Comparison of machine learning models for MRI image-based brain tumor classification and segmentation

Yiming Liao

School of Medical Technology and Information Engineering, Zhejiang Chinese Medical University, Hangzhou, Zhejiang, 310053, China

202012213501017@zcmu.edu.cn

Abstract. Brain tumors have a high-risk factor and are extremely harmful to the human body. With the development of science and technology in recent years, automatic segmentation has become popular in medical diagnosis because it provides higher accuracy than traditional hand segmentation. At present, more and more people start to study and improve it. Due to the non-invasive nature of MRI, MR images are often used to segment and classify brain tumors. However, limited by the inaccuracy and inoperability of manual segmentation, it is very necessary to have a complete and comprehensive automatic brain tumor segmentation and classification algorithm technology. This article discusses the benefits, drawbacks, and areas of application of several traditional algorithms as well as more modern, improved, and more advanced algorithms. Segmentation methods and classification methods can be used to classify these techniques. Convolutional neural networks (CNN), Support vector machines, and Transformers are examples of classification methods. Random forests, decision trees, and improved U-Net algorithms are examples of segmentation methods. To discuss the capability of classification and segmentation, there are three sections in the area used for segmenting brain tumors with three types, including Tumor Core, Enhance Tumor, and Whole Tumor, which could be abbreviated as TC, ET, and WT. Through the comparative analysis of these methods, useful insights for future research are provided.

Keywords: brain tumors, segmentation, classification, MRI.

1. Introduction

In a healthy human body, cells undergo a cycle of regular metabolism. When this process is interrupted, old cells do not die and new cells grow wildly, which leads to abnormal growth of new cells, which in turn leads to a series of physiological disorders, which is the tumor.

From preprocessing, to feature extraction, and then segmentation, after that is postprocessing, these are typically the steps in the segmentation of an MRI brain tumor. Image registration, bias field correction, and non-brain tissue resection were all included in the preprocessing. The process of extracting useful features from MRI images, such as shape, texture, and intensity, is known as feature extraction. MRI images are divided into various regions, such as tumor regions and normal regions, in a process known as segmentation. ET, WT, and TC are examples of frequently used segmentation regions. Post-processing is the additional processing that is done to the segmentation results, including things like noise removal and hole filling.

A data collection called BraTS is concerned with the segmentation of pictures of brain tumors. According to each case's appearance, shape, and histology, BraTS employs four MRI scan modalities, including flair, t2, t1, and t1ce) to classify brain tumors. The BraTS 2015 dataset covers the MRI scans of two levels of gliomas including low-grade (LGG) and high-grade (HGG). There are 54 patients suffer from LGG and 220 patients from HGG. Each of the 285 case images in BraTS 2018 practice materials has four aforementioned modalities, and there must be three sections for each case, including ET, WT, and TC.

In this article, various segmentation and classification methods based on MRI brain tumor pictures are compared. This paper provides a discussion of the advantages, disadvantages, and scope of application of several classic algorithms and currently more advanced and improved algorithms and models, including segmentation methods (random forest, decision tree, UNet), classification algorithms (Convolutional Neural Network (CNN), Transformer, and Support vector machine). And introduced the commonly used data sets, and divided the brain tumor segmentation block into 3 parts, including ET, WT, and TC to discuss the ability of segmentation and classification.

The following describes the organizational structure of this essay: The segmentation and classification algorithms for brain tumors are introduced in Section 2, as shown in Figure 1, along with some segmentation and classification methods, and the study's conclusions are presented in Section 3.

2. Method

The segmentation and classification algorithms for brain tumors are demonstrated in Figure 1 and will be elaborated in the subsequent paragraphs.

