

Brain Tumor Segmentation And Detection Using Deep LearningMohd Arshad Siddique¹, Arham Ansari², Mohd Asif Siddique³, Dr. Mohd Riyazoddin Siddiqui⁴^{1,2,3} Final year Student, Department of I.T, M.H. Saboo Siddik college of Engineering⁴ Associate Professor, Department of I.T, M.H. Saboo Siddik College of Engineering

Abstract — A brain tumor is a collection, mass, or growth of abnormal cells in the brain. It occurs due to abnormal formation within the brain. Recently it is becoming a major cause of death of many people, so to save a life, immediate detection and proper treatment need to be done. Determination of tumor extent is a major challenge in treatment planning of brain tumor. Diagnosis and treatment of brain tumors require a delicate segmentation of brain tumors, as a prerequisite. Non-invasive technique like MRI has emerged as a frontline diagnostic tool for brain tumor diagnosis. Manual segmentation of brain tumor extent from MRI volumes is complicated and time-consuming task due to complexity and variance of tumors. This conventional method relies on physician's experience and knowledge which conventionally cost a lot of precious time. In this context, a fully automatic segmentation method is needed for an effective brain tumor detection assisting the doctor in diagnosis and treatment planning. Recently various techniques have been developed for automatic detection of brain tumor. Deep learning method have been proved to be popular compared to other state of the art method as it achieves promising result. In this paper, we have presented several works performed by the different authors for detecting the brain tumor using deep learning techniques such as DNN and CNN, and also highlight the proposed method of various authors by summarizing the papers.

Keywords — Brain Tumor, Glioma, MRI, Deep Learning, CNN, Segmentation.

I. INTRODUCTION

Brain tumor is a growth of abnormal cells and uncontrolled cells divisions within the brain. There are many different types of brain tumor exist. Malignant and benign are the two main types of brain tumor that have been identified. Malignant are cancerous tumor that contain cancer cells, while Benign tumor are non-cancerous tumor. Generally, brain tumour can be categorized as primary brain tumor or secondary brain tumor. Primary brain tumors originate in the brain while secondary brain tumor or metastatic tumor occur due to spreading of cancer cells in the brain from another organ of the body, such as your lung or breast.

Gliomas are one of the most common types of primary brain tumors that originate from glial cells [1]. It accounts for 80% of primary brain tumor in adults, and lead to very short life expectancy. According to World Health Organization (WHO), Glioma can be categorized into viz. Low-grade gliomas (LGG), (WHO grades II and III), and high-grade gliomas (HGG) or glioblastoma (grade IV) [2]. Glioblastoma is one of the most deadly and aggressive disease with poor prognosis [3]. According to report published by CBTRS, for study conducted on people treated between 2000-2014 for glioblastoma, the relative survival rate for 5 year it was seen to be 19% for age group of 20-44, 8% for age group of 45-54, and 5 % for age group of 55 and above.

Medical imaging techniques are used in diagnosis and treatment of brain tumor. There are various imaging modalities available such as: X-ray, CT (Computed Tomography) and MRI (Magnetic Resonance Imaging), Ultrasound, SPECT, PET and X-ray. When compared to other medical imaging techniques, Magnetic Resonance Imaging (MRI) is extensively used as it provides good soft issue contrast and doesn't expose patient to ionizing radiation [4]. MRI is a non-invasive medical imaging modality which provide crucial information about tumor extent shape, size and its impact on the surrounding areas. MRI-scan uses a combination of powerful magnetic field and radio waves to produce detailed images of organs, soft tissues, bone and other internal structures of human body with high spatial resolution. As shown in Fig (1), MRI scans comes with different sequences. T1, T1Gd, T2, and T2-FLAIR are the most common MRI sequences that provide valuable structural information for glioma diagnosis.

The detection of tumor size and location from MRI images plays a significant role in diagnosis and surgical planning. Once the tumor has been clinically identified by analysing MRI images, a radiologist may assess the tumor and plan treatment, such as surgery, chemotherapy, etc [5].

