University of Baghdad
College of Engineering
JE
JOURNAL OF ENGINEERING

Journal of Engineering

journal homepage: www.joe.uobaghdad.edu.iq

Volume 28 Number 12 December 2022

Electronics and communications, and Computer Engineering

Deep Learning-Based Segmentation and Classification Techniques for Brain Tumor MRI: A Review

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ABSTRACT

Early detection of brain tumors is critical for enhancing treatment options and extending patient survival. Magnetic resonance imaging (MRI) scanning gives more detailed information, such as greater contrast and clarity than any other scanning method. Manually dividing brain tumors from many MRI images collected in clinical practice for cancer diagnosis is a tough and time-consuming task. Tumors and MRI scans of the brain can be discovered using algorithms and machine learning technologies, making the process easier for doctors because MRI images can appear healthy when the person may have a tumor or be malignant. Recently, deep learning techniques based on deep convolutional neural networks have been used to analyze medical images with favorable results. It can help save lives faster and rectify some medical errors. In this study, we look at the most up-to-date methodologies for medical image analytics that use convolutional neural networks on MRI images. There are several approaches to diagnosing and classifying brain cancers. Inside the brain, irregular cells grow so that a brain tumor appears. The size of the tumor and the part of the brain affected impact the symptoms.

Keywords: Brain Tumor, Magnetic Resonance Imaging (MRI), Convolutional Neural Network (CNN), Classification, Segmentation, Feature Extraction.

تقنيات التجزئة والتصنيف المعتمدة على التعلم العميق لصور الرنين المغناطيسي لورم الدماغ:مقال مراجعة

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Peer review under the responsibility of University of Baghdad.
https://doi.org/10.31026/j.eng.2022.12.07

Article received: 28/6/2022
Article accepted: 2/8/2022
Article published: 1/12/2022

الخلاصة

يعد الاكتشاف المبكر لأورام الدماغ أمرًا بالغ الأهمية لتعزيز خيارات العلاج وإطالة فترة بقاء المريض. يوفر التصوير بالرنين المغناطيسي (MRI) معلومات أكثر تفصيلاً ، مثل تباين ووضوح أكبر ، من أي طريقة مسح أخرى. يعد تقسيم أورام الدماغ يدويًا من عدد كبير من صور التصوير بالرنين المغناطيسي التي تم جمعها في الممارسة السريرية لتشخيص السرطان مهمة صعبة وتستغرق وقتًا طويلاً. يمكن اكتشاف الأورام وعمليات التصوير بالرنين المغناطيسي للدماغ باستخدام الخوارزميات وتقنيات التعلم الآلي ، مما يسهل العملية على الأطباء. أيضًا ، لأن صور التصوير بالرنين المغناطيسي يمكن أن تظهر صحية عندما يكون الشخص مصابًا بورم خبيث. في الآونة الأخيرة ، تم استخدام تقنيات التعلم العميق القائمة على الشبكات العصبية التلافيفية العميقة لتحليل الصور الطبية مع نتائج إيجابية. يمكن أن يساعد في إنقاذ الأرواح بشكل أسرع وتصحيح بعض الأخطاء الطبية. في هذه الدراسة ، ننظر إلى أحدث المنهجيات لتحليلات الصور الطبية التي تستخدم الشبكات العصبية التلافيفية على صور التصوير بالرنين المغناطيسي. هناك عدة طرق لتشخيص سرطانات الدماغ وتصنيفها. داخل الدماغ ، تنمو الخلايا غير المنتظمة بحيث يظهر ورم في المخ. يؤثر حجم الورم وجزء الدماغ المصاب على الأعراض.

الكلمات الرئيسية: ورم الدماغ ، التصوير بالرنين المغناطيسي (MRI) ، الشبكة العصبية التلافيفية (CNN) ، التصنيف ، التقسيم ، استخراج الميزات.

1. INTRODUCTION

In the latest years, machine learning approaches have grown in popularity in medical image analysis. In contrast to traditional methods of extracting manual features, these machine learning algorithms are used to extract succinct information to improve the performance of medical image analysis systems **(Adnan Qayyuma, 2018).**

Machine learning is a field of deep learning that uses several layers to learn a hierarchy of more complicated representations from raw data. Machine learning models are all about finding acceptable representations for their incoming data. With record achievements in recent years, deep learning has become a quantitative analysis solution **(Viriri, 2021)**. Deep learning is a set of machine learning techniques representing high-level abstractions in data using deep architectures made up of various non-linear transformations. Deep learning operates similarly to the human brain, with a deep architecture that replicates how information is processed in the brain via several levels of change **(Adnan Qayyuma, 2018).** With its capacity for feature extraction and data differentiation, deep learning is a potent machine learning technique that has appeared and produces trimming prediction results **(Abdulhakeem Q. Albayati, 2020).**

The development of artificial intelligence and its training algorithms has a significant impact on many facets of daily life **(Al-Jamali, 2020)**. On the other hand, artificial-intelligence-based medical image analysis relies on the skills of a skilled surgeon to recognize the image with the naked eye. The problem with this strategy is finding doctors who can perform medical picture analysis is incredibly difficult. Compared to the tremendous demand for medical image analysis, the number of professional doctors in developed and developing countries worldwide is insufficient. Second, human eyes can become tired, and medical skill levels vary. As a result, errors in judgment are common, leading to incorrect diagnoses and even delayed sickness. Because of the flaws in manual medical image analysis, scientists have been researching methods to replace people with computers to increase the competence and accuracy of medical image analysis **(Jian Wang, 2020)**. Radiologists can increase their performance using automatic approaches such as computer-aided detection (CAD) systems and Deep Learning, thanks to developments in digital image processing. To help the radiologist, computer-aided diagnosis (CAD) tries to improve the technique's predictive value by pre-reading medical images to highlight the areas of worrisome anomalies and assess their features **(Dougherty, 2009)**.

