Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 8 Issue 12, December-2019

# Recent Advancements in Brain Tumor Segmentation and Classification using Deep Learning: A Review

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***Abstract*—Brain tumor is a deadlier disease with more fatality rate than the survival rate. Nowadays, with the advent of technology, it is becoming desirable to perform automated computer-based brain tumor image analysis. The two most important tasks covered in literature for brain tumor analysis are tumor segmentation and tumor classification. Deep learning approaches are gaining popularity because of their self-feature learning capability. The review aims to provide an introduction to recent works that use deep learning methodologies for brain tumor analysis. The manuscript first describes the problems in computer vision for brain tumor segmentation. Then, the recent cutting-edge works are discussed for segmenting brain tumor along with its prediction.**

***Keywords*— Brain tumor; classification; segmentation; deep learning; recent trends.***

## I. INTRODUCTION

Machine learning (ML) [1-7] is a center of manmade consciousness [8]. It is the principal approach towards planning wise computers. AI for the most part utilizes acceptance and blend hence enabling PCs to get new information by reproducing human learning conduct. It redesigns current learning to ceaselessly improve computer execution. AI has additionally been broadly applied in numerous fields, for example, medical diagnosis [9-21], agriculture [22, 23], scene analysis [15, 24, 25] and computer vision [5, 26-33]. With the advancements of neural networks [34, 35], the idea of deep learning (DL) has been proposed. DL isn't just an improvement in neural systems, yet additionally another field in ML research. The effective utilization of DL brings ML closer to manmade reasoning. Since profound learning comprises of progressively concealed layers in contrast with neural systems, an increasingly conceptual significant level element portrayal for various classes is framed by utilizing different layers to join low-level features. Like computerized reasoning, deep adapting endeavors to fabricate and reproduce human mind to examine the learning procedure of neural system which mimics the learning component of human cerebrum when it happens to comprehend obscure ideas. DL can be utilized to consequently discover features from a given dataset for every application. By and large, traditional techniques depend on some earlier knowledge to concentrate in a specific application. In this manner, these techniques are hand crafted feature extraction strategies. DL can discover new features that are reasonable to explicit applications yet have never been recently found by specialists. These methodologies are also known as automatic features acquisition strategies [36-38]. The medical business is one of the most noticeable enterprises where DL can assume an immense job particularly with regards to medicinal imaging. There are various research works that demonstrated productivity and adequacy of the utilization of DL in the field. Brain is a vital part of human body [39] and comprised of many specific regions.

Brain tumor is incited because of an ordinary boom of cells [40]. It comes under two categories that are malignant or benign. The benign tumors do not contain cancerous cells while the malignant tumors are comprised of cancerous cells [39, 41, 42]. Brain tumors associations [43] classify the brain tumor in four grades where grade I and II are referred to as benign and the remaining III and IV are labeled as malignant. The development rate of benign is relatively low when contrasted with malignant. When the benign isn't dealt with opportune then it is changed into malignant tumor.

Along these lines, early discovery of tumor is desirable[44]. Grade II patients require ordinary treatment and checking through magnetic resonance imaging (MRI) [9, 42, 45, 46]. MRI depicts one of radio imaging types. Some more types include computed tomography (CT) and positron emission tomography (PET) [47] with the help of which brain tumor can be diagnosed in medical imaging[48]. MRI is mostly useful to analyze tumors in general clinical routines. It provides minute information about human cerebrum. One advantage of MRI is its non-intrusive nature and no ionization radiation.

DL is most broadly utilized for brain tumor investigation in numerous scenarios for example, ordinary or irregular cerebrum tumor categorization and segmentation. A convolution neural network (CNN) represents a most famous DL structure utilized generally for characterization and segmentation of brain tumors. This is accomplished by convolving the images utilizing learned channels to assemble a chain of features activations. This deep learning work is done in a few layers to such an extent that the features acquired are interpretation and twisting invariant bringing about the high level of exactness.

General computer vision steps for image analysis include: image acquiring (input), pre-processing [49-53], segmentation (to highlight required regions)[54], feature extraction (to

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 8 Issue 12, December-2019

acquire best characteristic points in an image) [55-57], features reduction (to acquire optimized features) [35, 41, 58-61] and classification (to predict the image types e.g. HGG or LGG).

Programmed division and prediction of brain tumors with the help of PC vision is significant for medical specialists as a second opinion for better treatment. Be that as it may, it stays hard for automated techniques to precisely segment and predict brain tumors. This is because of the reason that the tumor regions have a variety of variations in terms of shape, size and textures. Also change in the location of tumor regions is a real problem. Nowadays, deep learning strategies have become the cutting-edge strategies for brain tumor analysis as contrasted to old traditional methods. This manuscript mainly encompasses on a survey about recent trends for brain image segmentation and classification by employing DLstrategies. The major focus of this work is to give the readers an insight to these areas so that they can contribute further in an effective manner for brain tumor research.

