

Deep Learning-Based Approaches for Machine Interface Analysis Using MRI Images

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Abstract: The tumor is a lethal illness that initiates due to unregulated growing of cells in the organs of the body like the brain, iris, spleen, lungs, etc. It is crucial to make an early diagnosis. There are numerous medical imaging methods, including CT, PET, Ultrasound, and MRI and so on, but MRI is frequently approached modality for its less ionization and less radiation. Recently, DL techniques are more popular in medical imaging technology. The important contribution of the article is to compare the effectiveness of the deep learning types/techniques for detecting any tissue from the T1-weighted (T1w) MRI abnormal brain images. In this article, the most used DL methods like CNN, RNN, and DBN are used, and analyzed the performance of each method in terms of DSC (dice score coefficient), PPV (positive predictive value), and sensitivity by using the BraTS 2020 dataset. The results of this segmented image have obtained the scores of 0.89, PPV of 0.87, and sensitivity of 0.90 for the CNN method. The C.N.N-based method is more effective for the brain tumor detection than RNN and DBN techniques.

Keywords: Tumor, Segmentation, MRI, CNN, RNN, and DBN.

1. Introduction

One of the human body's most intricate organs, the brain functions with a huge number of cells. The normal brain is shown in Fig. 1, which consists of grey matter, white matter and cerebrospinal fluid [1]. The GM consists of neuronal bodies, WM contains axons and extension of neurons and the CSF is surrounding the brain and spinal cord [2]. When cells divide out of control and form an abnormal mass of cells near or inside the brain, a brain tumour develops [3]. That particular cell population has the power to kill healthy cells and interfere with brain activity as it normally occurs. Brain tumors are categorized as malignant or high-grade (grade III and IV), benign or low-grade (grade I and II) tumors [4].

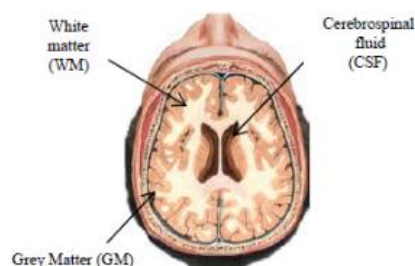


Fig.1. The normal brain

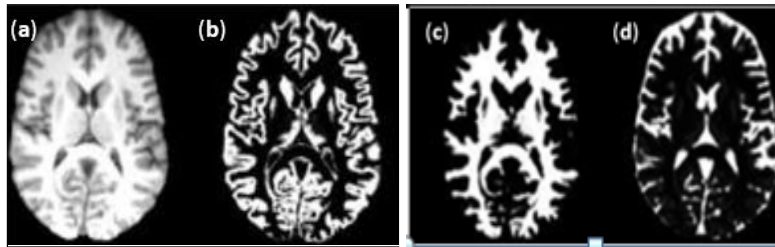


Fig. 2. MRI images of normal brain (a) original, (b) GM, (c) WM and (d) CSF

Benign tumours began in the brain and develop slowly, making them less aggressive because they are non-progressive (non-cancerous) and have defined limits. Primary malignant tumours are those that begin in the brain itself, and secondary malignant tumours are those that start elsewhere within the body and extend to the brain [5, 6]. There are different types of imaging techniques to acquire the images based on the type of tissue (soft or hard) such as CT, MRI, US, and PET [7, 8]. Among the best imaging methods for detecting brain cancers and simulating the tumor's growth during both the detection and treatment stages is magnetic resonance imaging (MRI). For their great resolution, MRI images have a big impact in the field of automatic medical image processing because they may provide a great deal of data on the brain anomalies and structure inside the brain tissues [9-12]. Fig. 2 shows the GM, WM, and CSF of normal MRI images.

The MRI was most suitable for the soft tissues (brain) and visualizing the three planes of the brain's anatomy, including sagittal, axial, and coronal view [13, 14].