One of the most frequently utilized deep learning techniques for brain tumor segmentation is the convolutional neural network (CNN). It's a feed-forward neural network that's typically used for image processing and recognition **(Roohi Sillea, 2021)**. A convolutional layer in CNNs can extract deep features from medical images. CNNs can further process these deep features to accomplish various medical image analysis jobs such as segmentation, detection, classification, and sickness expectation **(Jian Wang, 2020)**. Therefore, it is necessary to know about the CNN infrastructure, some of the most prevalent optimization techniques, as well as several classic and typical CNN models currently in use. This aspect will be discussed more in the next sections of this paper.

The term "brain tumor" means abnormal grouping of cells in the brain. When a brain tumor begins to grow in size and shape every day and is not diagnosed at an early stage, it becomes a life-threatening disease. Secondary brain tumors occur when cancer cells move from other body portions to the brain **(Roohi Sillea, 2021)**. Brain tumor detection and disintegration are now the most important procedures. In clinical and pharmaceutical preparation, it is hard to segment the tumor region on MRI because the edges are difficult to approach, and the boundaries are rather clear **(Madhavi, 2020)**.

Medical image analysis is very important in both scientific research and scientific analysis. Computed tomography (CT), MRI, Positron Emission Tomography (PET), and X-ray analysis are some examples of public medical imaging systems **(Jian Wang, 2020), Fig 1**. MRI is the most reciprocal approach to examining MRI brain regions **(Sarwar, 2019)**. MRI for the brain, spinal cord, or both may be ordered by the doctor depending on the type of tumor suspected **(Ahmad M. Sarhan, 2020).** As a result, MRI is a useful tool for diagnosing brain tumors in people. Furthermore, there are no known health risks associated with exposure to the MR environment for a short time **(Roohi Sillea, 2021).**

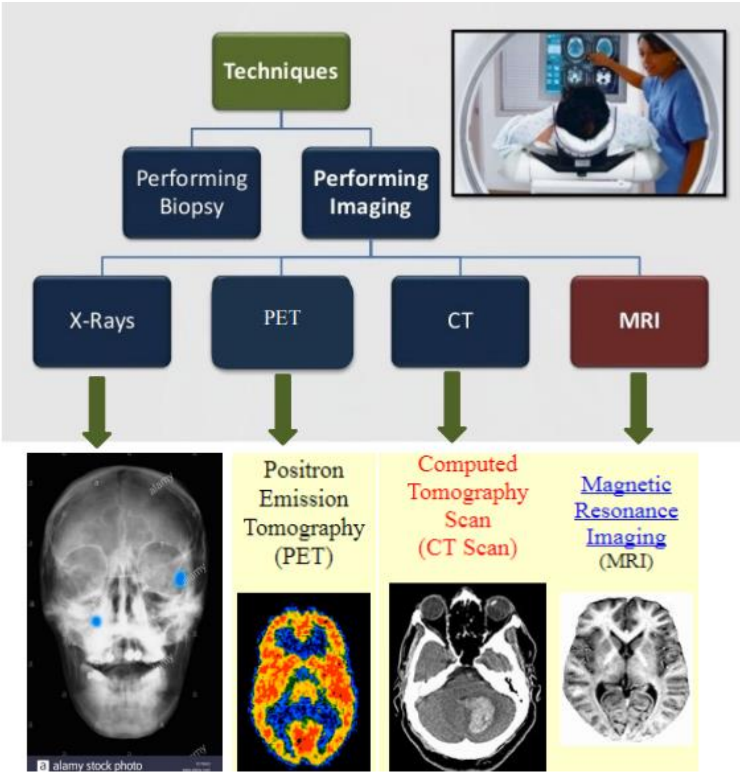

Figure 1. Brain tumor imaging techniques ***(Tahir, 2018)***

1.1 MRI Dataset

The most common application of an MRI scan is in neurology, where it is used to visualize the intricate details of the brain and other cranial structures. MRI can be defined as a scan form that produces detailed images of the inside of the body using radio waves and powerful magnetic fields. An MRI scan can be used to help diagnose diseases, plan therapies, and assess the effectiveness of previous treatments **(Anon., n.d.).** The anatomy may be seen in 3 distinct planes using MRI: axial, coronal, and sagittal. The 3 distinct anatomies of the human brain are shown in **Fig. 2,** which depicts the axial, sagittal, and coronal planes of the brain acquired from MRI.T1-weighted, T2-weighted, and Fluid Attenuated Inversion Recovery (Flair) are the three MRI sequences depicted in **Fig. 3**.

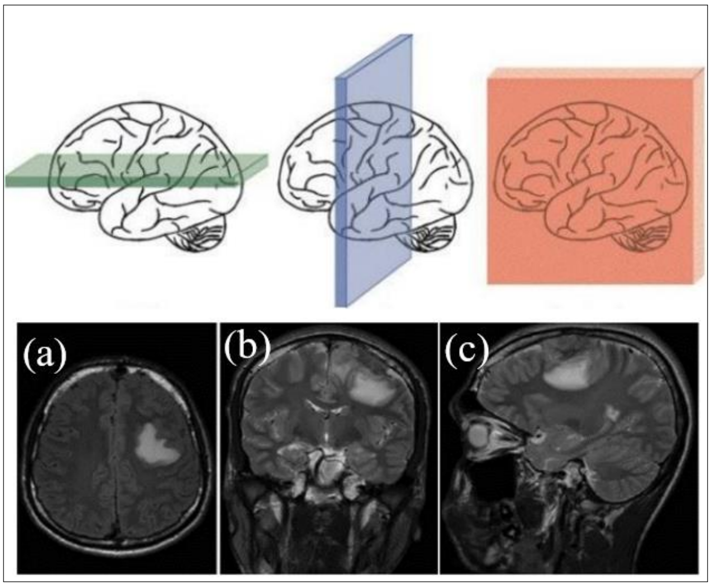

Figure 2. (a)Horizontal Plan, (b)Colonel Plan, (c)Sagittal Plane for the MRI image brain ***(Arti Tiwari, 2019)***

