Turkish Online Journal of Qualitative Inquiry (TOJQI)
Volume 12, Issue 10, October 2021: 582-589

Analyzing the Performance of MRI-Based Brain Tumor Detection and Segmentation with Deep Convolution Neural Networks

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Abstract

A brain tumour is an uncontrolled development of irregular cells formed in various parts of the brain. The image processing based approach is one of the promising solutions for accurate identification of tumour's in a brain like Magnetic Resonance Imaging (MRI) and Computer Tomography (CT). Manual segmentation of tumour's lead to errors in detection and is more time-consuming. Recently, many segmentation approaches have been developed for brain tumour segmentation and classification, among them, deep learning (DL) methods have a good impact and outperform other machine learning algorithms. In this work, a complete summary of MRI-based brain tumour segmentation methods is explained. Primarily, basic steps of image processing steps are explained. Then, segmentation methods proposed by various researchers using deep learning algorithms are summarized. Finally, performance parameters used for segmentation is presented.

Keywords: Magnetic Resonance Imaging (MRI), Computer Tomography (CT), Deep learning, Brain Tumour Segmentation

1. Introduction

A brain tumour (BT) is a growth of uneven cells in the brain which causes a severe threat to human life. Brain tumours based on the cause can be Primary tumours and Secondary tumour's. The primary tumours are Gliomas, meningioma and nerve sheath tumour's originated from the brain itself. The secondary tumours are originated from the human body and spread into the brain also named metastatic tumour's. Based on a world health organization survey, nearly 600,000 people in the world have a BT. As such, researcher's and medical field experts shows interest in identifying new BT identification techniques.

There are two common imaging techniques used to identify the tumours based on structure and shape are MRI and Computer Tomography (CT). MRI based imaging systems are normally preferred by doctors due to their clear and more exhaustive view of internal organs than CT without the radiation exposure related to CT. Automated detection methods lead to higher accuracy of detection than manual identification.

Recently, Machine learning (ML) and Deep learning(DL) systems are successfully applied in medical image processing for reconstruction, segmentation, medical preparation and decision-support devices. The ML algorithms of K-means for clustering, Hierarchical clustering, Support Vector Machine (SVM), Naive Bayes (NB), and decision tree techniques are used for segmentation and disease classification tasks.

Segmentation of brain tumours is normally classified into two categories: generative models (GM) and discriminative models (DM). GM is based on the structure and spatial spreading of both normal and abnormal tissue. DM are depending on a large number of extracted features and data given for training. DL algorithms are considered as one of the well known DM techniques where the model learns the feature without prior data.

The difficulties associated with brain tumour segmentations are Location Uncertainty (LU), Morphological Uncertainty (MU), Diffusion and Low Contrast, Annotation Bias and Imbalanced Issues. LU are spatial spreading of High-Grade Glioma (HGG) or Low-Grade Glioma (LGG) regions inside the brain. MU defines structural and shape variations of tumour regions. Due to the low resolution nature of the image, the visibility and patterns of the image were extracted very poorly. The annotation biases have a massive influence on the segmentation technique which may be disordered by the biases through the training and classification process. Further, an unbalanced count of voxel greatly affects the training and learning process.

This work reviews various deep learning algorithms developed to handle the above difficulties and results achieved from that models. The basic steps DL based tumour segmentation includes four steps: data set collection, pre-processing, DL model development and performance analysis as shown in Figure 1. The most common data set used for segmentation is the Multimodal Brain Tumour Segmentation Challenge (BRATS) data set which consist of MRI scans of 260 patients, to train and test the DL model. Data prepossessing steps include noise filtering, RGB to grayscale conversion, image resizing and data augmentation etc. DL model development constructs a layer model to extract and learn features from images for segmentation and classification

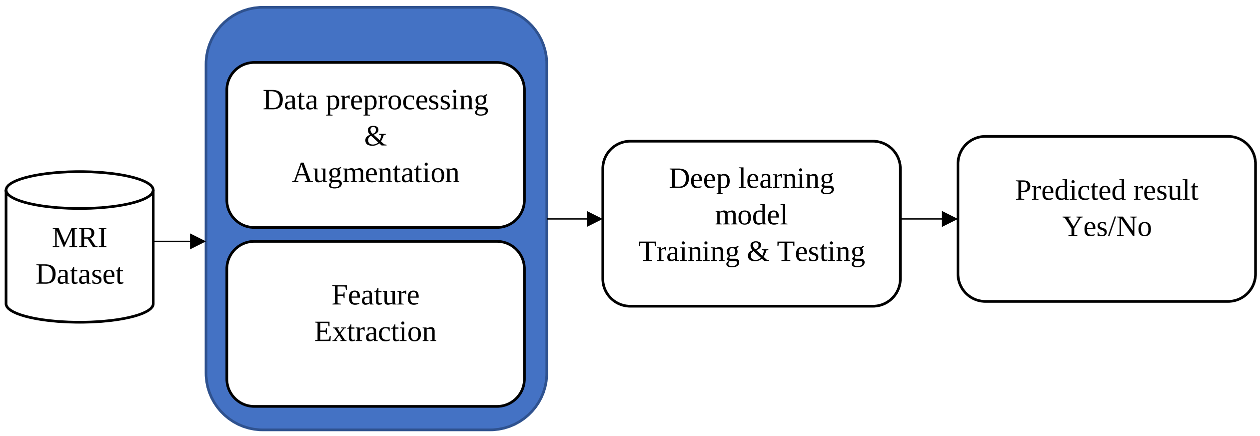

Figure 1: Workflow brain tumour segmentation using DL.

