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A Review of deep learning based brain tumor segmentation

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Abstract: Brain tumor segmentation is one of the most challenging jobs in medical image analysis. The goal of this process is to accurately delineate the regions affected by brain tumors. In recent years, deep learning techniques have producedencouraging outcomesin various computer vision challenges, like image classification, object detection, and semantic segmentation. These techniques have also been effectively applied to brain tumor segmentation, yielding encouraging outcomes. This review provides a comprehensive analysis of the latest deep learning-based approaches for brain tumor segmentation, highlighting the significant advancements made with cutting-edge technologies. Initially, a brief outine of brain tumors and the methods used for their segmentation is presented.Next, cutting-edge algorithms are covered, with an emphasis on the most current evolutions in DL

techniques. Ultimately, a review of the situation is given, along with an outlook on how MRI-based brain tumor segmentation techniques will progress going forward

addressing in great detail technological topics including multi-modality processes, segmentation under imbalanced situations, and network architecture design. We also offer enlightening talks about potential future paths for development.

Keywords: Image Segmentation, Brain Tumor, Deep learning, Convolution neural networks (CNNs).

I.Introduction:

A brain tumor refers to abnormal growth of cells in the brain. Possible reasons: Although the exact causes are often unknown, certain things can increase or influence someone's chances of getting a brain tumor such as exposure to radiation and a family history of brain cancer; All classes, throughout the world in all age groups suffered an escalation in brain neoplasia incidence over the past years. An estimated 78,980 new cases of primary malignant and non-malignant brain tumors were diagnosed in the US in 2018. Even though there has been a wealth of studies, it is still a challenging task to perform accurate patient diagnosis in brain tumor through segmentation. Adult brain tumors are almost always high-grade (either gliomas or glioblastomas) or low-grade (meningiomas). They usually grow slower, and so patients live longer, often several years; high-grade gliomas are fast-growing with a median survival of lower than 2 years.

Medical imaging techniques such as CT scans, PET scans, and magnetic resonance imaging (MRI) play a crucial role in diagnosing brain tumors and assessing their progression before and after treatment. MRI is particularly preferred due to its high resolution, excellent soft tissue contrast, and non-invasive nature. Treatment typically involves surgery, although radiation and chemotherapy are also used to control tumor growth. Multiple MRI slices, including T1, T2, T1 with contrast, and FLAIR images, are needed to visualize different regions of the brain effectively.

Once more, in clinical practice, tumor delineation is typically accomplished by hand. A skilled radiology tech will thoroughly review the patient's scanned medical photos, identifying every area that is impacted. In addition to being laborious, manual segmentation is reliant on the radiologist and is highly variable within and across raters. As a result, manual segmentation can only be done by visual inspection or qualitative judgment.

In the meantime, quantitative evaluation of brain tumors offers important data for improved comprehension of the tumor's features and treatment strategy. A quantitative examination of the impacted cells provides information about the course of the illness, its features, and how it affects a specific anatomical structure. The work proved to be challenging due to the significant variation in the lesions' shape, size, and placement. Furthermore, for successful lesion segmentation, multiple imaging modalities with different contrast levels must be taken into account. Therefore, for larger investigations, manual segmentation—which yields what are undoubtedly the most precise segmentation results—would not be feasible.The majority of current research projects concentrate on the automatic tumor segmentation process utilizing computer algorithms, which has the potential to provide unbiased, repeatable, and scalable methods for the quantitative evaluation of brain tumors.

These methods fall into two categories: deep learning and traditional machine learning techniques. Conventional machine learning approaches typically use statistical learning methods for low-level features in brain tumor classification, focusing primarily on identifying and estimating tumor boundaries. These methods heavily rely on human expertise for feature engineering and preprocessing techniques, such as image sharpening, contrast enhancement,

and edge detection/refinement. Wadhwa et al. provide a concise summary of techniques in this category.
In contrast, deep learning techniques require less manual preparation and depend on large-scale datasets for training. Over the past few years, convolutional neural networks (CNNs) have become predominant in brain tumor segmentation. Alom et al. offer a comprehensive analysis of deep learning techniques across various application fields.
Early studies recognized deep learning as a promising approach for automatic brain tumor segmentation. Unlike other automatic segmentation techniques that require feature engineering, deep learning directly learns a hierarchy of sophisticated features from domain-specific data. The main focus, therefore, is on designing and fine-tuning network architectures for the specific task. The remarkable success of deep learning methods in computer vision tasks is attributed to the availability of large datasets, advancements in learning techniques, and the development of powerful CPUs and GPUs. However, in the medical domain, there is often insufficient training data to train deep models effectively without the risk of overfitting.
Nevertheless, there aren't nearly enough training data in medical domain to allow deep models to be trained without experiencing over-fitting. Moreover, the work of ground truth annotation for 3D magnetic resonance imaging is a specialized and time-taking one that requires the expertise of experts, usually neurologists. Therefore, freely accessible image databases are uncommon and frequently contain a small number of people [13].

We showcase cutting edge deep learning methods in this survey as they relate to MRI brain tumor segmentation. There is also discussion of particular difficulties in medical image analysis and potential remedies.