Depending on the needs, various forms of MRI are employed in this process. T1, T2, and FLAIR are examples of MRI sequences, **Fig. 3**, that are utilized as input in the preprocessing stage **(Tahir, 2018).**

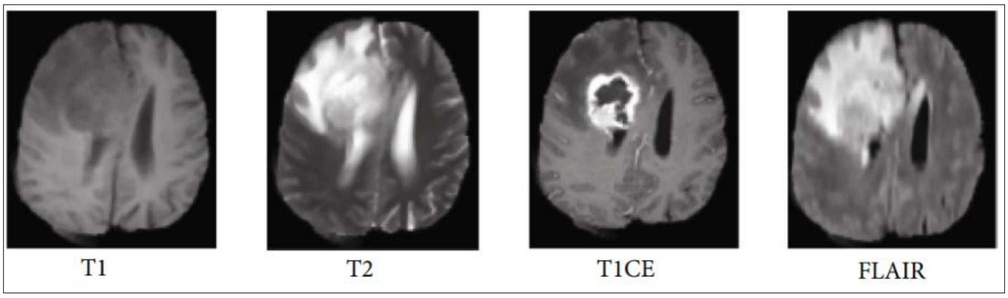

Figure 3. Multimodal MRI Dataset Sample

T1 imaging detects tissues, but T2 MRI treats the edema area with positive signals. T1CE images reveal tumor boundaries without the expert's fantastic signal in complicated tumor tissue cells "gadolinium particles". Because the necrotic cells cannot be discriminated from the surrounding regions, the impressive hyposecretion of the tumor mass implies that it can only be separated using a similar cell area approach. Molecular water signals are muted in FLAIR pictures, allowing the CSF region to be recognized **(Sahar Gull, 2021).**

2. Deep learning Based on Convolutional Neural Network

Deep learning algorithms generate automatic features that eliminate or reduce the requirement for handcrafted features. A number of deep learning algorithms for segmenting brain tumors have been proposed in the literature. Convolutional neural networks are used in several of these blocks (CNN).

CNN is the most commonly utilized and traditional DL approach in medical image processing (CNN), **Figure 4 (b) (Jian Wang, 2020).** These deep networks use multiple layers of neurons and the shared weights of each convolutional layer to examine a small area of the input image called the receptive field **(Adnan Qayyuma, 2018)**. The CNN model can learn the spatial hierarchy of features in the data. For example, the first layer of the convolution learns a small local pattern, such as an edge, and the second layer learns a larger pattern consisting of the features of the previous layer **(Viriri, 2021)**.

Feature learning and limitless precision are the key advantages of CNNs over standard ML and traditional NN that can be gained by raising the number of training samples to generate more reliable and accurate models. Convolutional filters operate as feature extractors in CNN construction and go deeper; they extract more and more complex features of "spatial and structural information". The feature extraction is done over converging minute filters with input patterns, then selecting the best distinguishing features before training the classification network **(Wadhah Ayadi, 2021)**.

Some articles focus on reviewing the properties of machine learning algorithms that attempt to describe multi-layer networks' methodology in backpropagation and weight updates. Others have dedicated themselves to reviewing the properties of machine learning algorithms that have tried to explain the multi-tiered networks' methodology in backpropagation and weight updates.

A higher number of multiple layers and the type of activation function and optimizer algorithm will result in improved performance and higher accuracy. **(HOSSAM H. SULTAN, 2019)** used 16 layers from the input layer containing augmented images from the preceding preprocessing step over the convolution layers and their activation functions (Three convolutional layers, three ReLU, normalization, and three layers of Maxpooling), the ReLU is the activation function and is defined as follows:

$$f(x) = \max(0, x) \tag{1}$$

Where x is the input value at the feature map at the layers from the neurons, as in **Fig. 4 (b).** This proposed CNN method is an approach without segmentation because it loaded images of brain tumors to obtain the corresponding layer directly. Two dropout layers have also been utilized to avoid over-fitting, tracked by a fully connected layer and softmax layer to forecast the output, and lastly, a classifier to generate a prediction class. This architecture achieves a high accuracy of 96.13%. In a work by **(Isselmou, 2021)**, five proposed convolutional layers and five Maxpooling layers are sandwiched between the convolutional layers in a distinct deep CNN model. Deep CNN has a significant advantage when it comes to representing acquired features. Previous studies have shown that a correspondingly significant reduction in fully matching layer size in CNNs does not reduce network performance. This proposed differentiation deep CNN model used in the classifier achieved the best performance with a 99.25% accuracy.