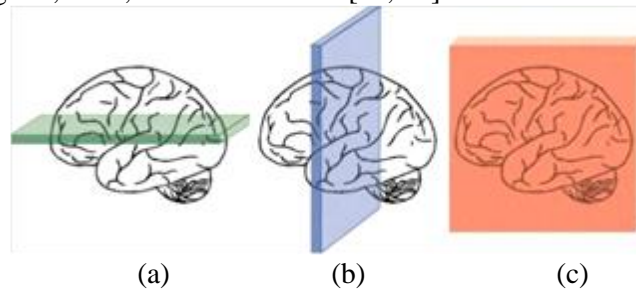


Fig. 3. Brain MRI images were acquired in different plans (a) Axial, (b) Coronal, and (c) Sagittal

Fig. 3 depicts the most used axial, coronal, and sagittal images of the brain that have been recorded using an imaging technique like as MRI. Among all the directions, the axial plan gives clear information about the human brain from MRI [15]. Based on this repetition time (RT) and time to echo (TE) of MRI, the tissue is characterized by relaxation time such as T1-weighted (T1w), T2-weighted (T2w), and fluid-attenuated inversion recovery (FLAIR) [16]. Different types of MRI devices are shown in Fig. 4. The T1w modality gives the high resolution and contrast images as compared with other modalities.

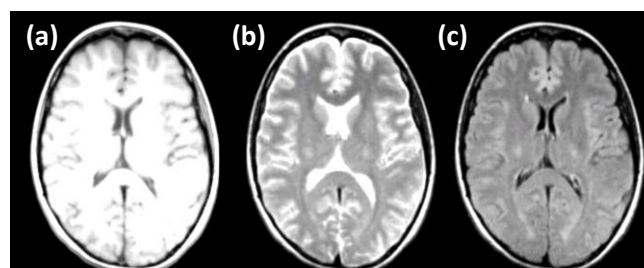


Fig. 4. Types of MRI modalities (a) T1w, (b) T2w, and (c) FLAIR

Researchers demonstrated various automated methods for classifying the type and location of brain tumours using MRI scans of brain, but, because of their successful execution over the past few years, SVM and NN are the most utilised techniques [17]. As opposed to shallow architectures like SVM and K-nearest neighbour (KNN), DL models recently created an interesting pattern in ML [18]. This is because deep learning model can effectively describe complicated relationships without using a large number of nodes. Because of this, they expanded quickly to set the standard in a variety of health informatics fields, including bioinformatics, healthcare analytics, and image analysis in medicine

[19-22]. The contribution of this study is the automatic separation and categorization of brain tumours utilising brain MRI images using DL architectures, along with performance review [23, 24].

Multiple organs in the body are segmented by using automated segmentation, where every organ in the body has defects from the tumour. The regions of the organ are evaluated properly by their colour, shape, contrast, intensity, etc. to develop the undercover. Some of the organs are:

There are three distinct types of categorizations employed. Although manual segmentation techniques like evolution and evolutionary algorithms have been used earlier, they are hardly dependable. Furthermore, it is dependent on the doctors' individual expertise. Additionally, semi-automated segmentation methods have been evolved that have enhanced detection. These methods include Fuzzy algorithm, K-means clustering, hybrid clustering, morphological function, etc. However, more effort and larger datasets are needed for model testing. Segmentation is crucial in this approach since tumor diagnosis necessitates exceedingly accurate methods.

DL methods have gained popularity in machine learning recently. Therefore, DL techniques including CNN, RNN, and DBN techniques are included in the proposed article. These methods are being employed to segment images of tumor and identify the condition of the region. To identify a more effective method for creating the future diagnosis method, the strategies are further evaluated.

This work is partitioned as follows: The second section covered the literature survey on recent works, deep learning latest techniques concepts briefed in section 3; obtained results analyzed and explained clearly in section 4, and finally concludes the performance of each method.

2. LITERATURE SURVEY

This section contains few of the newly published models were researched and briefed in below paragraph:

Mohammad.H et al. [10], (DNN) analysis in picture segmentation for brain tumor detection has been proposed. To assess the CNN outputs, the two path CNN architecture is prepared to cascade architectures. The lowest amount of time required for CNN models for segmenting the brain was between 25 sec and 180 sec. The input cascaded model, according to whole analytics, produces excellent results for testing the dataset through proper label distribution.

A.Myronenko et al. [11], had suggested a technique employing 3D MR images and auto encoder regularization. To use the VAE branch to determine the size of the image, this approach provides the encoder and decoder. The time needed to train the data for a single model using all of the cases is 0.4 seconds.