IITechniques for Segmenting Brain Tumor Images: Brain tumor segmentation techniques can be classified into three categories based on the level of user interaction required: fully automatic, semi-automated, and manual.

a. Manual Techniques for Segmentation:

In order to do manual segmentation, the radiologist must combine their training and experience-derived anatomical and physiological knowledge with the multi-modality datasupplied by the MRI scans. During the procedure, the radiologist meticulously draws the tumor regions by hand after examining several image slices slice by slice and diagnosing the tumor. Manual segmentation is time-consuming, relies heavily on radiologists, and can result in significant intra- and inter-rater variability. However, manual segmentation is often used to evaluate the results of fully automatic and semi-automatic techniques.

b. Approaches for Semi-Automatic Segmentation:

Semi-automatic techniques for brain tumor segmentation involve three main user interactions: initialization, intervention or feedback, and evaluation. Initialization typically involves identifying a region of interest (ROI) for the automatic algorithm to process, including the approximate location of the tumor. Users can also adjust preprocessing parameters to suit the provided images. Automated algorithms can be guided to a target outcome through user input and necessary adjustments. Additionally, users can assess the results and make changes or restart the process if unsatisfied.
Hamamci et al. [14] proposed the "Tumor Cut" approach, a semi-automated segmentation method where the user must draw the maximal tumor diameter on the input MRI images. After initialization, a user-supplied tumor seed set and background seed set are used twice in a cellular automata (CA)-based seeded tumor segmentation approach to create a tumor

probability map. This method is applied to each MRI modality (such as T1, T2, T1-Gd, and FLAIR) separately, with the final tumor volume obtained by merging the data.
A recent semi-automatic method employed a novel classification strategy. This approach transformed the segmentation problem into a classification problem, training and classifying a brain tumor within the same brain alone. Typically, a large number of brain MRI scans with known ground truth are required to train machine learning classification algorithms for brain tumor segmentation. Consequently, noise and intensity bias correction must be addressed. In this method, the user selects a subset of voxels from a single case representing each tissue type. These voxel subsets are used to extract spatial coordinates and intensity values as features, which then train a support vector machine (SVM) to classify all voxels in the same image to the appropriate tissue type.
While semi-automatic techniques for brain tumor segmentation can be effective and save time compared to manual methods, they are still susceptible to intra- and inter-rater variability. As a result, current brain tumor segmentation research primarily focuses on fully automatic techniques.

c. Completely Automated Segmentation Techniques:

Completely automatic brain tumor segmentation techniques require no user intervention. They primarily combine artificial intelligence with prior knowledge to address the segmentation problem.

DL methods for segmentation:

Deep learning techniques are become more and more popular for segmenting images. The goal of these tactics is to have a classifier system that is operational. The classifier is typically trained by the extraction and selection of ROI characteristics. These procedures have outperformed alternative machine-learning techniques in terms of effectiveness. But as a training data set, it needs a sizable amount of data [15]. Consequently, the usage of this technique is limited to real-world settings due to the tedious nature of finding huge datasets that are publicly available.By Freiman et al. [16], a novel automatic method for segmenting liver tumors was put forth. To develop a new batch of superior seeds, the SVM classifier was employed to differentiate between healthy and diseased tissues from computer tomography scans. In contrast to numerous prior semi-automatic processes, the suggested approach is both efficient and dynamically active. The authors of [17] proposed a fully automated segmentation method for using CT scans to identify cancers in patients' livers. This approach was special because it combined convolutional neural networks with follow-up detection (CNN). A CNN was trained using automatic feature learning to generate a voxel classifier. This approach is robust and effective in terms of accuracy, outperforming the others by 60.29 percent.Another study is planned that will use a fully convolutional neural network, which produces a more thorough ROI segmentation. The methodology that follows applies mostly to problems with biological segmentation [18]. The application of the model to biomedical segmentation produced outstanding performance with a limited number of training datasets. In terms of how much time is needed for training, the method works as well. A Fully Convolution Neural Network was employed by Christ et al. [19] to segment the liver and lesions in patients' abdominal CT imaging. The cascaded Fully Convolution Network approach offers improved segmentation precision compared to single fully convolutional networks.

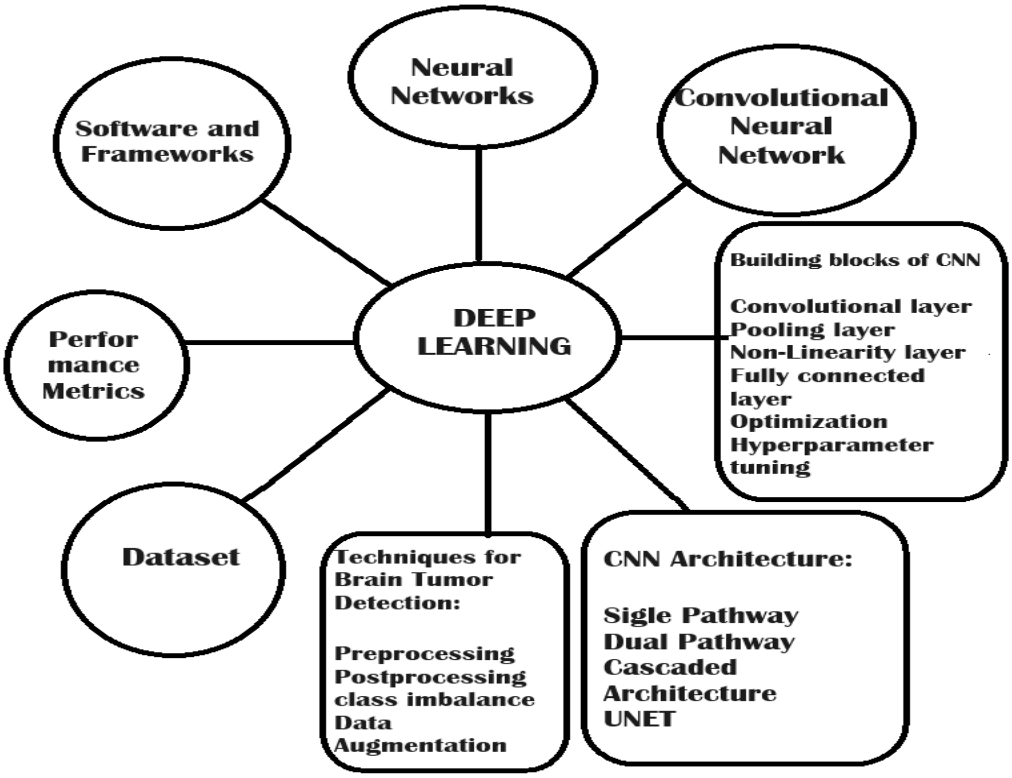

Fig 1: components, designs, and methods for segmenting brain tumors using deep learning algorithms.