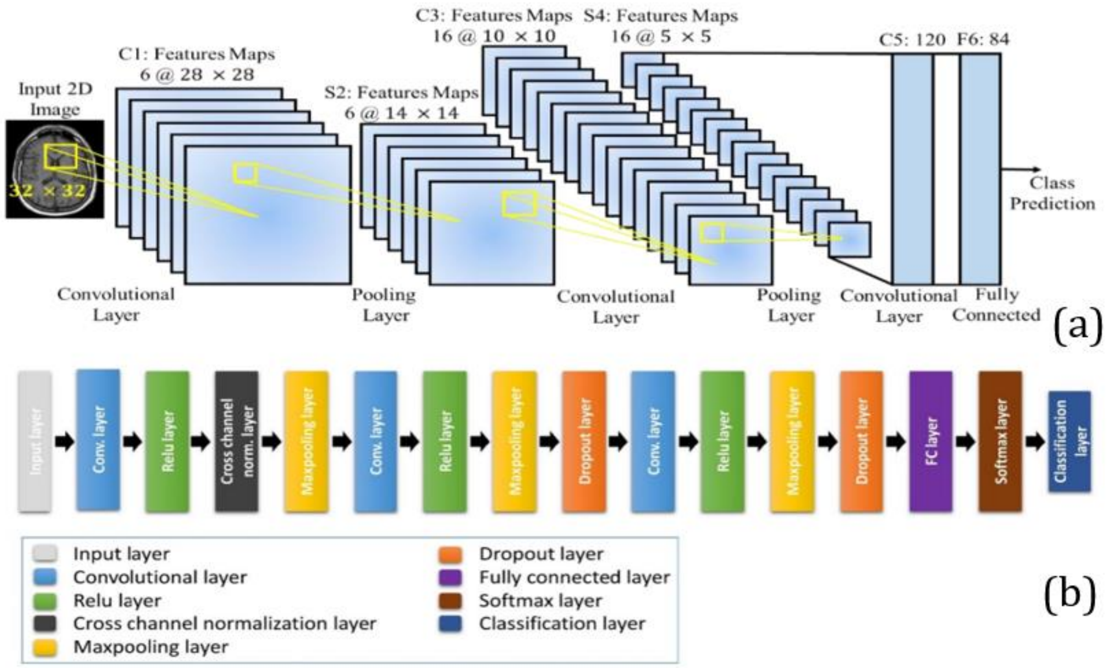

Figure 4. (a)Normal CNN ***(Jian Wang, 2020),*** (b) CNN with multiple layers ***(HOSSAM H. SULTAN, 2019)***

2.1. Performance Measuring Metrics

A research project's evaluation of a machine learning algorithm's segmentation and classification performance is significant. When an ML model is assessed using a metric, it may produce a satisfactory outcome. This is why numerous evaluation criteria are frequently utilized in order to quantify and compare model performance, for instance, accuracy, specificity, F1 score, and many other metrics **(Erena Siyoum Biratu, 2021)**; the following are some metrics:

Accuracy determines a model's ability to recognize all positive and negative classes or pixels accurately:

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+TN+FPFN}} \tag{2}$$

$\boldsymbol{F1_{Score}}$ this is the most widely utilized metric for the combination of accuracy and recall. The harmonic means of the two is expressed by it.

$$\boldsymbol{F1_{Score}} = \boldsymbol{2} \times \frac{\boldsymbol{Precision} \times \boldsymbol{Recall}}{\boldsymbol{Precision} \times \boldsymbol{Recall}} \tag{3}$$

The precision indicates the accuracy rate of the positive predictive models:

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \tag{4}$$

Recall represents the fraction of classes/pixels explained in our base actuality, which is similarly used to forecast the model:

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+TN}} \tag{5}$$

Sensitivity measures the model's capability to detect positive samples/pixels:

$$\boldsymbol{Senseitivity} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \tag{6}$$

Specificity indicates the percentage of classes /pixels which cannot be precisely determined:

$$\boldsymbol{Specificiy} = \frac{\boldsymbol{TN}}{\boldsymbol{TN+FP}} \tag{7}$$

The spatial overlap between the ground truth tumor and model segmentation region is measured using the Dice similarity coefficient (DSC). A value of the DSC of 0 indicates that the ground truth tumor zone and the model explained result have no spatial overlap, whereas a value indicates that there is total overlap:

$$\boldsymbol{Dice\ Score} = \frac{\mathbf{TP}}{\mathbf{1/2(2}\boldsymbol{TP+FP+FN})} \tag{8}$$

Here, in the confusion matrix, as shown in **Table 1**, the number of instances that have been correctly recognized as a disorder is represented by **TP** (true positive), and the number of cases that have been correctly specified as a disorder is represented by **TN** (true negative), the number of cases that have been wrongly identified as a disorder is represented by **FP** (false positive), and **FN** (false negative) represents many cases that are mistakenly identified as having no defects **(Adnan Qayyuma, 2018).**

Table 1: Confusion Matrix

Actual	**Prediction**	
	1	**0**
1	true positive **(TP)**	true negative **(TN)**
0	false positive **(FP)**	false negative **(FN)**

3. RELATED LITERATURE ANALYSIS

In recent years, there has been a search for a better approach to detecting and classifying brain tumors, allowing doctors to diagnose the condition more quickly and accurately. Various segmentation and classification methods and approaches to brain tumors are available in the literature, often classified as either traditional or deep learning approaches. So, we summarized deep learning-based brain tumor segmentation approaches and deep learning-based brain tumor classification approaches that were papers published in journals between 2018 and 2021.

3.1. Segmentation

Segmentation can be defined as a division of an image into numerous non-overlapping parts based upon a set of criteria, such as pixels or intrinsic properties like color, contrast, and texture. In general, segmentation is useful in image processing applications, including biometrics, contour detection, object matching, and object recognition. Several image segmentation techniques based on thresholding, region expanding, clustering, edge detection, active contour models, graph cut, and mean shifts have been presented in the literature **(Adnan Qayyuma, 2018).**

In these works, the authors presented an automated approach for segmenting brain tumor procedures that produce objective, repeatable findings comparable to those obtained manually. Challenges involved with manually assessing brain tumors may be alleviated by using automated brain tumor segmentation. This will expedite the process of analyzing brain images, enhance diagnosis outcomes, and make illness follow-up easier by allowing for the evaluation of tumor growth.

