Current Trends on Deep Learning Models for Brain Tumor Segmentation and Detection – A Review

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Abstract: **Critical component in diagnosing tumor, designing treatment and developing an outcome for evaluating brain tumor segmentation needed to be highly accurate and reliable. Magnetic Resonance Imaging (MRI) help and support the health care field to detect the very minor abnormal growth in any part of the human being. While deep neural networks (NNs) and machine learning techniques have good achievement in 2D image segmentations, but it's a challenging task for NNs to segment critical organs from 3D medical MR images. Segmentation relating tumor detection includes several processing techniques that are categorized into Pre-Processing, Segmentation, Optimization and Feature Extraction. Study focuses mainly on 3D-based Convolution neural network (CNN), ANN (Artificial Neural Networks), SVM and Multi-class Support vector machines (MCSVM) for Deeper Segmentation. To remove computational burden of processing 3D medical scans, this survey paper plan to review the current development in image segmentation and image classification based on efficient and effective towards processing of tumor infected human brain MRI adjacent image patches that can pass through the network with a target on gliomas, while robotically adapting towards an imbalance present in the data. Thus, more discriminative 3D NNs and Computational Machine learning that assists in processing the input images at multiple scales simultaneously. Finally, this article implying about present status on segmentation and Detection of tumor-based image processing through deep learning models.**

Keywords: **Deep Learning, 3D Neural Networks, Computational Classification, MRI, Brain tumor**

I. INTRODUCTION

Usually gliomas are common brain tumours which can be less aggressive also called as low grade in a patient and its' life time is more years. Gliomas with more aggressive which is also called High grade and its life time may be up to 2 years. MR image gives us in depth images and frequently prescribed tests used to identify brain tumours. Brain tumour segmentation help us to find growth rate forecast and conduct medical procedures (Havaei, 2017). MR image of brain has proved more powerful procedure not tending to spread harmfully and 3D assessment of tissue processing, imaging and analysis, metabolism, physiology and function (Prasad, 2006). MRI Results increases the knowledge of normal and diseased study of structure of organism and their parts for medical research.

Few tumours like meningioma's are easily segmented, gliomas and glioblastomas tumours are not easy to localize. Gliomas and glioblastomas tumours are frequently diffused, contrast is poor and makes difficult to segment images. Pathology Image segmentation perspective, pathology of interests can be large and there is only one in the above figure (e.g. brain tumour – Figure 1), latest technology has managed to explore some previous experience, knowledge and texture information to define in pathology. Experts can influence texture homogeneity in sub-regions (Subbanna, 2013; Bauer,2011 and Hao,2012).

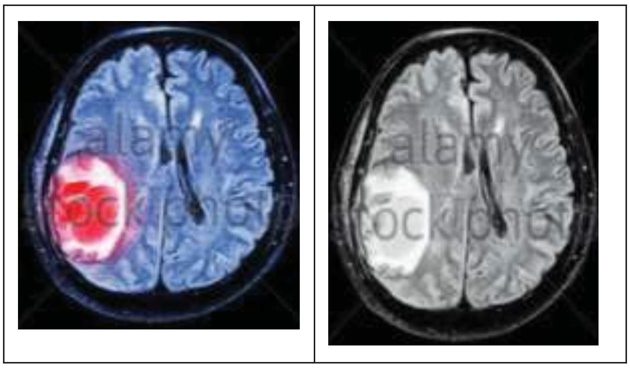

Fig.1 Brain Tumor at right parietal lobe of cerebrum
(Source: Puwadol, 2014)

II. CLINICAL IMAGING PREPARATION

Tissue appearance is challenging when its image or existing generative examples or prototype detect a tumor as shape or as signal and differ from a normal brain (Clark et al., 1998). These methods depend on anatomical models acquired after aligning of 3D MR images on a template calculated from many normal brains (Doyle et al., 2013). The classic reproductive model of MRI brain images available in Prastawa et al. (2004). Test data collection or Collecting different stages of Low-grade ad High grade MR images are comes under Clinical Imaging Preparation stage. Due to practical clinical applications the tumor structures are grouped in 3 different tumor sections. Menze et al. (2015), described tumor sections as below.

a) Four tumor structures - complete tumor area/section
b) All tumor structures except 'edema'– Core tumor section
c) Enhancing tumor section/area.

III. PROCESS AND PRE-PROCESSING

Pre-processing of images are implemented on the MR images by removing non-brain portions from the image, correct nonuniform properties and bring MR images into one common spatial and intensity space then MR images used for further processing (Karimaghaloo Z. 2016). According to (Mohsen, H, 2017) developing new architecture looks like neural networks (NN) architecture and need less hardware requirements and take suitable time of processing for big size images (256 x 256). Engaging dense-inference with 3D CNNs, Brosch et al. (2015) and Urban et al. (2014) stated total time of few seconds and maximum to one-minute duration for processing of one MR brain image. Noise removal, converting color image to gray scale, salt and pepper, applying different techniques like improving contrast to get clarity of images comes under Process and Pre-process stage. This pre-processing plays important role for next stages like Segmentation and classification. If pre-processing is done properly classification become easier.

IV. SEGMENTATION

Image segmentation is a process to divide or partitioning the digital image into multiple segments. Cardoso et al. (2015) provide a reproductive prototype for image synthesis and produce a accurate segmentation of abnormal in post-processing of network's soft segmentation. Erihov et al. (2015) proposed another unsupervised technique a saliency-based method that explores brain asymmetry in pathological cases.

V. FEATURE EXTRACTION

Texture analysis perform a critical role in tissue classification for many types of medical images (Yao et al., 2015). Approach fall into one of two categories of structure-based approach samples include filtering and statistical approach. In filtering, the texture feature vectors are generated from the local energy of filter responses.