The components, as well as more contemporary methods and designs, of deep learning algorithms for brain tumor segmentation that we discovered in the publications we reviewed for this work, as shown in Figure 1.

Obstacles:

Glioma segmentation automatically is a very difficult topic. Brain MRI data with tumors present in it is a 3D data set in which patient-to-patient variations exist in tumor location, size, and shape. Furthermore, tumor boundaries are frequently erratic, uneven, and discontinuous, which presents a significant difficulty,particularly when compared to conventional edge-based techniques. Furthermore, brain tumor MRI data from synthetic databases11 or clinical scans are intrinsically complicated. From scan to scan, MRI equipment and acquisition techniques might fluctuate significantly, imposing biases in intensity and other differences for every distinct image slice in the dataset. The complexity is further heightened by the need for multiple imaging modalities to accurately distinguish tumor sub-regions.

III.Literature Survey:

Díaz-Pernas, F. et al. [1] presented a Deep Convolutional Neural Network model based on a multiscale approach for brain tumor segmentation and classification. This model differs from other approaches by processing input images through three distinct pathways at varying spatial scales, inspired by the natural functioning of the Human Visual System. Unlike other models, it does not require pre-processing of input images to remove skull or vertebral column components. It is capable of analyzing MRI scans of three tumor types—meningioma, glioma, and pituitary tumor—across sagittal, coronal, and axial views. The method was tested on a publicly available MRI dataset containing 3064 slices from 233 patients, outperforming previous deep learning and classical machine learning methods with a tumor classification accuracy of 0.973.

Gunasekara, S. R. et al. [2] introduced a triple DL architecture for brain tumor segmentation. First, a region-based CNN is used to identify tumor regions of interest in classified images. Next, the Chan–Vese segmentation algorithm is employed to delineate the tumor boundaries. An active contour technique using the level set function is developed, addressing the limitations of standard edge detection algorithms based on pixel intensity gradients. The Chan–Vese algorithm successfully identifies tumor borders, and the final segmented boundary area is compared to expert demarcations to calculate metrics such as the Dice Score, Rand Index (RI), Variation of Information (VOI), Global Consistency Error (GCE), Boundary Displacement Error (BDE), Mean Absolute Error (MAE), and Peak Signal to Noise Ratio (PSNR). The proposed architecture achieved an average Dice Score of 0.92, along with RI of 0.9936, VOI of 0.0301, GCE of 0.004, BDE of 2.099, PSNR of 77.076, and MAE of 52.946, demonstrating excellent reliability for both meningioma and glioma segmentation.

Brain tumor segmentation using magnetic resonance imaging (MRI) is crucial in the medical field as it aids in patient care planning, tumor growth prediction, density measurement, diagnosis, and prognosis. The diverse structures, shapes, locations, and visual characteristics of brain tumors, such as intensity and contrast variations, make segmentation challenging. Recent advancements in Deep Neural Networks (DNN) for image classification, especially in intelligent medical image segmentation, represent a promising new direction in brain tumor research. However, training DNNs is time-consuming and computationally intensive due to the complexity and difficulty of gradient diffusion.

Aggarwal, M. et al. [3] proposed an effective brain tumor segmentation technique based on an Improved Residual Network (ResNet) to address the gradient problem in DNNs. This enhanced ResNet improves upon the existing model by maintaining the details of every connection link or by enhancing projection shortcuts. These details are input into the later stages of the system, helping the improved ResNet achieve higher precision and accelerate the learning process.The three primary elements of the current ResNet—the projection shortcut, the residual construction block, and the flow of information via the network layers—are all addressed by the suggested enhanced ResNet. This method expedites the procedure and reduces computational expenses.

Based on an empirical examination of the BRATS 2020 MRI sample data, the suggested approach outperforms conventional techniques such as CNN and FCN by more than 10% in terms of f-measure accuracy and recall.

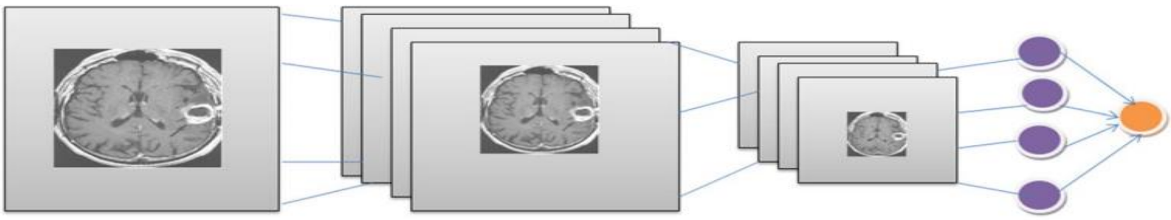

Fig 2: Convolution neural network architecture (CNN)[3]

Figure 2 depicts CNN's architectural layout. This figure displays three layers: fully connected, pooling, and convolutional.