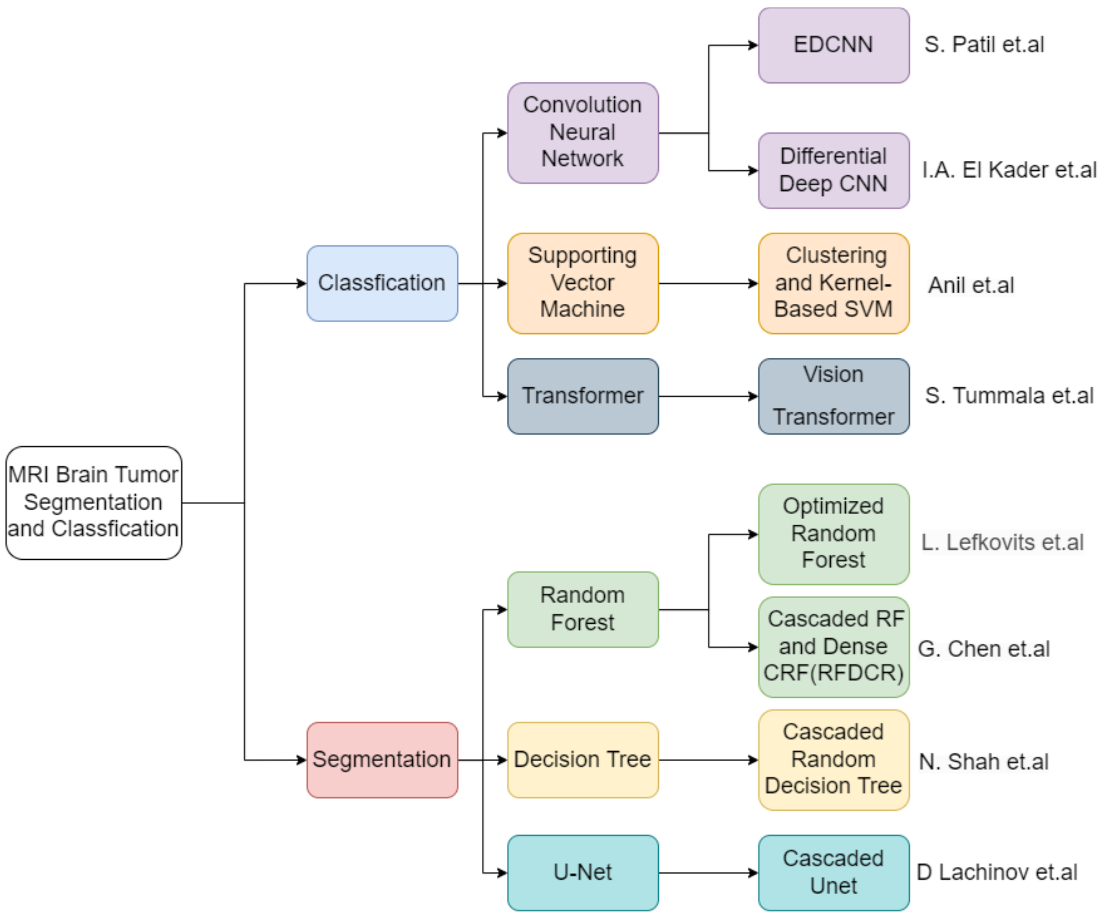

Figure 1. Segmentation and classification methods compared in this paper.

DOI: 10.54254/2755-2721/19/20231007

2.1. Decision tree for segmentation

In data mining and supervised learning methods of machine learning, classification, and regression tasks can be accomplished using a non-parametric approach called Decision Tree. In order to follow the branch and move on to the next node, the algorithm starts at the root node of the tree and compares the value of the root attribute with the value of the record attribute. Both categorical and numerical data can be included in Decision Tree. The interpretability, usability, and handling of categorical and numerical data are all benefits of the Decision Tree. Using a cascaded random decision tree (RDF) model, N. Shah et al. classified T1, T1c, BRATS 2013 3D MRI images of T2 and Flair MRI sequences and measure the performances via Dice. WT has the highest performance at 0.90. ET performs the second highest which is 0.84, while TC has the lowest performance at 0.79 [1]. Decision Tree's performance can be affected by the selection of hyperparameters, and they can be vulnerable to overfitting when the model is overly complex.

2.2. Random forest for segmentation

The results of numerous decision trees are combined by an algorithm known as Random Forest (RF) to yield a single result. It is a popular machine-learning algorithm. The results of the unit votes cast by each classifier tree for the most popular class are combined to produce the outcome [2]. Random forests have no overfitting, strong noise and outlier tolerance, and high classification accuracy for a range of data sets. There are numerous instances of the random forest method being improved. For instance, A discriminant model leveraging RF was developed by L. Lefkovits et al. for segmenting the tumorous regions in brain using various MRI modalities. Before optimizing the segmentation framework, RF is tuned for the evaluation of variable importance. The discriminative model was evaluated using the BRATS picture collection, and the outcomes were comparable to the best ones previously obtained using BRATS [3]. In the BRATS2015 and 2018 brain tumor datasets, A two-stage paradigm for supervised learning was presented by G. Chen et al. It is based on random forest cascaded RF and dense CRF (RFDCR), which showed promising results in comparison to other segmentation methods, with the accuracy of the various brain tumor regions being 86%, 79%, and 75% [4].