As an example, one type of architecture suggested by **(Mohammad Havaeia, 2017)** was regular CNNs that performed where each pixel was its classification task. **Fig. 5** depicts the architecture. As a result, a sliding window would be used, with a portion of the complete input image as input and the center pixel of this patch anticipated. The sliding window was then shifted one pixel in the following phase, and a fresh patch was transmitted to the network. The network receives 4 × 33 × 33 tensors as input, after which numerous convolutions are done, the feature maps are flattened, and a softmax layer is used to classify the input patch's center pixel.

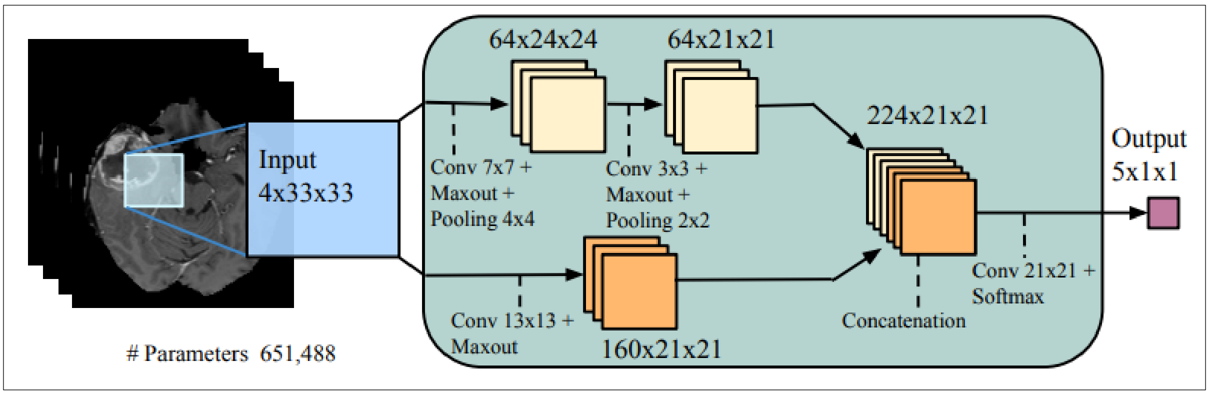

Figure 5. Architecture using a sliding window approached **(Mohammad Havaeia, 2017)**

(Tanzila Saba, 2020) used the Grab cut method to segment the Glioma using MRI. In addition, as shown in **Fig. 6**, segmented pictures are fed into the suggested deep learning model. The VGG19 model is utilized in order to obtain the deep features vector in this approach. Following that, handmade (texture and shape) features and deep features are serially concatenated. For accurate and rapid classification, those features are optimized with the use of the entropy, and classifiers are given a fused vector. **Fig. 7** shows some results for segmentation. **Table2** summarized the other methods of DL, and machine learning algorithms.