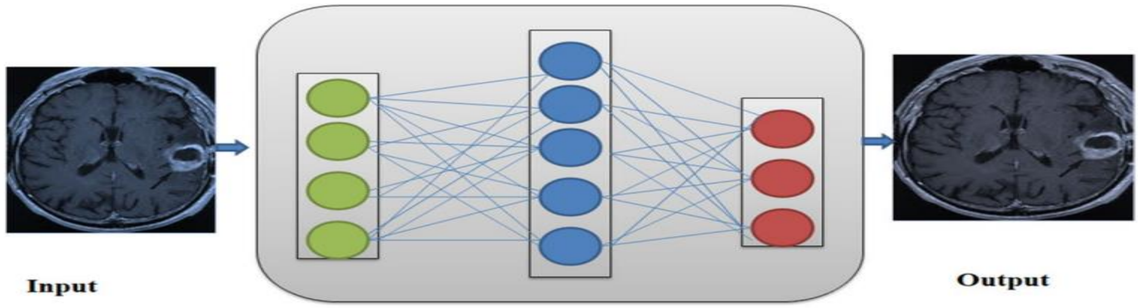

Fig 3: Fully Connected Structure (FCN) [3]

The operation of the FCN architecture for picture segmentation is depicted in Figure 3. In FCN, every layer is essentially a three-dimensional array with varying dimensions, including height and width. The first layer is the image, which contains the dimensions of the color space, height, and width of each pixel. Higher-level locations are based on routes and have a visual field that correlates to the image regions.

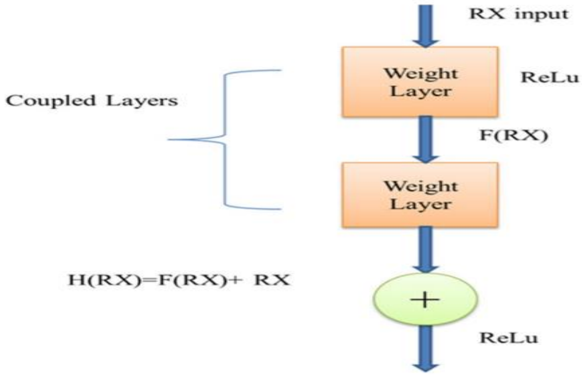

Fig 4:The working structure of ResNet [4]

Khan, A. H. et al. [4] introduced a system that classifies brain tumors into four categories: glioma, meningioma, pituitary tumor, and no tumor. This system achieves a precision of 92.13% and a miss rate of 7.87%, outperforming previous methods for brain tumor detection and segmentation. This advancement is expected to significantly benefit the medical field. The proposed approach, Hierarchical Deep Learning-Based Brain Tumor (HDL2BT) classification, utilizes CNN for the detection and classification of brain tumors.

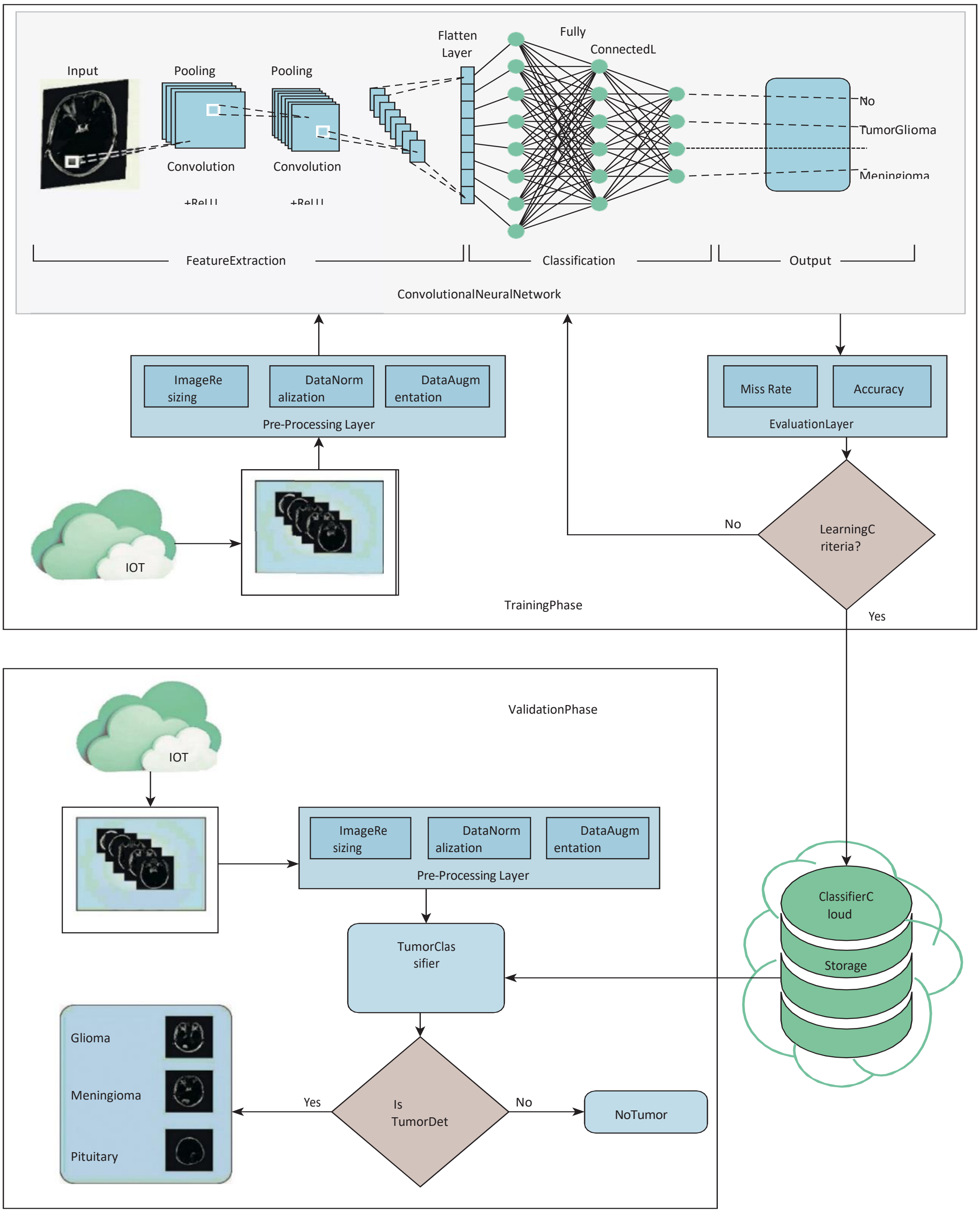

Fig 5: A comprehensive model of the HDL2B-Tumor-Classifier [4].