Guotai Wang et al. [12], the version of three networks for the brain tumor segregation at the three binary cascaded challenges were constructed utilizing cascaded anisotropic CNNs. To acquire the segmented convolution outputs, the author segregated the core of the tumor, improved the tumor core, and then segmented the entire tumor. The approach suggested dice scores of 0.7859, 0.9, and 0.8 using CRFs, respectively. Instead of employing a single neural network, the CRFs enabled separation for hierarchical structures via anisotropic cascade for multi-class sections.

J.Nalepa1 et al. [13], a concept of the feature extraction created with certain techniques for the image classification. To accurately change the properties of medical images, refined image modifications, artificial data generation, It is recommended to use elastic image transformation and pixel-level image transformation methods. Measure maximum accuracy of the data augmentation process, 78% of the cases are accurately detected. To create the images, the actual data is transformed using an intelligent machine; however it has with the high time complexity of $O(n^2)$.

Sheng Cong et al. [14], used a multi-level hierarchy and a DF-CNN to segregate brain tumors. In order to determine the loss functions, the authors combined certain evolutionary processes using the multi-level medic deep, innovative dual force, label delivery system, and ultimately generated unique multi-levels for segregating the M.R.I images. Following MRI scan evaluation, the sophistication of the testing and training a collection of data is enhanced by 10%. The author came to the conclusion that D-FCNN may be used to execute such procedures.

Paweł Młynarski et al. [15], Brain tumor categorization were investigated utilizing DL and mixed supervision. The data used for training takes into account MRI pictures that are both completely and poorly labeled. A small variety of features are used in the classification stage, which is based on the number of examples. The number of photos with poor annotations is decreasing over time in comparison to the ground segmentation process. This supervision strategy can therefore be used to

extend the separation networks.

Nilesh Bhaskarrao Bahadure et al. [16], for segregating brain tumors and classifying tumor images, a genetic algorithm is utilized. In order to decide the optimum method for high precision, the author presented a number of segmentation strategies, including watershed segmentation, Berkley wavelet transformation, fuzzy clustering procedures, etc. Using BWT-segmentation, the approach achieves classification scores with 97% precision. As a result, the author considered a major development in medicinal uses with no complications.

Dingwen Zhang et al. [17] developed a cross-modal DL method for segmenting brain tumors. Different modalities of data are presented to the CMFT and CMFF. The test speed is 3.2 seconds, and the training period was 18 hours. Utilizing adverse network learning, the picture data from several methods is segmented utilizing identified tumor core images.

Jie. C et al. [19] suggested a technique for brain-tumor classification utilizing CNN and FCRF with automated mix pooling. By using data preprocessing and categorization with CNN and FCRF, the creator of this technique adopted a specific procedure to improve the CNN results. Each set of MRI images has a normalizing technique in place. The highly effective CNN and multi - threading execution of the suggested methods produces very quick, effective results.

3. METHODOLOGY

In this section, the three most popular deep learning architectures (CNN, RNN, and DBF) were explained briefly. To achieve accurate and automated tumor segmentation from MRI datasets, each model can play an important role by reducing the computational burden of the training and testing process.

Convolutional neural networks (CNNs)

The existing extraction method CNN has improved capabilities to optimize features and image classification. This involves the process of classifying DNNs developed in various ways. A convolution operation is performed at the convolution layer to extract features from the input. The weight of each layer is added to measure the distribution of images and combine weighting metho. Fig. 5 depicted CNN's physical layout.