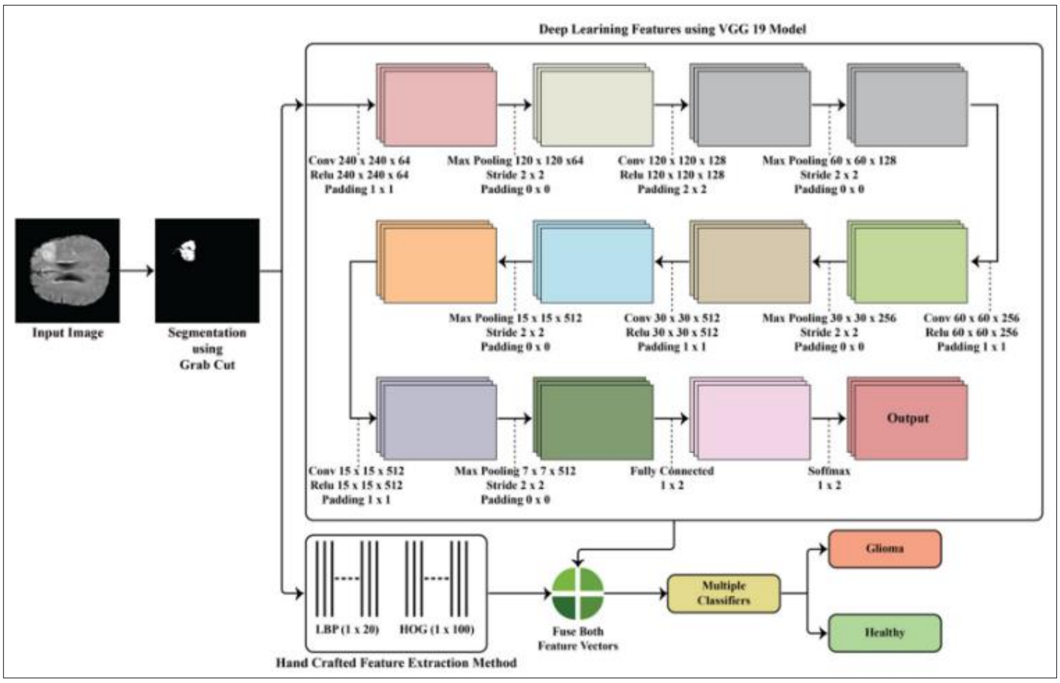

Figure 6. Handcrafted and deep features fusion ***(Tanzila Saba, 2020)***

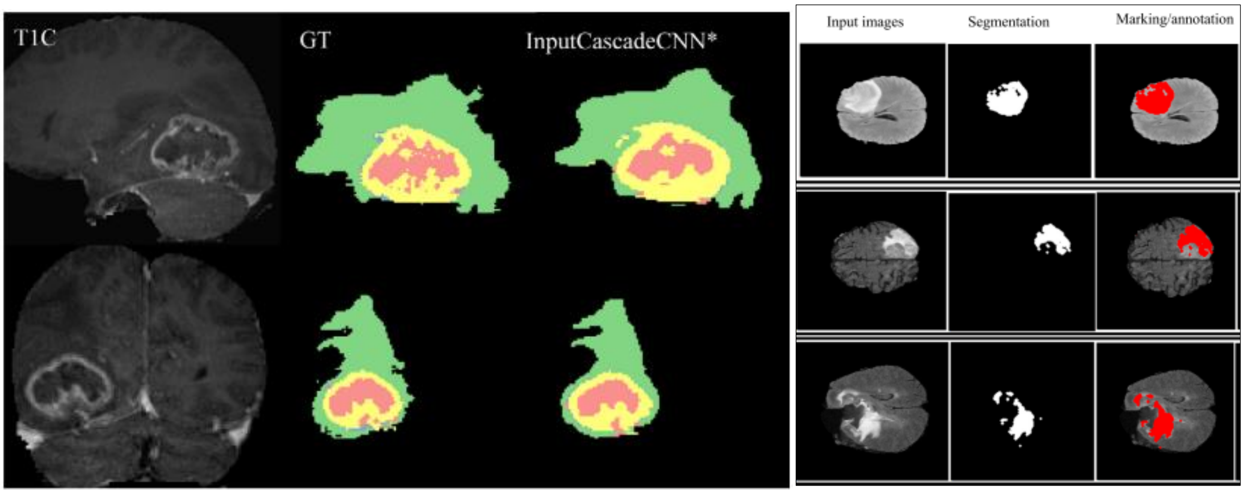

Figure 7. Some results for segmentation (Mohammad Havaeia, 2017) and (Tanzila Saba, 2020)

Table 2. DL-based MRI segmentation methods for brain tumors using classification techniques: A Summary.

Author, year	Dataset	Pre-processing Method	Segmentation technique	Feature Extraction Method	Classification	Classified Result	Accuracy
(Mohammad Havaeia, 2017)	BRATS 2013	-	Brain tumor segmentation using CNN architectures.	Feature extraction from convolution with linear, e.g., Gabor filter bank	-	-	about 0.88
(J. Seetha, 2018)	BRATS dataset	image resizing	FCM-based segmentation, texture, and shape feature extraction	The value of the feature from CNN itself	Convolutional Neural Networks (CNN)	tumor and normal brain images	97.5%
(Archa S. P, 2018)	MRI images	median filter N4ITK method	Brain tumor segmentation using CNN	Through CNN	classification via CNN	Low-Grade Gliomas (LGG) and High-Grade Gliomas (HGG)	high accuracy.
(R.Vinoth, 2018)	MRI images	standard scale histogram	Segmentation using Convolutional Neural Network	Through Convolutional Neural Network	SVM classifier	LGG and HGG	99%
(Tonmoy Hossain, 2019)	BRATS dataset	stripping of skull Filtering and Enhancement (Gaussian filter)	A fuzzy C-Means clustering algorithm has been utilized for the segmentation	Texture-based features like (Dissimilarity, Energy, Homogeneity, Correlation, ASM) Statistical-based features that include (Entropy, Mean, Standard Deviation, Centroid, Skewness, Kurtosis)	K-Nearest Neighbor (FCM), Logistic Regression, Multilayer Perceptron, Naïve Bayes, Random Forest, and SVM	Non-Tumor and Tumor	97.87%
(Alpana Jijja, 2019)	3D MRI images	Median filtering	K-means clustered to and morphological to segmented.	Through Convolutional Neural Network	Water cycle optimization algorithm	-	98.5%.
(Miss. Krishna Pathak, 2019)	brain scanned MRI image	Medium filter for to remove noise	watershed segmentation (MARKER BASED)	multiple convolution layers with a Deep neural network	CNN	Tumor or nontumor	98%
(M. Mohammed	BRATS dataset	Skull stripping and image enhancement	BAT algorithm	Morphological operation ‘thicken	Enhanced Convolutional Neural	Tumor or nontumor	92%

Thaha, 2019)					Networks (ECNN)		
(Sourabh Hanwat, 2019)	MRI image dataset from Kaggle.	median filtering resize image	the morphological technique (Binary thresholding, erosion, and dilation operations)	used Hu Moment, Haralick, and color Histogram for extracting various features like shape, texture, and color	CNN Random Forest K-Nearest Neighbors	benign, malignant, and normal	98% 89% 88%
(R. Thillaikkarasi, 2019)	MRI image	combine LoG with CLAHE	deep learning algorithm	SGLDM feature extraction	combination of CNN with M-SVM classifier	benign and a malignant tumor	84%
(Akila Gurunathan, 2020)	BRATS dataset	resized brain image	the morphological technique (dilation and erosion)	local binary pattern (LBP) feature with gray level co-occurrence matrix (GLCM) features	CNN [LeNET CNN architecture]	tumor case or non-tumor. And segment into “Mild” and “Sever”	98.3%
(Mohamed A. Naser, 2020)	Collection by Authors	clip unnecessary regions. padded with zeros. Resized.	CNN with the U-net architecture	Through Convolutional Neural Network	VGG16 network.	tumor images, and normal images	0.92 (92%)
(Tanzila Saba, 2020)	BRATS 2015, BRATS 2016, BRATS 2017,	converted RGB images into grayscale.	Segmented images using the Grabcut algorithm	Handcrafted feature extraction and deep learning features are extracted	logistic regression (LGR) K Nearest Neighbor (KNN) Linear Discriminant Analysis (LDA) and SVM	LGG and HG	0.9982 0.8143 0.9909
(Venkata Ramakrishna Sajja, 2020)	BRATS dataset	Reduce the noise by increasing the convolutional layer (Proposed CNN model)	FCM segmentation K-Means segmentation	CNN	SVM and Hybridized CNN	normal and abnormal	96.15%

DL algorithms may be regarded as current state-of-the-art for tumor segmentation, based upon observed outstanding performance. CNNs have the trait of learning rep complex features for healthful as well as malignant brain tissues from MRI images. A summary of state-of-the-art DL methods is given beside a quick overview of some classic techniques in the table above. which consist of some tumor segmentation strategies with DL classification or clustering algorithms.