Rajendran, S. et al. [5] proposed a method that uses a Gray Level Co-occurrence matrix to extract features and remove extraneous details from images. By utilizing Convolutional Neural Networks (CNNs), which are extensively used in biomedical image segmentation, this method significantly enhances the accuracy of brain tumor segmentation compared to the current state of the art. The approach combines the outputs of two distinct segmentation networks—a Three-Dimensional Convolutional Neural Network and a U-Net—resulting in more accurate and comprehensive estimates. The combined models achieve mean accuracies of 99.40%, 98.46%, and 98.29%, precisions of 99.41%, 98.51%, and 98.35%, F-Scores of

99.4%, 98.29%, and 98.46%, and sensitivities of 99.39%, 98.41%, and 98.25% for the whole tumor, enhanced tumor, and tumor core on the validation set, respectively.
Pereira, S. et al. [6] proposed an automatic segmentation approach based on Convolutional Neural Networks (CNNs) using small 3x3 kernels. These small kernels help prevent overfitting and allow for the creation of a deeper architecture due to fewer weights in the network. Additionally, they investigated intensity normalization as a pre-processing step, which, although uncommon in CNN-based segmentation, proved highly effective when combined with data augmentation for brain tumor segmentation in MRI images. Their method was validated on the Brain Tumor Segmentation Challenge 2013 (BRATS 2013) database, achieving first place in the Dice Similarity Coefficient measure (0.88, 0.83, 0.77) for the full, core, and enhancing areas, respectively. This approach also secured the top overall position on the online assessment platform. Using the same method, they competed in the on-site BRATS 2015 Challenge, placing second with Dice Similarity Coefficients of 0.78, 0.65, and 0.75 for the core, enhancing, and full areas, respectively.

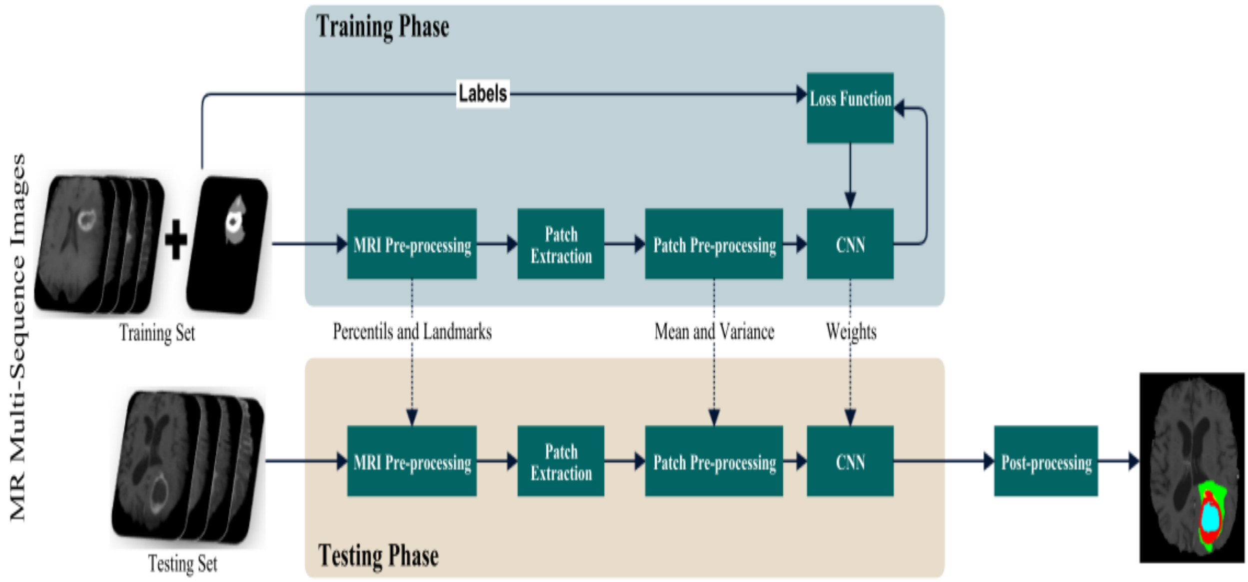

Fig 6:An outline of the segmentation approach [6].

To assist practitioners, Khan, A. R. et al. [7] developed a deep learning method for classifying brain cancers using MRI data analysis. The proposed method consists of three primary stages: preprocessing, brain tumor segmentation using k-means clustering, and classification of tumorsinto benign or malignant categories through an improved VGG19 model (a 19-layered Visual Geometric Group model). Additionally, the method incorporates synthetic data augmentation to enhance classification accuracy by increasing the amount of training data available. Extensive experiments using the BraTS 2015 benchmark datasets were conducted to evaluate the proposed technique. The results demonstrate the method's effectiveness, achieving higher accuracy compared to previously published state-of-the-art methods.