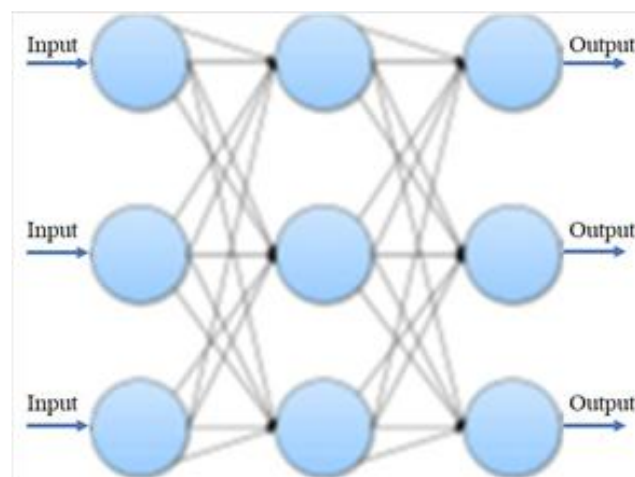


Fig.5. The CNN representation diagrammatically

Convolutional procedures and one kind of neural network are worked on by CNNs. Conventional and DL approaches are examples of two different sorts of methodologies. The categorization of low-grade brain tumours, a typical task in traditional ML modals, is implemented using learning strategies from statistics. The segmentation of brain tumours using CNNs, which require less pre-processing procedures and can train on enormous datasets, has become the standard method in recent years [25]. CNN is one of the most popular methods used today to handle computer and medical imaging issues, particularly for the classification of brain tumours. Convolutional filters are used by the multiple layers of the CNN to convert the input images into output images (normal or abnormal) as it learns the high-level features [26]. The attributes in the provided data have been taught to the CNN models. The very first convolutional layer can pick up low-level edges, and the second layer can pick up really high

features. Then, by dispersing the weights, the convolutional layer components reduce the number of variables that must be learned. Consequently, the network's effectiveness will increase [27].

The fundamental distinction between MLTs and CNNs is that the weights used by the network to execute the convolutional operation are shared, learning does not require the use of separate detectors, and the weights are independent of the size of the original picture [28]. Additionally, the neighbourhood pixel values are accumulated by applying the "max or mean" functions [27, 28] thanks to the pooling layer in CNNs. Regular neural networks (totally connected layers), in which the weights are not shared, are added after CNN. The dispersion across classes is created by putting the activations into the final layer when the softmax function is used. Conditional probability is used in the network's training [29]. From the initial provided data, the convolutional layer learns the local and complicated characteristics in the hierarchy. In order to reduce the large variables and then advance to downstream layers, the Pooling is inserted in between the subsequent convolutional layers. The acquired patterns can be recognised regardless of geometrical modifications thanks to the translation constant [30].

The input layer, convoluted layer, pooling layer, and other layers are included in the network. The input MRI picture is segmented into manageable pieces. A pooling layer is used to define each segment's class of 0, 1 state.

Recurrent neural network (RNN)

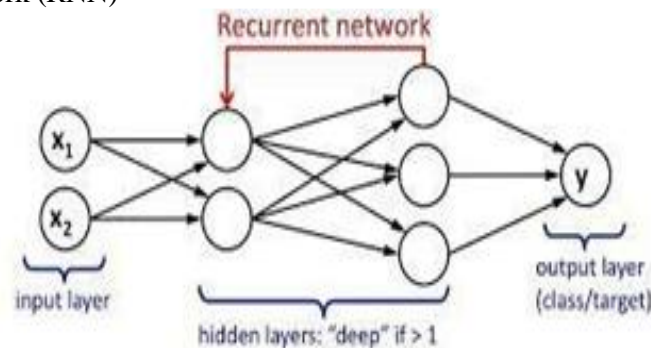


Fig.6. Process of RNN

An RNN stands out among neural networks due to its distinct approach within the realm of deep learning. Unlike conventional algorithms, it specializes in processing time series data, making it particularly adept at tasks like language translation and speech recognition. While both RNNs and traditional neural networks undergo training using input data, their operational principles diverge significantly.

Unlike traditional models, which treat input and output as independent entities, RNNs incorporate dependencies among sequential elements. This unique characteristic allows RNNs to consider prior elements within a series when generating outputs, distinguishing them from other neural network architectures. [30-32].

Deep belief network (DBN)

The DBN, short for Deep Belief Network, stands as a prominent unsupervised deep learning algorithm. Operating as a hybrid generative graphical model, it combines both directed and undirected layers. The upper layers function as undirected, while the lower layers establish direct connections with those above them. To facilitate learning, DBNs employ Greedy Learning algorithms for pre-training. This method adopts a layer-by-layer approach, progressively learning from the top down and generating weights accordingly. [33].