2.3. U-Net for segmentation

The University of Freiburg's Department of Computer Science developed the U-Net model to segment biological pictures. It is a modified and extended convolutional neural network architecture. On the market, there are also numerous enhanced and expanded UNet-based models. To automatically segment brain tumors using neural networks, D Lachinov et al. proposed a deep cascade method (Cascaded Unet). This method uses the method data set from BRATS 2018 to improve results, which are 90.06%, 83.6%, and 77.2% in WT, TC, and ET areas, respectively [5]. This method modifies 3D UNet to effectively process multimodal MR image input.

2.4. Support vector machine (SVM) for classification

A well-liked, flexible machine learning under supervision method named SVM is used to resolve the problems with classification and regression issues in machine learning. By using an optimal hyperplane as a decision boundary, the algorithm analyzes data for classification and regression analysis. It is particularly suitable to segment and categorize brain tumors due to its flexibility in handling continuous variables [6]. Anil et al. proposed and implemented an automated framework. It leverages Kernel-based SVM, abbreviated as K-SVM, and K-means for segmenting and classifying brain tumors. After texture feature transformation (DWT) feature extraction, K-SVM was employed to classify various brain tumor kinds. They had a 98.75% accuracy rate, 95.43% fineness, and 97.65% recall with their suggested framework [7]. However, it should be noted that the performance of the algorithm will be impacted by how the kernel function and its parameters are chosen as the SVM is very sensitive to these choices.

DOI: 10.54254/2755-2721/19/20231007

2.5. Convolutional neural network (CNN) for classification

Among most common kind of artificial neural networks, CNN is broadly applied for image and video analysis. The popularity of CNN has greatly increased in recent years because it can learn directly from data and does not require manual feature extraction [8]. To address the issues of inaccurate tumor localization and challenging tumor classification, S. Patil et al. used a deep ensemble model. This technique solves the partially imbalanced dataset model overfitting issue by combining the VGG16 network and shallow convolutional neural network (SCNN), increasing their loss and accuracy, and then enhancing the three brain cancers' classification accuracy. The model has a classification accuracy of up to 97.77%. The EDCNN model has produced results that are competitive with those of other studies [9]. A model using a differential CNN was put forth by Abd El Kader et al. for the grading of different kinds of brain tumors. The differential model extracts a novel differential representations from conventional feature map using a differential operator. Achieving 99.25% accuracy on a dataset that has over 25,000 MRI images of the brain, including abnormal and several normal images. The automatic classification of brain tumors can be facilitated by differential deep CNN models, as this study shows [10].

2.6. Transformer for classification

Transformer is a deep learning model that makes use of a self-attention mechanism, a type of neural network architecture frequently used in computer vision, natural language processing (NLP), and other areas like speech processing. Due to the transformer model's tremendous success in the recent past, using the transformer as a foundation, various better versions have been developed [11]. Based on VisionTransformer (ViT), the deep neural network architecture has drawn wide attentions to computer vision research for dividing up and categorizing many brain tumors. Using enhanced (CE) MRI slices of 3064 meningiomas from the Figshare brain tumor dataset, S. Tummala et al. evaluated the viability of utilizing the pre-trained and improved ViT model on ImageNet to verify a three-class classification job. The outcomes demonstrate that the test's total accuracy is 98.7% [12].

3. Result

This work discovered that the most widely used data set for MRI brain tumor segmentation algorithms is called BRATS. Although there are more data sets, the overall usage of classification algorithms is not uniform as shown in Table 1 and Table 2. Cascaded Unet provided the most accurate performance on tumorous region segmentation, while accuracy of WT and TC was 90.06% and 83.6%, respectively, and the accuracy for the ET region was Cascaded Random Decision Forest at 84%. Although Differential Deep CNN achieved the highest classification accuracy, which is 99.25%, the overall classification accuracy for MRI brain tumors is relatively close to 100%. The segmentation accuracy of MR Image brain tumors may generally still be improved.

Table 1. Contrast of segmentation techniques.

