create tools that can distinguish between normal and abnormal MRI images and aid in clinical diagnosis. This will allow doctors to determine which stage of cancer a patient is in and conduct the necessary and appropriate treatment measures based on that information.

In paper [3], a new tumor classification method is proposed which is based on advanced features selection methodology. Image pre-processing, segmentation, feature extraction, and classification are four pipeline techniques used in the described method. The proposed strategy is put to the test on two different data sets: Harvard and Private. Nishtar Hospital in Multan, Pakistan, provided the private data set. For both data sets, the suggested technique attained an average classification accuracy of over 90%, demonstrating its validity. The geometric and four texture features are retrieved in the third stage. A serial-based method is utilised to fuse the extracted features, and the best features are chosen using a Genetic Algorithm (GA). Finally, for the categorization of selected features, a support vector machine (SVM) with a linear kernel function is used. The proposed strategy is put to the test on two different data sets: Harvard and Private. Nishtar Hospital in Multan, Pakistan, provided the private data set. For both data sets, the suggested technique attained an average classification accuracy of over 90%, demonstrating its validity. This integrated model was created to produce tumor segmentation findings that were both visually and spatially consistent. The results of the experiments showed that their method could create a segmentation model with Flair, T1c, and T2 scans that were performed as well as those created with Flair, T1, T1c, and T2 scans.

The authors of [5] presented a Half Dense U-net network that combines the benefits of Dense-Net and U-Net, decreases the number of Dense-Net parameters and increases segmentation accuracy. In comparison to existing models such as U-Net, Dense-Net, and Res-Net, our suggested model can correctly pinpoint the tumor boundary of brain tumors, resulting in greater recognition quality. In the data set BRATS2015 Challenge, the suggested model HDU achieved good segmentation results.

The authors of the study [6] offer an MRI-based tumor segmentation technique. The VGG-16 network was used to accomplish robust tumor segmentation utilising transfer learning. The proposed architecture consists of encoder and decoder networks, as well as a pixel-wise classification layer. The accuracy of the result is 0.97785. Pre-processing and segmentation were used to improve the images.

according to [7] Because the suggested method takes fewer resources, our neural network architecture is easier to train and may be performed on a different computer. The dataset included 3064 images of various tumors. The neural network is implemented in blocks, each of which contains a variety of layers. For the data set employed, the overall accuracy rate obtained from the suggested technique was (98,029 per cent) in the testing stage and (98.29 per cent) in the training stage.

According to a study [8], the authors suggest a pre-processing method to produce a flexible and efficient tumor segmentation technique by focusing just on a tiny portion of the image. Using this method, the Cascade Deep Learning model's overfitting issue is resolved and the processing time is decreased. The second step suggests a straightforward and effective cascade convolutional neural network, the suggested model produces effective results. This technique has limits when dealing with high tumor volumes.

The authors in the paper [9], suggested a Deep Learning based model. The approach was tested on BRATS 2017 datasets, which included HGG and LGG patients. This technique produces efficient and resilient segmentation, according to the experiments. In the study [10] the authors proposed CNN based automatic segmentation method that explored small 3*3 kernels. These small kernels enable a more complex architecture to be created, as well as a reduction in overfitting due to the reduced number of weights. The authors also looked at an uncommon pre-processing step, which is quite effective for tumor segmentation, when combined with data augmentation. Their solution was validated in the Brain Tumor Segmentation Challenge 2013 database. According to [11], this study uses a deep learning-based approach. This technique recommended three primary phases. Furthermore, this technique also used a data augmentation method to expand the available data size for classifier training, which improves classification accuracy.

According to [12], the segmentation is done using a CNN and a probabilistic neural network. The authors proposed an architecture based on (CNN) with both 3*3 and 7*7 in an overlapping way and built a cascaded architecture to be able to segment a tumor properly and effectively. They utilise a probabilistic neural network to detect cancers in the same way and compare the results. They suggested new CNN and PNN designs that are distinct from those utilised in traditional image processing and computer vision approaches. Their model takes into account both local and global factors.

According to [13] the authors present an early and late fusion CNN architecture for segmenting brain tumors which utilises various combinations of multi-sequence MRI datasets.

The authors of the research publication [15] developed a model for tumor identification. The proposed model for detecting tumors has 95.55 per cent data accuracy. When using K-means to segment a tumor image, it can result in a noisy, poorly segmented image. As a result, the authors integrated Autoencoders with K-means for segmentation, resulting in more exact and clear segmented images with reduced noise. As a result, an effective model for detecting and segmenting brain tumors is developed, saving both human work and time.

The authors of the paper [17] suggested a light and clean deep model that performs single-pass brain tumor segmentation and addresses the class imbalance problem better than the model cascade. They propose a multi-task deep model that trains them concurrently to leverage their underlying correlation. First, they deconstruct brain tumor segmentation into three independent but related tasks. Second, they design a curriculum-based learning-based training technique for more effective teaching of the aforesaid multitask model. Finally, they present a simple yet effective post-processing strategy that can greatly increase segmentation performance. The suggested approaches have been thoroughly tested on the BRATS 2017 and BRATS

2015 datasets, with the proposed methods placing first on the BRATS 2015 test set and outperforming 60+ rival teams on the BRATS 2017 validation set. When they employ their recommended strategy, the spatial decision of the snapshot is better. However, remarkable ways for improving the photograph's spectral high quality may be developed. They propose a multi-task deep model that trains them concurrently to leverage their underlying correlation. First, they deconstruct brain tumor segmentation into three independent but related tasks. Second, they design a curriculum-based learning-based training technique for more effective teaching of the aforesaid multitask model. Finally, they present a simple yet effective post-processing strategy that can greatly increase segmentation performance. The suggested approaches have been thoroughly tested on the BRATS 2017 and BRATS 2015 datasets, with the proposed methods placing first on the BRATS 2015 test set and outperforming 60+ rival teams on the BRATS 2017 validation set. When they employ their recommended strategy, the spatial decision of the snapshot is better. However, remarkable ways for improving the photograph's spectral high quality may be developed.