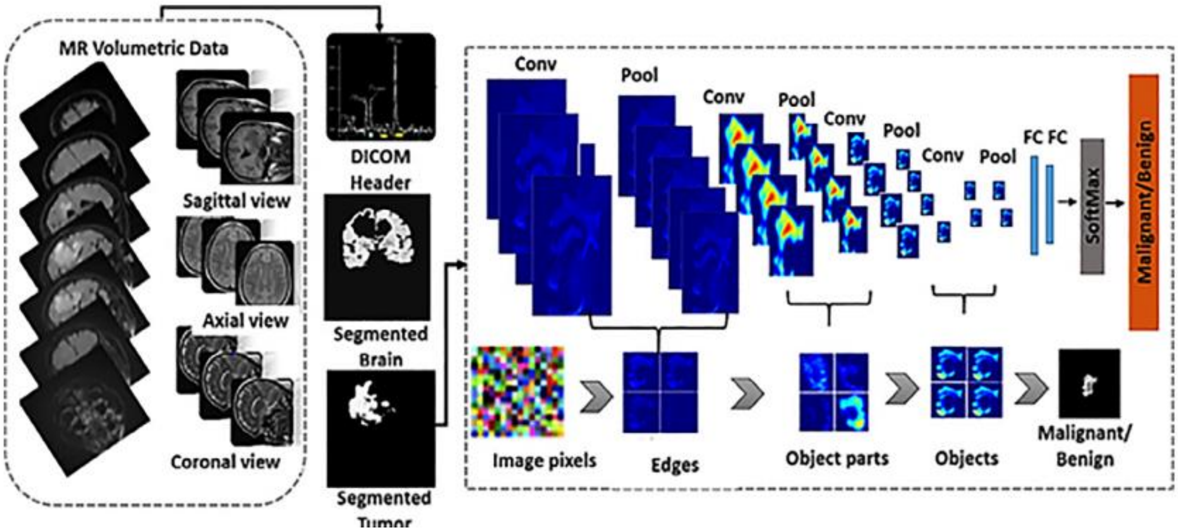

Fig 7: Classification and segmentation of brain tumors by MRI [7]

This study presents a hybrid approach that combines artificial intelligence (AI) support with a fine-tuned CNN model and k-means clustering. The proposed method involves three main steps: (a) normalizing and classifying the intensities of MR modalities in an unbiased manner, (b) segmenting the tumor area using k-means clustering, and (c) augmenting synthetic data, extracting deep features from the region of interest (ROI), and classifying brain tumors as benign or malignant using an optimized CNN model. The CNN model was trained through the following phases in order: convolution, pooling, ReLU layer, flattening, and full connection. Figure 7 illustrates the entire process.

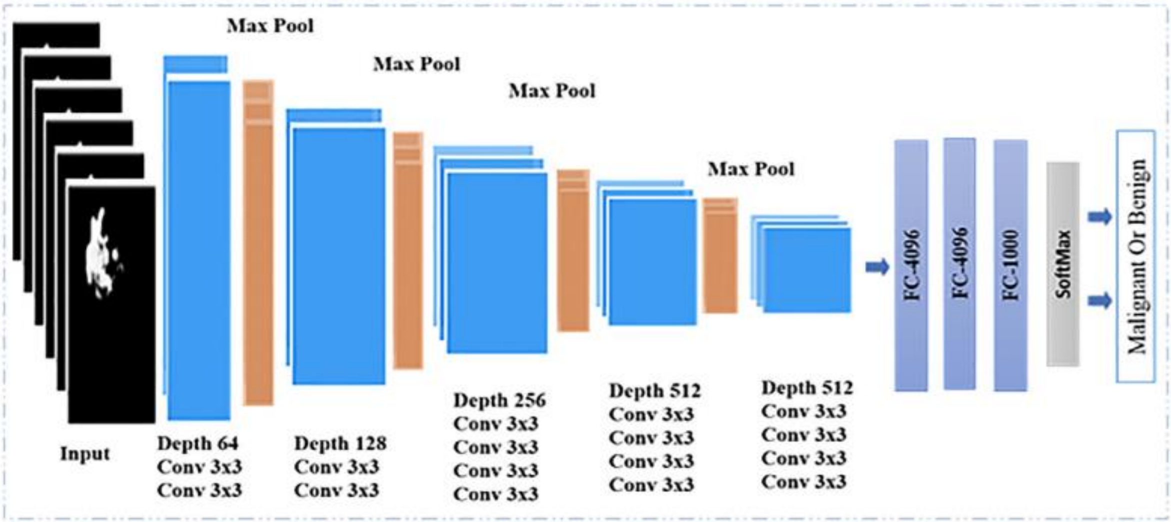

Fig 8: The suggested adjustment CNN model VGG19 for classifying brain tumors[7]

The proposed method utilizes the VGG19 CNN model with transfer learning, as illustrated in Figure 8.

Ali, M. et al. [8] developed a straightforward yet powerful combination technique involving an ensemble of two segmentation networks: a 3D CNN and a U-Net. Each model was independently trained using the BraTS-19 challenge dataset to generate segmentation maps highlighting different tumor sub-regions. These maps were then combined in various ways to produce the final prediction. Compared to current state-of-the-art approaches, the ensemble method demonstrated superior performance, achieving Dice scores of 0.750, 0.906, and 0.846

for enhancing tumor, whole tumor, and tumor core segmentation, respectively, on the validation set.
Wu, W. et al. [9] proposed a deep convolutional neural network fused with a support vector machine (DCNN-F-SVM) technique for brain tumor segmentation. The method consists of three main stages: firstly, training a deep CNN to map image space to tumor marker space; secondly, feeding test images and predicted labels from the deep CNN into an integrated support vector machine classifier; and finally, combining a deep CNN with an integrated SVM classifier to train a deep classifier. The model was evaluated on both their own dataset and the BraTS dataset, demonstrating superior segmentation performance compared to standalone SVM and deep CNN approaches.