Refs	Segmentation Method	Year	Accuracy			Dataset
			WT	TC	ET	
[3]	Optimized Random Forest	2016	75-91%	71-82%	-	BraTS 15
[5]	Cascaded Unet	2019	90.06%	83.6%	77.2%	BraTS 18
[1]	Cascaded Random Decision Forest	2017	90%	79%	84%	BraTS 13
[4]	cascaded RF and dense CRF (RFDCR)	2020	86%	79%	75%	BraTS 15 BraTS 18

Table 2. Comparison of classification methods.

Refs	Classification Method	Year	Accuracy	Dataset
[10]	Differential Deep CNN	2021	99.25%	TUCMD
[9]	EDCNN(SCNN+VGG16)	2023	96.49%	Figshare

Table 2. (continued).

[12]	VisionTransformer	2022	97.71%-98.70%	Figshare
[7]	Clustering and Kernel-Based SVM	2022	98.75%	AANLIB OASIS Harvard Medical School

4. Conclusion

In this essay, a number of cutting-edge technologies for segmenting and categorizing brain tumors are studied horizontally, including the evaluation for a summary of many models against three distinct areas of brain tumors including TC , WT, and ET, and segmentation accuracy and overall classification accuracy (Accuracy). Segmentation methods include discussions on random forests, decision trees, and improved algorithms of U-Net, and classification methods include discussions on convolutional neural networks (CNN), support vector machines, and Transformers. Data sets like BRATS and Figshare are frequently used. Following a comparison of these techniques, it is determined that Differential Deep CNN has the highest classification accuracy while Cascaded Unet and Cascaded Random Decision Forest have the best effects on brain tumor segmentation. The primary and current research directions for segmenting and categorizing brain tumors involve improving the existing models and searching for higher accuracy classification methods and segmentation classification models.

References

[1] Shah, N., Ziauddin, S., & Shahid, A. R. (2017). Brain tumor segmentation and classification using cascaded random decision forests. In 2017 14th international conference on electrical engineering/electronics, computer, telecommunications and information technology (ECTI-CON), 718-721.

[2] Qi, Y. (2012). Random forest for bioinformatics. In Ensemble machine learning: Methods and applications. 307-323.

[3] Lefkovits, L., Lefkovits, S., & Szilágyi, L. (2016). Brain tumor segmentation with optimized random forest. In Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries: Second International Workshop, BrainLes 2016, with the Challenges on BRATS, ISLES and mTOP 2016, 88-99.

[4] Chen, G., Li, Q., Shi, F., Rekik, I., & Pan, Z. (2020). RFDCR: Automated brain lesion segmentation using cascaded random forests with dense conditional random fields. NeuroImage, 211, 116620.

[5] Lachinov, D., Vasiliev, E., & Turlapov, V. (2019). Glioma segmentation with cascaded UNet. In Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries: 4th International Workshop, BrainLes 2018, 189-198.

[6] Nandpuru, H. B., Salankar, S. S., & Bora, V. R. (2014). MRI brain cancer classification using support vector machine. In 2014 IEEE Students' Conference on Electrical, Electronics and Computer Science, 1-6.

[7] Mandle, A. K., Sahu, S. P., & Gupta, G. (2022). Brain Tumor Segmentation and Classification in MRI using Clustering and Kernel-Based SVM. Biomedical and Pharmacology Journal, 15(2), 699-716.

[8] Ranjbarzadeh, R., Tataei Sarshar, N., Jafarzadeh Ghoushchi, S., Saleh Esfahani, et, al. (2022). MRFE-CNN: multi-route feature extraction model for breast tumor segmentation in Mammograms using a convolutional neural network. Annals of Operations Research, 1-22.

[9] Patil, S., & Kirange, D. (2023). Ensemble of Deep Learning Models for Brain Tumor Detection. Procedia Computer Science, 218, 2468-2479.

[10] Abd El Kader, I., Xu, G., Shuai, Z., Saminu, S., Javaid, I., & Salim Ahmad, I. (2021). Differential deep convolutional neural network model for brain tumor classification. Brain Sciences, 11(3), 352.

[11] Hossain, M. Z., Sohel, F., Shiratuddin, M. F., & Laga, H. (2019). A comprehensive survey of deep learning for image captioning. ACM Computing Surveys (CsUR), 51(6), 1-36.

DOI: 10.54254/2755-2721/19/20231007

[12] Tummala, S., Kadry, S., Bukhari, S. A. C., & Rauf, H. T. (2022). Classification of Brain Tumor from Magnetic Resonance Imaging Using Vision Transformers Ensembling. Current Oncology, 29(10), 7498-7511.