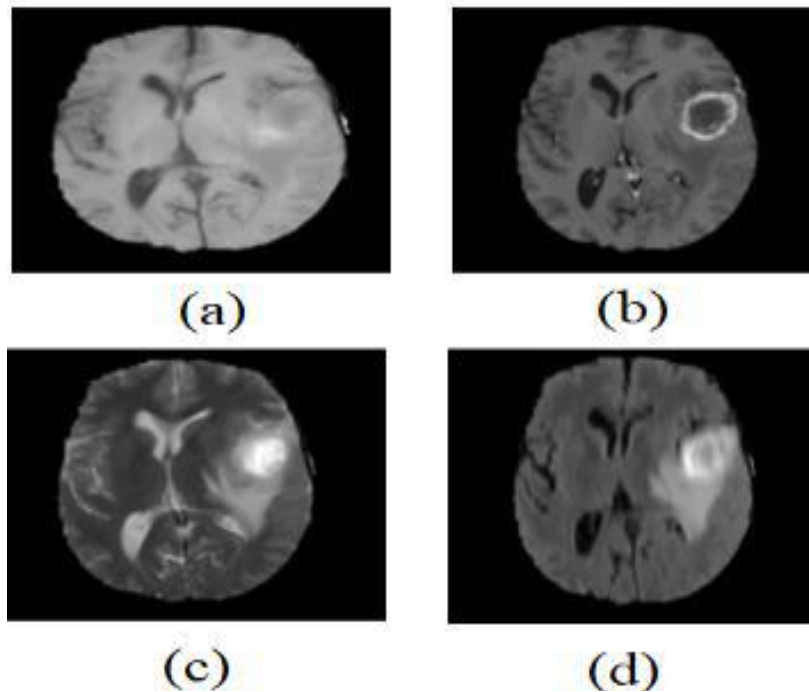


Fig. 1. Four sequences of MRI :(a) T1, (b)T1Gd, (c)T2, and (d)T2- FLAIR (BRATS Dataset [8])

This identification of tumor from MRI images is done manually. Because of the complex brain structure manual marking and delineation task is tedious and labour sensitive, and the outcome depends on the skill of operator. Therefore, fully automatic segmentation methods are required which will detect the tumor and improve patient survival rates. Hence, researchers developed various deep learning model and proposed several machine learning and deep learning method for the precise segmentation and detection of these diseases.

II. METHODOLOGY

A. Automatic Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks

Dong et al. [6] proposed a fully automated system for the segmentation of brain tumors. The system uses a deep neural network approach based on the U-Net model proposed in [7] for the detection of brain tumors. BRATS 2015 datasets were taken from [8] to evaluate the model. Fivefold cross-validation method was used for model evaluation. This dataset contains 220 high-grade gliomas (HGG) and low-grade glioma (LGG) patient's MRI scans. Each patient scan has four MRI sequences that were resampled and interpolated to an image size of 240*240*155. They used sets of data augmentation techniques on the training datasets as a pre-processing step before training the model to increase the training dataset size, and to improve the performance of the model. The model as shown in fig (2) consists of two paths: encoding path and decoding path. These two pathways are linked using skip-connections. The encoding path is a stack of convolutional and max-pooling layers that are used to capture the context in the image. In encoding path image

size gradually decreases while the depth gradually increases. The Decoding path is the symmetrical expanding path used to enable precise localization employing transposed convolutions. In the decoder path, the size of the image gradually increases and the depth gradually decreases. Encoding path has 4 convolution blocks where each block consists of two 3x3 convolutions layers, each followed by the ReLU activation function and a 2x2 max pooling operation with stride 2 for down sampling. At each down sampling path, the number of features map is doubled and the size of the feature map is reduced. The decoding path consists of up sampling and concatenation followed by regular convolution operations. While training this model, Dong et al. used soft dice loss function describe in [9] rather than cross-entropy function as a cost function because it is adaptive to unbalanced samples. They used a stochastic gradient optimization technique to minimize the cost function, adopted Adam optimizer, and set its parameters to value: learning rate to 0.0001, maximum no of epochs to 100. Therefore, compared to other state-of-the-art methods, their method achieves an accuracy of (0.86) Whole tumor (0.86) Core tumor, and (0.65) Enhancing tumor.