Section 2 explains a detailed survey of existing deep learning models. Section 3, describes the performance parameter used for segmentation evaluation. Finally, we conclude this work by summarizing the advantages of DL algorithms with future work.

2. Related work

This section summarize the related works that are performed to segment BT's using existing DL techniques.

Pereira, S et al 2016 have proposed a 3*3 kernel-based CNN for brain tumour segmentation. The process of Intensity normalization has been used for pre-processing. The Kernel-based approach has reduced the overfitting problem effectively and is used to get deeper details of an image. The proposed method was tested on BRATS 2013 data set and compared against various existing methods. Results show that the proposed system achieves a Dice Similarity Coefficient parameter of 0.89, 0.76, and 0.86 for the complete, core, and enhancing regions, respectively.

Zhou, T et al 2021 have proposed a multi-encoder based segmentation model for brain MRI images. The proposed model includes four blocks namely encoder, correlator, fuser and decoder. The proposed model has been introduced particularly to concentrate on the latent multi-source correlation. The fusion block is used to combine all spatial features of an image. The proposed model has been implemented on BraTS 2018 and BraTS 2019 dataset, it achieves on average Dice Score (DC) of 3.5%, 6.9%, 20.8% for whole, core and enhancing tumour, correspondingly.

Yu, B et al 2021 have proposed deep SA-LuT-Net model tumour segmentation and classification. It includes both the LuT element and a segmentation element to capture a nonlinear intensity mapping function. The nonlinear intensity mapping functions are used to learn the piece-wise linear functions and the power functions from the pixels. For classification, an improved U net has been used. results show that the proposed method outperforms in terms of accuracy, dice coefficients and sensitivity etc.

Zhao, L et al 2015 have proposed a 2D-CNN model for brain tumour classification. The use of a 2D model instead of 3D reduces the overall complexity of an algorithm. It classifies the tumour into the types of necrosis, edema, non-enhancing and enhancing types. For evaluation, dice similarity is used to compare the segmentation results with ground truth images.

Alkassar, S et al 2019 have proposed a hybrid transfer learning and deep learning model for brain tumour segmentation. For pixel-wise classification, VGG-16 network has been utilized which consist of an encoder and decoders to process the features. Implementation results on the BRATS2015 database show that the proposed model achieves higher accuracy of 0.8992 and a DC of 0.89 which is higher than other traditional methods.

Chen, F et al have developed a Dense-Unet++ model for segmentation in MRI images. Unet++ is used for the fusion process in the deep net in order to reduce parameter processing complexities. The proposed model was constructed by series of bridges for different semantic levels to achieve an effect of fusion. The proposed model outperforms in terms of accuracy, precision and recall when compared to other methods. Derikvand, F et al have proposed a CNN based tumour segmentation algorithm which is constructed by the combination of all layers from a different network, the proposed model includes the different layers of Convolution layer, Max-pooling layer, Batch-normalization layer, Dropout layer and Up-sampling layer. For post-processing, morphological operations carry out to reduce false-positive rates. Outcomes show that the proposed model achieves a DC of 91.07% and sensitivity of 82% on BRATS2017 dataset. Mzoughi, H et al 2020 have developed an optimized deep learning model for Gliomas segmentation in brain tumours. To overcome the drawback of Fully Convolutional Networks, U-net is used for optimization to handle the data heterogeneity. Further, intensity normalization is performed followed by data augmentation improves the segmentation accuracy of the network. Three parameters of Whole Tumor (WT) , Tumor-Core (TC) and Enhancing-Tumor(ET) used for evaluation. The proposed method achieved a dice complete, core and enhancing values of 0.88,0.87 and 0.86 respectively.

Qamar, S et al 2018 have proposed a 3d hyper CNN model for brain tumour segmentation. It learns both global and local contextual features from the image and is processed separately to reduce complexity. The usage of the compressed DenseNet model reduces overall parameter processing. The proposed method achieved a DC, TC and ET values of 0.87,0.84 and 0.81 respectively. Compared to another network, the proposed model shows a higher accuracy value of 93%.

Deng, W et al 2020 have presented a developed Heterogeneous Convolution Neural Networks model for tumour segmentation. The proposed model contains of three steps: pre-processing, training by patching and picture slices, parameter tuning. Also, the voting fusion method is employed to increase segmentation accuracy.

Xu, F et al 2019 have proposed an LSTM and U-Net combined model for image segmentation. The features extracted using the U-Net model is used to train the LSTM model. LSTM works based series of data with previous memory to forecast labels called slice sequence learning. For evaluation, the parameter of intersection over union (IoU) has been used for each label. Implementation results on BRATS-2015 data set show the proposed model attain a higher IOU rate of 0.9921 than the conventional U-Net model.