3.2. Classification

Many researchers have proposed different classification strategies for identifying tumor kinds from brain imaging in various ways, including glioma, meningioma, and pituitary; glioma tumor grades; benign and malignant stages. CNNs are a subclass of neural networks that are primarily employed in image recognition applications. With no loss of information, its integrated convolutional layer lowers the high dimensionality of images. CNNs are, therefore, particularly well suited for this use case.

For example, **(Hassan Ali Khan, 2020)** used the CNN strategy to categorize brain MRI scan images as malignant and non-cancerous. They identified the benefit region in MRI and cropped them, thereafter using data augmentation and Image Processing to categorize them, **Fig. 8**. They achieved high accuracy on a small dataset which is 100%.

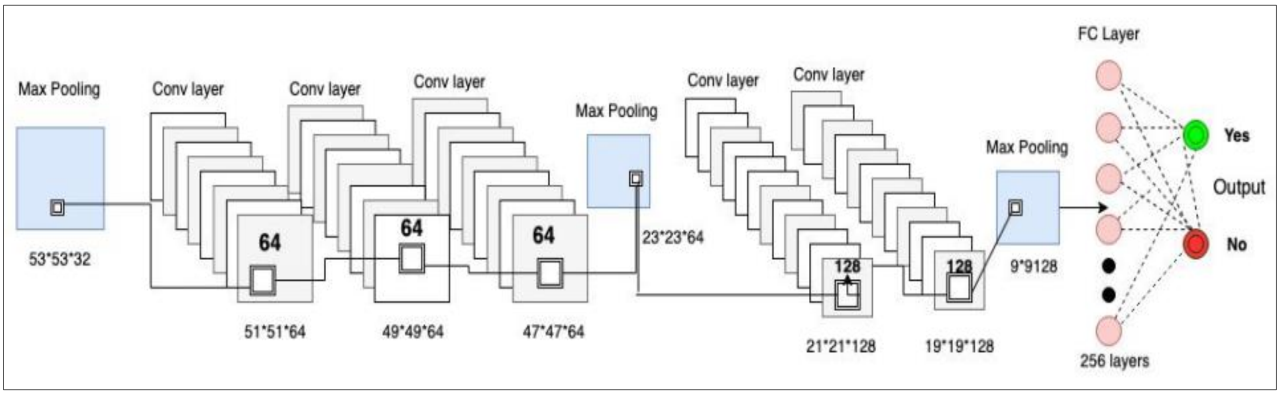

Figure 8. Proposed CNN architecture in **(Hassan Ali Khan, 2020)**

(Ali pashaei, 2018) tried extracting hidden features from the images; thereafter, a kernel ELM (KELM) classifies images according to those extracted features to 3 types of tumors: Glioma, meningioma, and pituitary tumor, **Fig. 9**. KE-CNN achieved a good classification rate of 93.68 % for brain tumor categorization. In **Table 3**, all of the other algorithms are briefly presented.

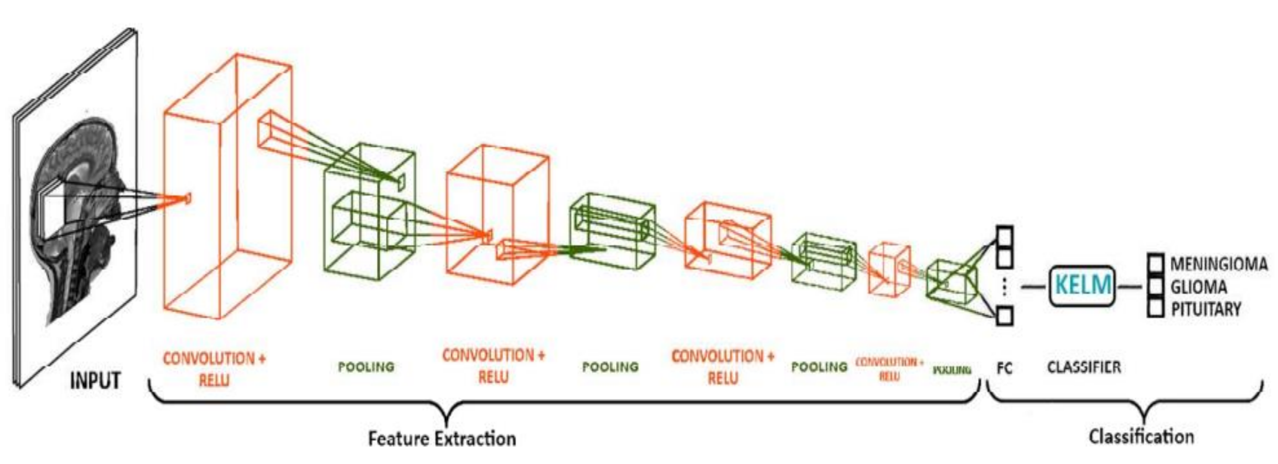

Figure 9: Proposed CNN architecture in ***(Ali pashaei, 2018)***

Table 3: Deep learning-based MRI Classification Techniques for Brain Tumours: A Summary