## II. LITERATURE REVIEW

### A. *Tumor segmentation*

To understand brain tumors and tumor structure, a preliminary study is presented below before discussing the literature for advanced deep methods in tumor segmentation.

#### *1) Preliminary study before segmenting tumor*

Gliomas are the most well-known brain tumors [62]. Some tumors because of low grade can be less destructive. Patients having such tumor can survive for many years [63]. Whereas some tumors of high grade are more destructive and can have survival duration of not more than two years [64]. Even though medical surgeries, which becomes a widely recognized treatment for brain cancers, along with other methods [65] are also the alternate solutions for tumor removal. MRI gives detailed pictures of cerebrum. Segmentation of some tumors, for instance, meningiomas can effectively be performed while it becomes hard to partition many other tumors, for example gliomas and glioblastomas[66]. These tumors are mostly combined with edema (swelling around the tumor region) and have poor contrast and structures [67]. This results in difficulty to fragment the tumor portion accurately. Additionally, images acquisition from different machines and different image sequence types may wind up having radically extraordinary grayscale esteem when envisioned in various clinics. The theme of segmenting tumor is to localize the tumor region. Types of tumor tissues include dynamic tumor, necrotic and edema. Glioblastomas are tough to detect because of their outskirts being frequently fluffy and difficult to differentiate from normal or healthy tissues. More than one MRI sequences are considered which include T1, T1C, T2 and FLAIR.

#### *2) Deep segmentation strategies*

There is a variety of DL building blocks used by the scientists for segmenting the brain tumor in recent times. Some of such blocks contain deep convolutional neural networks (DCNNs) [68], recurrent neural networks (RNN), long short-term memory (LSTM), deep neural networks (DNN), auto encoders (AE) and generative adversarial networks (GAN). The accompanying sections discuss the existing literature in terms of these building blocks.

Deep learning methodologies produce automatic features. The general strategy is to pass an image through the trained pipeline of deep learning building blocks and input image segmentation is performed depending on the deep features.

*a) DNN*

DNNs are the type of neural networks having a number of layers. DNN concentrates more on how the data from information is spoken to by means of a lot of nonlinear capacities before arriving at the yield layer. Havaei et al. [62] use a novel DNN model which encompasses both high and low level features. The authors claim that with support of GPUs, the approach is speedier as compared to cutting edge.

*b) RNN/ LSTM*

RNN is based on sequential data. S. Grivalskyet al. [69] select BraTS-17 dataset to perform HGG segmentation based on the proposed RNN architecture.

LSTM is an upgraded form of RNNs intended to design for sequence data [70]. Each LSTM unit views a pixel and gets contribution from previous LSTM units. In this way, it recursively assembles data with all different pixels in the figure. A small number of research works are presented on brain tumor segmentation using LSTMs. Stollenga et al. [71] propose epic Pyramidal Multi-Dimensional LSTM (PyraMiD-LSTM) systems to utilize a somewhat extraordinary topology for the segmentation of tumor. The strategy is simpler to parallelize, requires less calculations in general, and performs best on GPU designs and 3D images. Good results of segmentation are achieved on MRBrainS13 dataset. LSTM-MA [72] utilizes multimodality based segmentation. Pixel-wise and super-pixel features are considered with LSTM classifier to perform semantic segmentation. The method is assessed on BrainWeb and MR BrainS datasets.

*c) AE*

AEs are another DL building blocks. Various variants of AE are used by researchers in order to segment brain tumor [73, 74]. Three layers stacked denoising AE is deployed in a research work to reconstruct the input image for segmentation [75]. In another work, deep spatial auto encoding strategy is used for segmenting the brain tumor. Some more works that emphasize auto encoders are [76-79].

*d) CNN*

CNN models are progressively perplexing with certain frameworks having excess of 100 layers which depicts a large number of loads and billions of associations between neurons [80, 81]. A normal CNN design comprises of ensuing layers of convolution, pooling, initiation and prediction. A large variety of works is found in literature that utilizes CNNs for segmenting brain.

A novel method, Hough-CNN [82] is presented to deal with selected division by utilizing the deliberation qualities of CNNs. The technique depends on Hough casting, a methodology that takes into consideration completely programmed segmentation. This methodology doesn't just utilize CNN prediction results; however, it likewise performs casting by using the highlights delivered by the deepest segment of system.