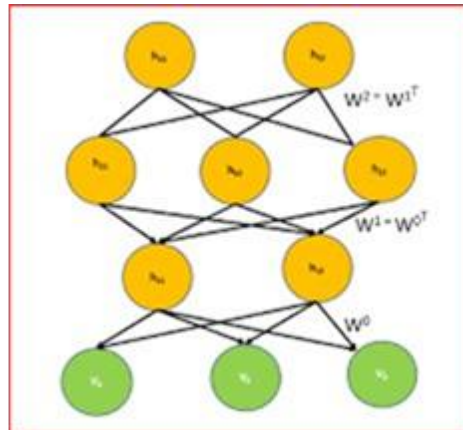


Fig.8. Representations of deep belief networks.

4. PERFORMANCE METRICS

Accuracy and percentage were calculated for each procedure while evaluating the effectiveness of performance measures such as dice score, positive probability (PPV), and precision. Similarly, for the machine learning applications, evaluation involves metrics including accuracy, precision, specificity, area under the curve (AUC), recall, and F1 scores. Each metric is meticulously calculated to provide a comprehensive understanding of the performance of the techniques employed [34]. They are:

$$DSC = \frac{2 * (TP)}{2 * (TP) + FP + FN} \tag{1}$$

$$PPV = \frac{TP}{TP + FP} \tag{2}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

Where, TN= True Negative, TP= True Positive, FP= False Positive, and FN=False Negative.

5. RESULTS

The DL methods CNN, RNN, and DBN are being contrasted by using the input MRI images and analyzing them using various techniques.

The total images are divided into testing and educational photos. Data provides primary and secondary features extracted from images uses in patient reports for training purposes. Deep learning techniques are then evaluated and prioritized based on the quality and efficiency of the output images they produce. In Fig. 9, four input images (a) are taken to evaluate the performance and output results of DL methods are represented in (b), (c), and (d).

Below images give an idea of the segmented results of brain tumors.

Table: 2 shows the performance metrics values of respective DL methods.

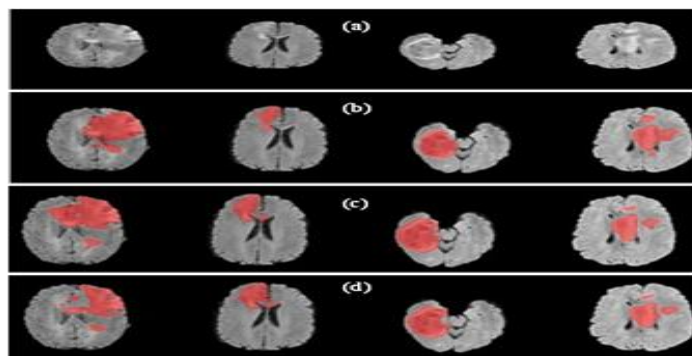


Fig.9. The results of deep learning methods (a) Sample images, (b) CNN, (c) RNN, and (d) DBN

Table 2: The performance metrics of DL methods

Input Image No.	Method	DSC			PPV			Sensitivity		
		Complete	Core	Enh	Complete	Core	Enh	Complete	Core	Enh
	CNN	0.85	0.71	0.64	0.86	0.86	0.62	0.89	0.69	0.63

1	RNN	0.82	0.69	0.62	0.84	0.84	0.6	0.87	0.66	0.62
	DBN	0.79	0.68	0.61	0.82	0.81	0.59	0.84	0.62	0.6
2	CNN	0.89	0.75	0.65	0.87	0.87	0.63	0.9	0.71	0.69
	RNN	0.87	0.71	0.61	0.84	0.85	0.61	0.88	0.69	0.65
	DBN	0.83	0.69	0.6	0.83	0.83	0.6	0.87	0.67	0.62
3	CNN	0.84	0.7	0.62	0.86	0.85	0.62	0.89	0.7	0.65
	RNN	0.81	0.68	0.6	0.82	0.82	0.6	0.87	0.66	0.64
	DBN	0.8	0.67	0.58	0.8	0.79	0.59	0.86	0.65	0.61
4	CNN	0.85	0.71	0.63	0.84	0.86	0.61	0.87	0.68	0.67
	RNN	0.83	0.7	0.6	0.83	0.83	0.59	0.86	0.65	0.63
	DBN	0.82	0.68	0.59	0.81	0.81	0.58	0.85	0.64	0.61

Input image 2 from all the input samples has greater DSC for CNN, RNN, and DBN and the highest accuracy out of all the samples used as input. The bar graphs of DSC for DL methods are results shown in Fig.10.