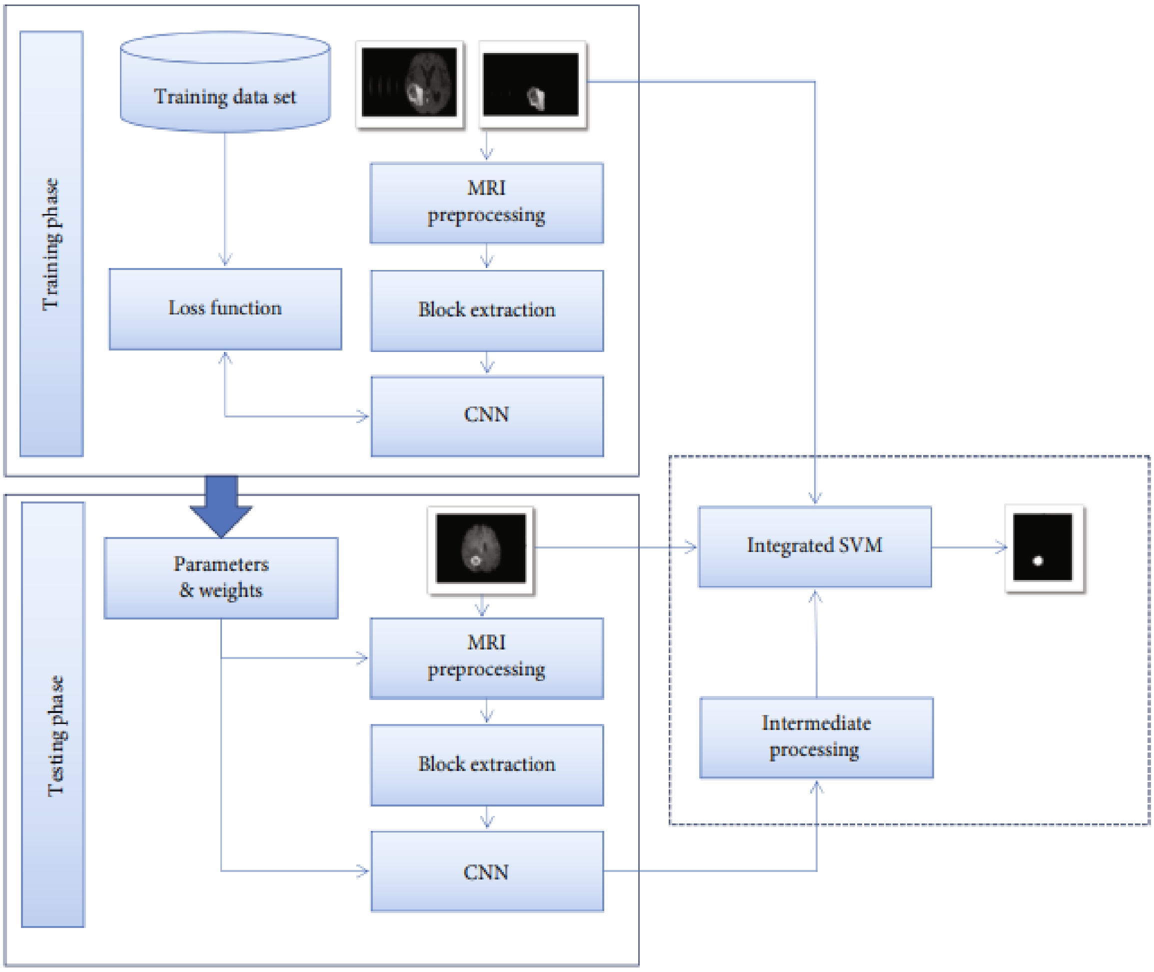

Fig 9: The suggested model flow chart[9]
This paper introduces a brain tumor segmentation model that combines convolutional neural networks (CNN) with support vector machines (SVM), as depicted in Figure 9.
Iqbal, S. et al. [10] presented deep learning models using Long Short-Term Memory (LSTM) and Convolutional Neural Networks (ConvNet) to accurately delineate brain tumors from standard medical images. The study utilized the MICCAI BRATS 2015 brain cancer dataset, which includes MRI images from four modalities: T1, T2, T1c, and FLAIR. Two distinct models—ConvNet and LSTM networks—were trained individually and then integrated into an ensemble approach to improve segmentation results. Various preprocessing techniques such as edge enhancement, histogram equalization, and noise reduction were explored to enhance image quality, with the best-performing combination selected for model training. Class weighting was employed to mitigate class imbalance issues. The models were evaluated on a validation dataset derived from the same image collection. The ConvNet

achieved an individual accuracy of 75%, while LSTM-based networks achieved 80%, and the ensemble fusion approach achieved an accuracy of 82.29%.