Javaria Amin et al. [32] introduce the concept of big data for DL in brain tumor segmentation. They propose seven-layer CNN architecture and assess their model on seven big MRI

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 8 Issue 12, December-2019

based tumor datasets. S. Hussain et al. [83] present five CNN methods to segment brain tumor. S Pereira et al. [84] use CNN with mini kernels, each having dimensions of 3×3. K Kamnitsas et al. [85] name their 3D architecture of CNN as DeepMedic. The authors include lingering connections on an early presented work. Cascaded fully CNN is applied for multi-class brain tumor extraction [86]. The anisotropic filters with multi fusion of layers make the approach more robust. U-net, also a variation of CNN, is used for tumor segmentation [87]. It is useful for training few numbers of images. A novel brain tumor division technique is proposed by incorporating a Fully-CNN with Conditional Random Fields (CRF) [88], as opposed to receiving CRF as a post-handling venture of FCNN. The model is prepared in three phases dependent on picture fixes and cuts individually. In another strategy [89], CNN is prepared legitimately on MRI modalities and in this manner gains a feature portrayal straightforwardly from the information.

A cascaded design is proposed with two pathways: one which spotlights on little subtleties in gliomas and one on the bigger setting. A two-stage fix savvy learning methodology is likewise recommended that permits to learn models in a couple of hours. Convolutional idea of model completely permits to section a total mind picture in 25 sec to 3 min.

Three distinctive 3D CNN models are investigated to take care of brain tumor division issue [90]. Two completely 3D CNN designs are suggested that propelled in two understood 2D models utilized for non exclusive image segmentation. A third model is additionally prepared which is a variation of two-pathway DeepMedic.

S Pereira et al. propose Leaky Rectifier Linear Units (LRLU) [91] in their CNN model for tumor segmentation. The tumor is divided utilizing a completely programmed DL strategy called Input Cascade CNN [92]. An interesting CNN design contrasts from other customary CNNs because of its two-route preparation of image.

U-net is also applied in [93] with dice loss function to handle unbalanced data. U-net is also considered in [94]. In this work, patch and semantic cascaded CNN models are proposed with the help of U-net architecture.

*e) GAN*

GAN is a variation of CNN and it produces great quality information by utilizing small data. GAN includes two turns, Generation turn and Discrimination turn. The former turn attempts to catch the model from which the information is taken hence creating pictures from irregular commotion inputs. The later stage utilizes traditional CNN that attempts to recognize genuine information and information produced by the generation stage.

*f) VoxResNet*

VoxResNet obtains the soul of deep residual learning. Chen et al. in their work [95] first propose a deep voxel wise lingering system alluded as VoxResNet which is then stretched out into a 3D variation for taking care of volumetric information, the learning on undertaking of volumetric cerebrum division.

*g) Ensemble methods*

Numerous research works are found that use ensemble of more than one DL building blocks to highlight brain tumor from MR images [96, 97]. Joint Sequence Learning (JSL) [98] highlights a hybrid method for multi modalities tumor segmentation. The proposed method depicts the blend of auto encoder, LSTM and a CNN. The two-sided learning mechanism is deployed to handle data imbalance. The model claims better segmentation results on BRATS 2015 dataset. Zhao et al. propose the merger of CNN with RNNs for effective tumor segmentation [99]. S. Iqbal et al. [100] use fusion of LSTM and CNN features to extract brain tumor region and perform evaluation on BRATS 2015 dataset. Y. Gao [101] introduce 4D MRI segmentation using hybrid of CNN and LSTM. The results are acquired on BRIC clinical and IBIS datasets. S. P. Ang et al. [102] also use LSTM and CNN based architecture for different brain tissues types segmentation. Better results are claimed on fMRI dataset. Table 1 depicts some more recent works regarding brain tumor segmentation.

TABLE I. RECENT METHODOLOGIES FOR BRAIN TUMOR SEGMENTATION

| **Ref** | **Year** | **Methods** | **Dataset BRATS** | **Result (Dice)** | | |
|---|---|---|---|---|---|---|
| | | | | **Complete** | **Core** | **Enhance** |
| [99] | 2018 | Integrating FCNNs and CRFs | 2015 | 0.81 | 0.65 | 0.60 |
| [83] | | Pach based DCNN | 2015 | 0.86 | 0.87 | 0.90 |
| [103] | 2019 | Mixed supervision with U-Net Extension | 2018 | 80.92 | 63.23 | 66.61 |
| [104] | | PPNet | 2018 | 0.94 | - | - |
| [105] | | Dual-force CNN | 2017 | 0.89 | 0.73 | 0.73 |
| [106] | | Patch based hybrid CNN | 2013 | 0.86 | 0.86 | 0.88 |
| [107] | 2020 | Rescue-Net | 2017 | 0.9463 | 0.856 | 0.9354 |

*B. Deep learning strategies for brain tumor classification*

The classification phase is generally dependent on a classifier method. As a general methodology, image features are extracted and passed to classifier for predictions [108]. Most of the research is focused on CNNs. In one research work, DNN is utilized as a classifier [109]. The preprocessing, feature extraction and reduction are performed using fuzzy c-mean and discrete wavelet transform (DWT) approaches. The reduced features are then transferred to DNN for predictions.