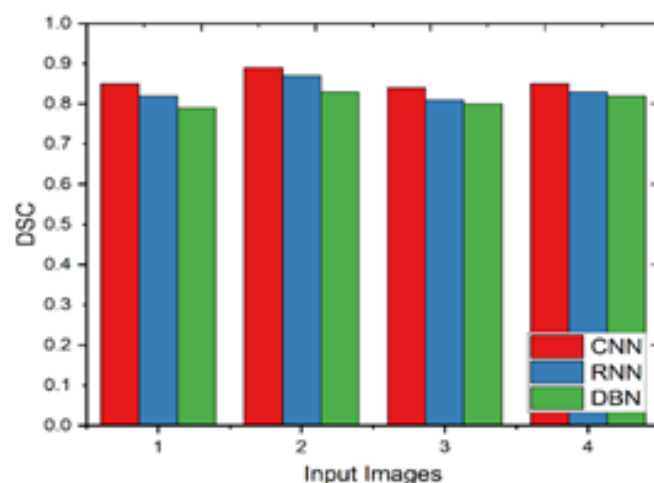


Fig .10. Bar graph of DSC over DNN methods

6. CONCLUSION

A method employing DNN-like architectures such as CNN, RNN, and DBN was proposed for precise tumor localization and Sizing during segmentation of MRI data. Use the BraTs-2018 dataset as input, each approach was rigorously tested to determine the most accurate one. Evaluation criteria including dice score, PPV, and sensitivity were employed alongside performance parameters to analyze their effectiveness. Following thorough analysis, it was concluded that:

- The average dice scores are 0.71 for CNN, 0.69 for RNN, and 0.67 for DBN
- Average PPV of CNN is 0.86, RNN is 0.83 and DBN has a value of 0.81.
- Sensitivity amount of 0.69 for CNN, 0.66 for RNN, and 0.64 for DBN.

When comparing both the Among ML and DNN methods, the CNN method has been shown to be the most preferred method in the classification of all organ regions, using more filters and giving the best results. Therefore, the CNN modal is counted as the effective modal to perform among DNN methods as well as ML methods.

References

1. Khan, Amjad Rehman, et al. "Brain tumor segmentation using K-means clustering and deep learning with synthetic data augmentation for classification." *Microscopy Research and Technique* (2021).
2. Naser, Mohamed A., and M. Jamal Deen. "Brain tumor segmentation and grading of lower-grade glioma using deep learning in MRI images." *Computers in biology and medicine* 121 (2020): 103758.
3. Rajesh Babu, K., et al. "Performance Analysis of Brain Tumour Detection Using Optimization-Based FCM Technique on MRI Images." (2019): 1717-1723with deep neural networks." *Medical image analysis* 35 (2017): 18-31.
4. Pei, Linmin, et al. "Context-aware deep learning for brain tumor segmentation, subtype classification, and survival prediction using radiology images." *Scientific Reports* 10.1 (2020): 1-11.