Ali, M et al 2020 have proposed a collaborative of two deep learning networks for accurate tumour segmentation. It combines U-Net model and 3D CNN model for effective description of tumours into intratumoral classes. The hyperparameters of the learning rate,input size, batch size and loss functions are tuned by using Adam optimizer. The proposed ensemble model was applied in BraTS 2019. Implementation results show that the proposed achieved a dice score of 0.860, 0.805 and 0.8211 on ET, WT, and TC, respectively.

Aboelenein, N. M et al 2020 have proposed a Hybrid Two-Track U-Net(HTTU-Net) for image segmentation. It involves a two-track model for utilizing different layers and kernel sizes. The output from layer and kernel tracks is added to get a final output. LeakyReLU activation function is used for patch normalization and accuracy improvements. implementation results on BraTS’2018 dataset show that improvement of dice scores was achieved from 0.81 to 0.89 when compared single track model.

Ahmed, S. F et al 2019 have developed U-net based semantic algorithm for Multimodal Brain Tumour Image Segmentation. The 2D operations of the convolutional U-net are replaced by 3D features mapping and extraction. To reduce computation time, augmentation is carried out into the small size $16 \times 16 \times 16$ patches with a batch size of 8. The proposed model takes less than 2 sec for execution which is comparatively lower than other models. Abdullah Rasyid, D et al 2021 proposed a hybrid model for segmenting Low-Grade Gliomas in brain tumours. It combines three models of U-net, VGG16 and transfers learning model to improve the segmentation accuracy. Transfer learning is used to reduce the training time of other models by utilizing extracted knowledge. The proposed model achieved an accuracy of 88.9% but requires higher resources to execute a model.

Majib, M. S et al 2021 have analysed 16 different transfer learning models to find the best model for tumour classification. The stacked model constructed by three layers outperforms other models. the first layer consists of neural, SVM and random forest classifiers. The second layer contains the regression model and the third layer combines all the outputs. Also, the F score obtained by the proposed model increased when compared to other models.

Neil Micallef et al 2021 have introduced a U-Net++ for medical image segmentation. U-Net++ varies from the traditional model by the loss function, several convolutional layers, and the technique of using deep supervision. It converts intensity contrast to segmentation operation to get an adaptation. It also acquires a nonlinear intensity mapping function to increase the segmentation accuracy.

Meng, Z et al have proposed a light noise suppression network for pre-processing in medical images. Initially, Slice-based Normalization is performed to improve adaptability. Then, Suppression U-net is used to extract features accurately. General simulation on BraTS 2016 datasets shows the proposed model shows superior performance than other methods in terms of accuracy, F score and DC etc. Recently proposed DL algorithms and their implantation results are given in Table 1.

Table 1: Survey summary

Author	**Modality**	**Method**	**Performance metric and results**
X. Kong et al	Tumour segmentation	Hybrid pyramid u-net	Accuracy- 93 %, sensitivity 74%
M. Shaikh et al	Tumour segmentation	Dense fully convolutional neural network	TC- 0.87, AT- 0.68 and DC- 0.65.
J. Liu et al	Genotype prediction	Cascaded deep convolutional neural network (CNN)	Dice similarity coefficient 77.03
Y. Yoo et al	Tumour segmentation	Euclidean distance transform (EDT)	Accuracy rate - 72.9
M. Cabezas et al	Tumour segmentation	Transfer learning	ET -0, WT-0.4367 and TC-0

Yan Hu et al	Tumour segmentation	3D Deep Neural Network	Dice similarity coefficients of 0.81, 0.69 and 0.55 in the segmentation of WT, CT and ET
Ronneberger, P et al	Medical image	U-Net	Accuracy 94.6

3. The performance metric for valuation

To evaluate the efficiency of DL algorithms in tumour segmentation, the following metric has been used. Evaluation Metrics were used to validate the proposed method with existing methods.

Dice Score (DS):

DS is calculated to find matching between segmented results to ground truth image. It varies from 0 to 1.

Dice Score = 2 *T P /2T P + F P + F N

Where TP denotes the true positive pixels, FP denotes false positive pixels, FN denotes false-negative pixels and TN denotes true negative pixels measured with respect to Ground truth (GT) image.

Sensitivity :

It calculates the correctly identified percentage of results

Sensitivity = T P T P + F N

Hausdorff Distance (HD):

It is calculated between the boundaries of the estimated results and GT. It is used to denote the largest segmentation error. The better result will have a minimum HD value.

4. Conclusion

This work reviewed the various Deep Learning based segmentation algorithm for MRI brain images. The steps involved in segmentation and performance parameters used for verifying accuracy also discussed. the challenges and open issues in brain tumour segmentation is discussed. Using different DL techniques is a challenging task due to its processing complexities and training. we also study the performance of existing DL algorithms in terms of performance parameters. Future, the accuracy and performance of DL techniques can be improved by tuning the hyperparameters of models using optimization algorithms.

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