Author, year	Dataset	Pre-processing Method	Feature Extraction Method	Classification	Classified Result	Accuracy
(Ali pashaei, 2018)	brain tumor dataset	-	features extracted by CNN	KE-CNN	Meningioma Glioma Pituitary	93.68%
(Iram Shahzadi, 2018)	BRATS2015 dataset	The datasets have been preprocessed and provided as skull-stripped by the organizers	VGG-16	CNN-LSTM network	HGG and LGG	84%
(Masoumeh Siar, 2019)	BRATS dataset	The images were collected from imaging centers. The edges have been cropped to avoid image noise.	the first-order clustering algorithm is used for feature extraction	Convolutional Neural Network (CNN) [Alexnet Architect for Classify Images] CNN-SoftMax	normal and patient classes	99.12%
(Sunanda Das, 2019)	brain tumor dataset	Resize the images Gaussian filter smooths the image. Histogram equalization	Through Convolutional Neural Network	Convolution Neural Network (CNN)	MRI brain images types (meningioma, Glioma, pituitary)	94.39%
(S. Deepa, 2019)	brain tumor dataset from figshare.	Normalize Resized	extracted features using modified GoogLeNet	Transfer the trained deep CNN model with the Softmax deep CNN model with the SVM classifier.	Classify into Glioma, meningioma, and pituitary tumors.	92.3% 97.8% 98.0%.

				deep CNN model with KNN classifier.		
(Ercan Avşar, 2019)	BRATS2015 dataset	preprocessed by the organizers	Through CNN	faster R-CNN algorithm	MRI brain images types (meningioma, Glioma, pituitary)	91.66%
(Chirodip Lodh Choudhury, 2020)	Brain MRI images	-	Through CNN	CNN [classifying using a fully connected network]	Tumor detected and tumor not detected	96.08%
(S. Deepak, 2020)	Figshare dataset	Resize the images converted to its grayscale	Features extracted by CNN	Use a one-to-all method using a 3-class ECOC model and 3 binary SVM classifiers. Softmax.	MRI brain images types (meningioma, Glioma, pituitary)	99.0% 95.7%
(Mohamed Arbane, 2020)	MRI images collected by Authors	Data augmentation normalization crop (normalization crop and resizing) and resizing	Through Convolutional Neural Network	In the classification deep learning model, the implemented system explores several CNN constructions: ResNet, Xception, MobilNet V2.	classify MRI image as "tumor" or "non-tumor"	98.42%
(Shubham Kumar Baranwal, 2020)	Brain Tumour Dataset	Resize to decrease the computational complexity at the same time as detaining the image's information, labeling it, and serializing.	5 statistical features (Contrast, Correlation, Energy, Homogeneity, Dissimilarity)	CNN and SVM [Linear SVM, Polynomial SVM]	MRI brain images types (meningioma, Glioma, pituitary)	98.85%
(Hassan Ali Khan, 2020)	Brain Tumour Dataset	Canny Edge Detection	features extracted by CNN	CNN	tumor and non-tumor	100%
(Manikanta, 2021)	brain tumor dataset	preprocessed resizing, normalizing	Through Convolutional Neural Network	Convolution Neural Network (CNN) [classification done by Fully connected networks.]	tumor and non-tumor	97 %

(N Saranya, 2021)	Brain MRI Images from Kaggle	Scaling Shearing, Zooming, Flipping orientation	Through Convolutional Neural Network	Convolution Neural Network	cancerous and non-cancerous	have better accuracy
(Aditi Kanwar, 2021)	MRI scans collected by authors	converted to its grayscale Image Resizing	Through Convolutional Neural Network	Convolution Neural Network (SoftMax multi-classification)	glioma, meningioma, pituitary, and no tumor	96.26%
(B Kokila, n.d.)	Dataset from Kaggle	Rescaling, Converting to JPG format, and	Through CNN	CNN multitasking classification is performed using Residual Network (ResNet34)	No Tumor, Tumor	92%
(Angona Biswas, 2021)	Brain MRI Images, from the dataset	Resizing Sharpening Filter Contrast Enhancement	Many features extracted are contrast, mean, correlation, variance, energy, RMS, homogeneity, deviation, kurtosis, entropy, smoothness, standard deviation, IDM.	K-Means and ANN	classification types Glioma, meningioma, and pituitary tumor	95.4%
(Sobhangi Sarkar, n.d.)	Figshare, brain tumor dataset	progress the visual appearance of the MRI, progress the signal-to-noise ratio, cut some unnecessary parts of the background, make the image smoother, and keep the edges.	Through Convolutional neural Network	Classification by 2D Convolutional Neural Networks	Glioma tumor, Meningioma Tumor, Pituitary tumor	91.3%

4. CONCLUSIONS

Deep learning or deep CNNs have demonstrated exceptional performance in medical image processing, and that improves key performance measures by a large amount. Following its success in confronting diverse issues in speech recognition, computer vision, and natural language processing, CNN-based models have become commonly used in medical image analysis.

This paper provides an overview of the field of brain tumors. The most accepted methods in this field of brain tumor MRI can include classification, detection, and segmentation. We compared several works and methods in this field and discussed their strengths and limitations; which methods produced better results? **Table 2** and **Table 3**, where the methods of segmentation of brain tumors are presented in **Table 2**, and a summary of several methods for classifying brain tumors in this paper is presented in **Table 3**.

In this paper, we tried to summarize some of the best recent studies on the classification and segmentation of brain tumors. Using the literature, we observed that deep learning techniques are the latest approach and have been the most active research field in recent years. The recent success of these deep learning techniques suggests that they would greatly benefit the advancement of medical image analysis, especially in the brain tumor field. However, there is currently no clinically appropriate automated method.

For future vision, an automated expert system must be implemented to identify the tumor at an earlier stage to better plan the treatment.

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