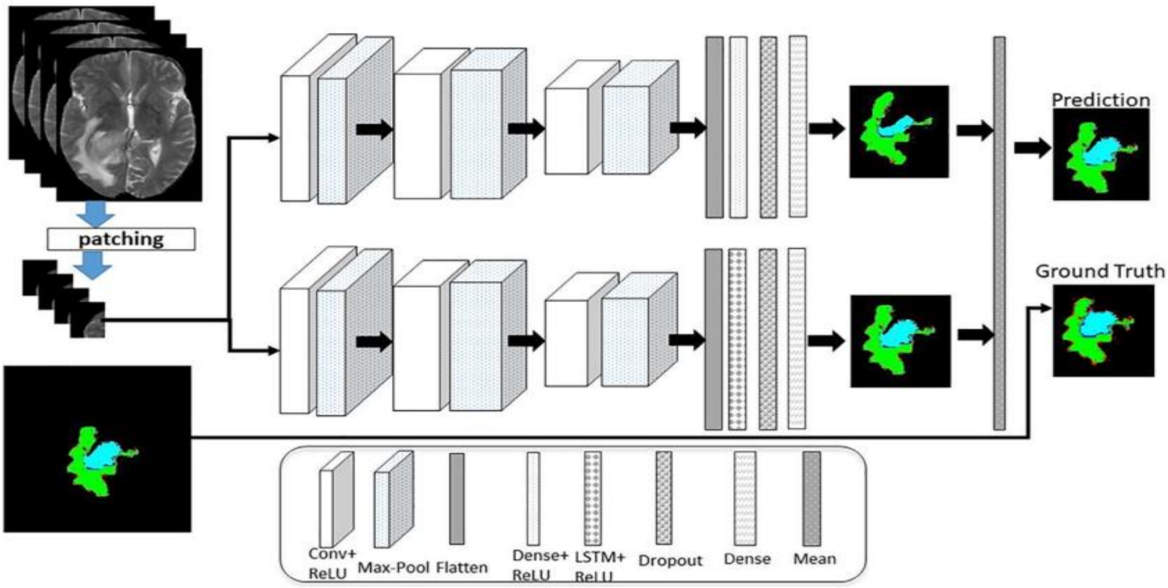

Fig 10: suggested ensemble model [10]

Kulkarni, S. M. et al. [11] proposed a method for classifying and detecting brain tumors that involves tumor segmentation, skull stripping, and preprocessing. The process employs morphological operations following the thresholding method. CNN models tend to overfit after a certain number of epochs due to the impact of training image quantity on feature extraction. To address this, transfer learning methods were integrated into deep learning CNNs. The AlexNet architecture, based on CNN, is utilized for classifying tumorous brain MRIs, while the GooLeNet transfer learning architecture is applied for classifying aggressive brain tumors. The approach's performance is evaluated using accuracy, precision, recall, and F-measure metrics.

Ottom, M. A. et al. 19] proposed a new pipeline combining 2D brain tumor MRI image segmentation system based on Deep Neural Network (DNN) with augmentation scheme. Specifically, their proposed method Znet transfers the intrinsic relationships of a few well-annotated diseases (such as those with hundreds or so of patients having low-grade glioma) to several thousands of virtual cases. Equipped with skip-connection, encoder-decoder architectures, and data augmentation. The mean dice = 0.96 for during model training and while the model was independently tested, it resulted in dice = 0.92 [40]. We also achieved other evaluation metrics including the Matthews Correlation Coefficient (MCC) of 0.81, F1 score 0.81, and pixel accuracy 0.996 which are noteworthy as well. We demonstrated the functional utility of our ZNet model by way of quantitative comparisons with the testing dataset results and qualitative assessments with visual annotations of DNN-derived tumor masks, for automatic brain tumor segmentation in MRI images. Not only can this approach be easily applied to volumetric 3D brain images, many different diseases and imaging modalities. But it is also reported that pixel accuracy may not be the appropriate metric for performance evaluation in semantic segmentation, since the background class prevails on the ground-truth images. Dice, IoU (Intersection over Union) type of metrics are therefore more appropriate to evaluate the performance of a semantic segmentation model.

IV.Research Vulnerabilities:

Using the preceding literature analysis as a starting point, various research gaps will be filled in order to create and investigate deep learning approaches for brain disease diagnosis. We enumerated the research challenges based on the state of this field's investigation. There is a lack of application for improving MRI picture quality in CNN-based work. To create standard and reliable methods for detecting brain tumors, extracting their quality for medical diagnosis, visualization, and presence prediction. Due to deep learning techniques that reduce the death rate as they are used, early diagnosis and illness forecasting are becoming increasingly accurate as computerized treatment knowledge grows exponentially over time. robust and scalable CNN-based picture segmentation and feature extraction that requires the least amount of computing power while taking into account various dataset types. It could be possible to speed up detection and increase accuracy by using the right feature extraction and reduction methods.A crucial component of the proper course of treatment that has not been taken into account in any contemporary research is severity analysis.

V.Future work:

Future improvements to current techniques could involve refining and modifying CNN architectures and integrating data from other imaging modalities, like Positron Emission Tomography (PET),Magnetic Resonance Spectroscopy (MRS) and Diffusion Tensor Imaging (DTI). These enhancements could lead to the development of clinically viable automatic glioma segmentation techniques for more accurate diagnosis. Advances in deep neural network execution will enable more powerful and efficient variations in the network's performance. CNN standards have surpassed traditional image processing methods in medical image analysis, achieving numerous milestones. Deep learning is transforming healthcare by increasing the accuracy and speed of diagnoses and discoveries. These exciting developments and continuous advancements in medical science contribute to better health outcomes.

VI.Conclusion:

It is difficult to automatically segmenting brain tumors for the purpose of diagnosing cancer. Recently, researchers have been able to design and objectively evaluate their approaches using available tools, due to the availability of public datasets and the widely accepted BRATS benchmark. This paper offers a concise summary of conventional techniques together with an analysis of the most recent deep learning-based approaches. For glioma segmentation, deep learning approaches are regarded as state-of-the-art due to their outstanding performance. Conventional automatic glioma segmentation systems encounter difficulties when attempting to select highly representative features for classifiers or creating probabilistic maps using past knowledge. Convolutional neural networks, on the other hand, automatically identify intricate representative features for both tumor and healthy brain tissue from multi-modal MRI data.

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