5. Babu, Rajesh, et al. "An Effective Brain Tumor Detection from T1w MR Images Using Active Contour Segmentation Techniques." *Journal of Physics: Conference Series*. Vol. 1804. No. 1. IOP Publishing, 2021.
6. Babu, K. Rajesh, et al. "CNN Fusion Based Brain Tumor Detection from MRI images using Active Contour Segmentation Techniques." *Journal of Physics: Conference Series*. Vol. 1804. No. IOP Publishing, 2021.
7. Lin, Chih-Wei, Yu Hong, and Jinfu Liu. "Aggregation-and-Attention Network for brain tumor segmentation." *BMC Medical Imaging* 21.1 (2021): 1-12.
8. P. V. Naganjaneyulu, and K. Satya Prasad. "Comparative Analysis of Active Contour Models for Brain Tumor segmentation from T1w MRI Images." 2021 International Conference on Computer Communication and Informatics (ICCCI). IEEE, 2021.
9. Rajesh Babu, K., et al. "Effective Detection of Brain Tumor on MRI Images Using Optimization-Based Segmentation Techniques." (2020): 1182-1185.
10. Havaei, Mohammad, et al. "Brain tumor segmentation with deep neural networks." *Medical image analysis* 35 (2017): 18-31.
11. Myronenko, Andriy. "3D MRI brain tumor segmentation using autoencoder regularization." *International MICCAI Brainlesion Workshop*. Springer, Cham, 2018.
12. Wang, Guotai, et al. "Automatic brain tumor segmentation using cascaded anisotropic convolutional neural networks." *International MICCAI brain lesion workshop*. Springer, Cham, 2017.
13. Nalepa, Jakub, Michał Marcinkiewicz, and Michał Kawulok. "Data augmentation for brain-tumor segmentation: a review." *Frontiers in computational neuroscience* 13 (2019): 83.
14. Chen, Sheng Kong, Changxing Ding, and Minfeng Liu. "Dual-force convolutional neural networks for accurate brain tumor segmentation." *Pattern Recognition* 88 (2019): 90-100.
15. Mlynarski, Pawel, et al. "Deep learning with mixed supervision for brain tumor segmentation." *Journal of Medical Imaging* 6.3 (2019): 034002.
16. Bahadure, Nilesh Bhaskarrao, Arun Kumar Ray, and Har Pal Thethi. "Comparative approach of MRI-based brain tumor segmentation and classification using genetic algorithm." *Journal of digital imaging* 31.4 (2018): 477-489.
17. Zhang, Dingwen, et al. "Cross-modality deep feature learning for brain tumor segmentation." *Pattern Recognition* 110 (2021): 107562. 48
18. Li, Zeju, Yuanyuan Wang, and Jinhua Yu. "Brain tumor segmentation using an adversarial network." *International MICCAI brain lesion workshop*. Springer, Cham, 2017.
19. Chang, Jie, et al. "A mix-pooling CNN architecture with FCRF for brain tumor segmentation." *Journal of Visual Communication and Image Representation* 58 (2019): 316-322.
20. Zhao, Xiaomei, et al. "A deep learning model integrating FCNNs
21. and CRFs for brain tumor segmentation." *Medical image analysis* 43 (2018): 98-111 (2020): 1182-1185.
22. Havaei, Mohammad, et al. "Brain tumor segmentation with deep neural networks." *Medical image analysis* 35 (2017): 18-31.
23. Myronenko, Andriy. "3D MRI brain tumor segmentation using autoencoder regularization." *International MICCAI Brainlesion Workshop*. Springer, Cham, 2018.
24. Wang, Guotai, et al. "Automatic brain tumor segmentation using cascaded anisotropic convolutional neural networks." *International MICCAI brain lesion workshop*. Springer, Cham, 2017.
25. Nalepa, Jakub, Michał Marcinkiewicz, and Michał Kawulok. "Data augmentation for brain-tumor segmentation: a review." *Frontiers in computational neuroscience* 13 (2019): 83.
26. Chen, Sheng Kong, Changxing Ding, and Minfeng Liu. "Dual-force convolutional neural networks for accurate brain tumor segmentation." *Pattern Recognition* 88 (2019): 90-100.
27. Mlynarski, Pawel, et al. "Deep learning with mixed supervision for brain tumor segmentation." *Journal of Medical Imaging* 6.3 (2019): 034002.
28. Bahadure, Nilesh Bhaskarrao, Arun Kumar Ray, and Har Pal Thethi. "Comparative approach of MRI-based brain tumor segmentation and classification using genetic algorithm." *Journal of digital imaging* 31.4 (2018): 477-489.
29. Zhang, Dingwen, et al. "Cross-modality deep feature learning for brain tumor segmentation." *Pattern Recognition* 110 (2021): 107562. 48
30. Li, Zeju, Yuanyuan Wang, and Jinhua Yu. "Brain tumor segmentation using an adversarial network." *International MICCAI brain lesion workshop*. Springer, Cham, 2017.
31. Chang, Jie, et al. "A mix-pooling CNN architecture with FCRF for brain tumor segmentation." *Journal of Visual Communication and Image Representation* 58 (2019): 316-322.
32. Zhao, Xiaomei, et al. "A deep learning model integrating FCNNs and CRFs for brain tumor segmentation." *Medical image analysis* 43 (2018): 98-111.