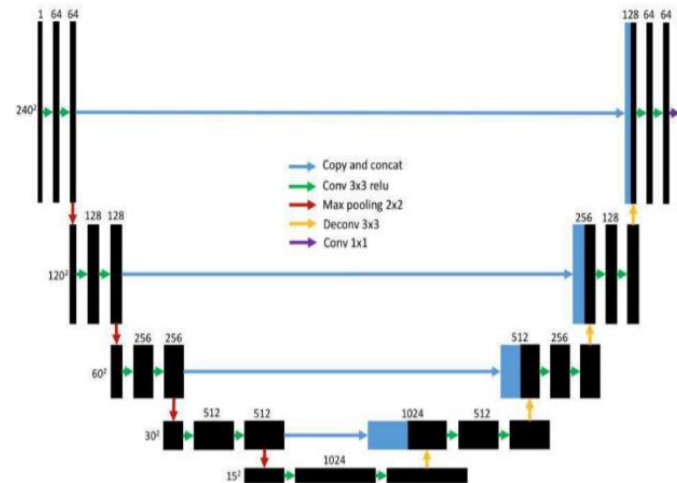


Fig. 2. U-Net architecture proposed by Dong et al.

B. Brain Tumor Segmentation Using Deep Learning by Type Specific Sorting of Images

In [10], authors have presented an automated technique for brain tumor segmentation which is based on a convolutional neural network. Convolutional neural networks (CNNs) do not use hand-designed features. CNN directly extracts features from pixel images with minimal pre-processing.

They used the T1-weighted MRI image dataset consisting of 3064 images belonging to around 233 patients and used Link-net CNN architecture to train it from scratch. Of the 3064 images, 708 are meningiomas, 1426 are gliomas, and 930 are pituitary tumors images. All these images are grayscale, and were captured from different angles of the skull. They partitioned and sorted these datasets images into three groups based on the image view, and trained each group on three Link-net networks separately to achieve accurate segmentation result. The Link-net Network [11] consists of the left part and right part, the left block is encoder block while the right part is the decoder block. The network starts with the Initial block, which implements a 7x7 kernel size, max pooling with stride 2. Binary cross-entropy was used as the loss function in this network. The encoder output is applied to the decoder to improve Link-net's efficiency and help the decoder recover the encoder layer information. As each group's images were trained on the Link-net network, about 900 images were used for training purposes in each group, and about 200 images were used as testing purposes. Dice criterion called the overlap index was used as a measure to evaluate the result. Therefore, the best dice score they obtained was 0.79 for the sagittal view which can be improved or increased by pre-processing the group of images.

C. Brain Tumor MRI Segmentation and Classification Using Ensemble Classifier

For tumor identification [12], an ensemble method was used. The Ensemble method is a combination of various processes such as neural network, support vector machine classifiers and extreme learning machine (ELM). This identification process has been divided into four steps: pre-processing, segmentation, feature extraction, and ensemble classification. In the first step, the image was pre-processed using a median filtering algorithm to eliminate unwanted artifacts and noise. FCM was used for the segmentation process in the second step. The third step involves the extraction of information. It is the most important step because it extracts the most relevant data from the input images. Contrast, Intensity Correlation, Shape, Color, Texture are some of the features that have been extracted using the GLCM method for the extraction of data. The final step i.e. Ensembled classification, consisting of the SVM classifier, ELM, and the Feed-Forward neural network, is used to classify tumor and non-tumor brain images. The performance of the ensemble classifier was compared with all other classifiers in terms of precision, sensitivity, accuracy and F1 score. Therefore, they concluded that the Ensemble Classifier produced the best results for various aspects compared to all other classifier techniques.

D. Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images

In [13], the author proposed an automatic brain tumor segmentation method as shown in fig (3) based on Convolutional Neural Networks (CNN). Their proposed method uses convolutional layers with small 3x3 kernels for deeper architectures which provide promising results. Smaller kernels can stack more convolutional layers and have fewer weights that make them less prone to overfitting while having the receptive field as that of the bigger kernel. In this proposed method BRATS 2015 dataset has been used to train the model. LeakyReLU proposed by [14] is used as an

activation function in their proposed CNN. They minimized the loss function and used Stochastic Gradient Descent as an optimization algorithm. Intensity normalization, Intensity bias correction and Input patch augmentation method have been implemented for pre-processing operations which provide effective results. Hence, the evaluation result obtained was 0.78(Complete tumor), 0.65(Core tumor), and 0.75(Enhancing tumor).

E. Brain Tumor Segmentation and Survival Prediction Using Multimodal MRI Scans with Deep Learning

In [15], After studying papers [16][17], the author found out that training different model independently and fusing their result would boost the performance. For accurate tumor segmentation, the author used an ensemble model approach through a majority rule. This approach reduces model bias and improves overall performance. An ensemble model is a combination of different CNN architecture.

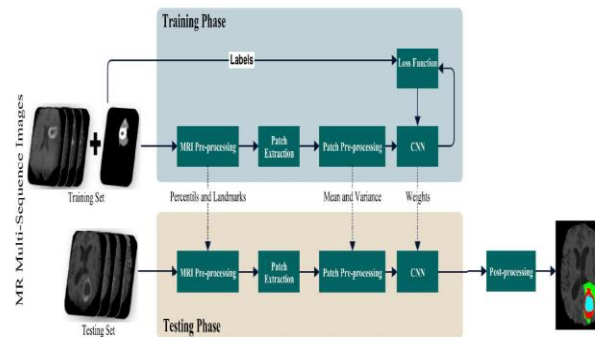


Fig.3. Overview of the proposed method of Pereira et al [13].

Their ensemble model comprises of three different CNN architecture: (1) CA-CNN [18], (2) DFKZ Net [19], (3) 3DU-Net [7]. They used BRATS 2018 dataset to evaluate their model performance.

This data set consists of three sets: the training set, validation set, and test set. The training set contains 210 HGG and LGG scans of 285 patients, the validation set contains MRI scans from 66 patient and the test set had images from 191 patients. These images were pre-processed by the intensity normalization method to alleviate the bias in images. They used the random flipping algorithm to reduce overfitting and random Gaussian noise for training set augmentation. The model was trained using the BRATS 2018 training set and applied the trained model on the validation set as well as a test set for prediction. During the training process, different models were trained independently and the result of each model was fused through the majority rule. They used the Dice metric to evaluate the segmentation result. The evaluation result of the segmentation obtained on the test set was 0.87 (Complete tumor), 0.79(Core tumor), 0.71(Enhancing tumor).

III. DISCUSSION

TABLE 1. Comparison of various method using different dataset to detect the brain tumor in terms of dice score.

Year	Author	Dataset	Method	Dice score		
				Complete Tumor	Core Tumor	Enhancing tumor
2016	Pereira et al. [13]	BRATS 2015	Convolutional Neural network with small filter of size 3*3	0.78	0.65	0.75
2017	Dong et al. [6]	BRATS 2015	U-Net architecture based fully connected neural network.	0.86	0.86	0.65
2017	Kamnitsas et al. [20]	BRATS 2015	3D CNN with fully connected CRF	0.87	0.77	0.78
2018	Isensee et al. [19]	BRATS 2015	U-net with more filters and data augmentation techniques	0.85	0.77	0.64
2019	Sun et al. [15]	BRATS 2018	Ensemble 3D CNN architecture	0.87	0.79	0.71

IV. CONCLUSION

As brain structure is complex in nature detection of brain tumor is a challenging and time-consuming task, early detection of brain tumor is needed to aid the physicians in diagnosis and proper treatment planning, thus increasing the patient survival chances. Various current state of the art method based on deep learning techniques have been introduced for early detection of brain tumor. After surveying several papers, it was found that current state of the art method used by Kamnitsas et [20] and Sun et al [15] yield better result as shown in table (1) for complete tumor compared to other methods. It was seen that Sun et al used ensemble approach which reduces model bias and increases the performance whereas Kamnitsas et al. used 3D CNN with CRF approach as it provide computational efficiency and alleviate inherent class imbalance.

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