IV. Conclusion

With deep learning's recent breakthrough advancements, multiple deep learning-based approaches for brain tumor segmentation have been reported, with promising outcomes. As a platform, this work presents a thorough and critical examination of existing deep learning-based brain tumor segmentation algorithms. This survey should provide relevant advice and technical insights to anyone considering deep learning as a development tool for brain tumor segmentation. We have given an overview of the most up-to-date deep learning-based brain tumor segmentation techniques.

V. References

[1] Ilhan, U., & Ilhan, A. (2017). Brain tumor segmentation is based on a new threshold approach. *Procedia computer science*, *120*, 580-587.

[2] Sanghavi, S., B., Shalke, R, J, (2018). Brain tumor classification and segmentation using PNN & FCM clustering. International Journal of Innovative Research in Computer and Communication Engineering, 3221-3227.

[3] Sharif, M., Tanvir, U., Munir, E. U., Khan, M. A., & Yasmin, M. (2018). Brain tumor segmentation and classification by improved binomial thresholding and multi-feature selection. *Journal of Ambient Intelligence and Humanized Computing*, 1-20.

[4] Zhao, X., Wu, Y., Song, G., Li, Z., Zhang, Y., & Fan, Y. (2018). A deep learning model integrating FCNNs and CRFs for brain tumor segmentation. *Medical image analysis*, *43*, 98-111.

[5] Wu, Z., Chen, F., & Wu, D. (2018, December). A Novel Framework Called HDU for Segmentation of Brain Tumor. In *2018 15th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP)* (pp. 81-84). IEEE.

[6] Alkassar, S., Abdullah, M. A., & Jebur, B. A. (2019, February). Automatic brain tumor segmentation using fully convolution network and transfer learning. In *2019 2nd International Conference on Electrical, Communication, Computer, Power and Control Engineering (ICECCPCE)* (pp. 188-192). IEEE.

[7] Fayyadh, S. B., & Ibrahim, A. A. (2020, December). Brain Tumor Detection and Classifiaction Using CNN Algorithm and Deep Learning Techniques. In *2020 International Conference on Advanced Science and Engineering (ICOASE)* (pp. 157-161). IEEE.

[8] Ranjbarzadeh, R., Kasgari, A. B., Ghoushchi, S. J., Anari, S., Naseri, M., & Bendechache, M. (2021). Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images. *Scientific Reports*, *11*(1), 1-17.

[9] Cherguif, H., Riffi, J., Mahraz, M. A., Yahyaouy, A., & Tairi, H. (2019, December). Brain Tumor Segmentation Based on Deep Learning. In *2019 International Conference on Intelligent Systems and Advanced Computing Sciences (ISACS)* (pp. 1-8). IEEE.

[10] Pereira, S., Pinto, A., Alves, V., & Silva, C. A. (2016). Brain tumor segmentation using convolutional neural networks in MRI images. *IEEE transactions on medical imaging*, *35*(5), 1240-1251.

[11] Khan, A. R., Khan, S., Harouni, M., Abbasi, R., Iqbal, S., & Mehmood, Z. (2021). Brain tumor segmentation using K-means clustering and deep learning with synthetic data augmentation for classification. *Microscopy Research and Technique*.

[12] Madhupriya, G., Guru, N. M., Praveen, S., & Nivetha, B. (2019, April). Brain tumor segmentation with deep learning technique. In *2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)* (pp. 758-763). IEEE.

[13] Rahimpour, M., Goffin, K., & Koole, M. (2019, November). Convolutional neural networks for brain tumor segmentation using different sets of mri sequences. In *2019 IEEE Nuclear Science Symposium and Medical Imaging Conference (NSS/MIC)* (pp. 1-3). IEEE.

[14] Somasundaram, S., & Gobinath, R. (2019, February). Current trends on deep learning models for brain tumor segmentation and detection–a review. In *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon)* (pp. 217-221). IEEE.

[15] Raut, G., Raut, A., Bhagade, J., Bhagade, J., & Gavhane, S. (2020, February). Deep Learning Approach for Brain Tumor Detection and Segmentation. In *2020 International Conference on Convergence to Digital World-Quo Vadis (ICCDW)* (pp. 1-5). IEEE.

[16] Liu, Z., Chen, L., Tong, L., Zhou, F., Jiang, Z., Zhang, Q., ... & Zhou, H. (2020). Deep learning based brain tumor segmentation: a survey. *arXiv preprint arXiv:2007.09479*.

[17] Zhou, C., Ding, C., Lu, Z., Wang, X., & Tao, D. (2018, September). One-pass multi-task convolutional neural networks for efficient brain tumor segmentation. In *International Conference on Medical Image Computing and Computer-Assisted Intervention* (pp. 637-645). Springer, Cham.

[18] Sharif, M. I., & Kaushik, K. (2019). Recent Advancements in Brain Tumor Segmentation and Classification using Deep Learning: A Review. *Int. J. Eng. Res.*, *8*(12), 319-325.

[19] Işın, A., Direkoğlu, C., & Şah, M. (2016). Review of MRI-based brain tumor image segmentation using deep learning methods. *Procedia Computer Science*, *102*, 317-324.

[20] Tairi, H. (2020, June). Segmentation of medical images for the extraction of brain tumors: A comparative study between the Hidden Markov and Deep Learning approaches. In *2020 International Conference on Intelligent Systems and Computer Vision (ISCV)* (pp. 1-5). IEEE.

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