Saba et al. introduce fusion between handcrafted and CNN features to perform tumor classification [110]. P. Afshar et al. use capsule network in their work for brain tumor prediction [111]. Capsule networks (alluded to as CapsNets) are fresh AI structures proposed to defeat the weaknesses of CNNs. More work on CapsNet is done in [112]. A new architecture of 3D CNN is proposed by D Nie et al. [113]. The deep features are obtained by the proposed deep model which are then trained by support vector machine (SVM) classifier for tumor predictions. YPan [114] perform grading of brain tumors using CNN. In a work by Yan Xu [115], a previous pre trained CNN model named AlexNet is used to collect deep features for tumor classification. CNN is also used in another study [116] to classify tumor from 3,064 T1-weighted images. Some more works using CNN include[92]. In addition, Hossam H. Sultan et al. [117] present CNN based multi-class predictions for tumor classification. Pre-trained GoogLeNet [118] based features are used as transfer learning to classify brain tumor.

I. Shahzadi et al. use cascade of LSTM and CNN for tumor classification [119]. Pre-trained VGG-16 is used as a CNN building block and output of this network is supplied to LSTM network.Table 2 illustrates some more recent deep learning based methodologies regarding brain tumor segmentation

TABLE II. RECENT METHODOLOGIES FOR BRAIN TUMOR CLASSIFICATION

| Ref | Year | Methods | Dataset | Accuracy |
|---|---|---|---|---|
| [92] | 2019 | Fine-tuned VGG19 +Softmax | radiopaedia | 90.67% |
| [120] | | CNN based transfer learning | CE-MRI | 94.82% |
| [121] | | Super resolution+CNN+ELM | LR MRI | 98.33% |
| [117] | | CNN | TCIA | 97.54% |
| [122] | 2020 | Fusion of shape and texture features with VGG19 | BRATS 2017 | 99% |
| [123] | | GAN | 3064 T1-CE MR images | 95.60% |

## III. DATASETS FOR BRAIN TUMOR ANALYSIS

It is observed as a practice that a huge dataset is used for performing deep learning tasks. For brain tumor analysis, various datasets are publicly offered. The images in most of them are available in cases form. One case represents images belonging to a particular patient. Normally one case contains 154-155 sliced human brain images. So, for example, 10 HGG cases of BRATS 2012 challenge subset means that there are total 155x10=1550 images in this subset.. The various datasets used for brain image analysis include RIDER [124], Harvard [125], IBSR [126], BRATS (2012-18) [127-129] and SISS-ISLES [130],

## IV. DISCUSSION

As a general practice, in clinics, brain tumor analysis is performed manually by medical experts. This becomes a challenging job because of varying appearances and confusing brain structure. As a result, manual brain image analysis becomes tedious. On the other hand, automated segmentation and classification ease the task of neurologists because these methodologies assist them in making the final decision.

The robustness in terms of speed makes such computer assisted systems a positive contributor in medical diagnostics. DL approaches are beneficial in brain tumor research by aiding in automatic feature acquisitions. This overcomes the consumption of time as compared to manual engineering of features. The advent of GPUs makes the computation processes very fast. In addition, performance increases with increase of training data. Apart from such advantages, some limitations are also observed by using DL approaches in brain tumor domain. The high cost of GPUs makes the DL process very costly. Also, no detailed literature is found to help in the selection of specific deep network architecture for particular brain analysis problem. This study will provide hint to the researchers in observing that what recent DL models are employed in brain analysis so that further research can be performed by keeping in view the existing DL methodologies.

## V. CONCLUSION

A lot of work in performed in recent days on brain tumor MRI image segmentation and prediction with deep approaches. Still MRI is a challenging area where room for further research is available. The segmentation and classification both provide the medical experts a major advantage of second opinion based on automated results and a quick time analysis response. This saves a lot of time in manual brain image analysis. At the same time, this domain suffers because of robustness issues in terms of accuracy. This manuscript mainly focuses on existing DL techniques of segmenting and classifying brain tumors. In addition, publicly available datasets are also discussed.

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