VI. CLASSIFICATION

Joining or combining Multiple modal data with a single modal data without any loss of values drastically increase the accuracy rate in classification, many test results has been proved. When training a classifier with single data method/approach or the multiple model data accuracy rate was less. For examples, Havaei et al. (2017) suggested two-pathway shallow networks with many waterfall architectures for low- and high-grade glioblastomas image segmentation for brain MRI brain images. Support Vector Machine (SVM) is a machine language developed classifier. Now a days many advanced classifiers has been developed like Deep Learning models, where we can train the classifier with thousands of MRI sample images with normal brain, low grade and High-Grade glioblastomas accordingly. For any new type of multiclass classifier for brain tumors by synthesizing 100 factors from Gabor, GLCM, intensity, statistical, and shape extraction factor methods. The author accomplished the experimentation on 98 imageries for organizing low-grade

abnormalities manually can be identified and train the classifier for future classification. Below sections discuss about the various techniques like ANN (Artificial Neural Network) and CNN (Convolution Neural Network).

VII. CURRENT TRENDS IN DEEP LEARNING MODELS

The following section gives detailed methodology of various

CAD schemes implemented for Neural Networks (NNs) and Computational machine learning categories based upon manual, semi-automatic and fully automatic level of user interactions (Gordillo N et al 2013).

Fig.2(a) Percentage of Deep Learning papers
Source: The Economist.

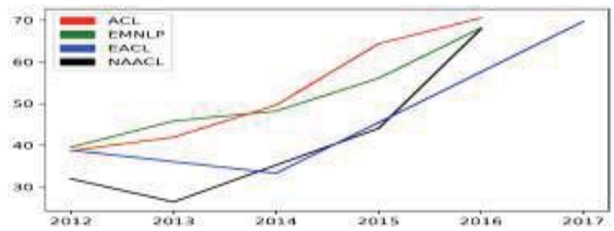

Fig.2 (b) Percentage of NBER papers
Source: The Economist

VIII. MULTI CLASS SUPPORT VECTOR MACHINE (MCSVM)

Although the various brain tumor segmentation and classification methods have been suggested, enhancing tumor segmentation methods and multiclass classification is still difficult due to complex characteristics of brain tumor, such as high diversity in tumor appearance and uncertainty in tumor boundaries. Kruti, G. K, 2016 addressed this problem by a proposed novel multiclass classification method for MR image. Finally, Classification of these five types of brain tumor is performed using Multiclass SVM. This SVM employs the one versus one approach for multiclass classification. The MATLAB simulation is carried out for all five types of classes using GUI. A CAD interactive system was developed to support radiology expert in brain-tumor multiclass classification. Zarcharaki et al. 2009 executed

glioblastoma, metastases, and gliomas multiforme. Precision acquired for every class were: 91.7 % for metastases, 90.9 % for low-grade glioma, and 41.2 % for glioblastoma multiforme. Also, classifying of multiclass models for segmenting brain tumors was suggested. According to Pathak A.N, 2014 the final stage classifying method, SVM for multi class data is engaged. MRI offers complete imageries of nerve and brain tissues in several planes without obstacle by covering bones. Also, SVM as a classification for class multiple recognition by an automated support from diverse sorts of brain tumors in different regions of brain.

Gaikwad, S.B, 2015 described that PCA approach alters the prevailing attributes into fresh ones measured to be vital in classification. Classifiers of multiclass models for organizing brain tumors were suggested by (Othman M.F, 2011). Also, the author suggested that PNN is extensively utilized for problem classifying. There are numerous benefits by utilizing PNN in place of multi-layered Back Propagation (BP) perceptron. PNNs are much swifter than BP networking multilayer. It affords good precision.

IX. ARTIFICIAL NEURAL NETWORK (ANN)

MR images with tumor are classified by Artificial Neural Network (ANN) approach in the first stage. PCA and Artificial neural network are combined and called PCA-ANN approach to make the system smarter. PCA is used for dimensionality reduction. According to Sachdeva et al 2013 various combination of tests were conducted to analyze the performance of the proposed system (PCA-ANN) for classifying six classes—five classes of brain tumors and a normal class. User friendly CAD system was developed to help radiologists for brain tumor classification. Along with the suggested technique marking of tumor limitations by CBAC, extraction factors from SROIs, selection of factors using PCA, and the (ANN) classifier modules were conferred. The comparative study with ANN method displayed that PCA-ANN has improved the total precision by 14 %.

Sachdeva et al 2016 conducted another work related with hybrid machine learning model using ANN/GA. Some factors were used as inputs to ANN. GA condenses the factor set and grouping of GA with ANN categorizes even those tumors which have likeness in size, shape, location, enhancement and morphology. Experiment outcomes of the initial dataset display that the optimization through GA approach has improved the total precision of SVM from 79.4% to 91.6% and of ANN from75.5% to 94.8%. Likewise, outcomes were acquired for the secondary dataset. The collective outcomes from both approaches will advantage the radiology expert directing with improved condition for brain-tumors classification.

Brain tumor recognition which is a performance in medical imageries plays a vital role. Brain tumor exposure depends on the inflated region of the brain alongside with its size, shape, and boundary (Selkar and Thakare, 2014). For such obligations, processing techniques for imageries were used with the help of ANN. The author suggested two phases named it as Processing with Neural Networks (PWNN), and Image (PWNN). Furthermore, to accomplish processing techniques for imageries, as well as ANN and their interconnected exploration approaches to initiate patients with brain tumors. Result relay on quantifiable data for example, the size, ratio and the shape of the affected cells based on their previous work (Dimilier K, 202 and 2013).

Finally, Dimililer and Ilhan, 2016 reported that their outcomes acquired when analyzing the suggested system displayed that the detection system in developed brain-tumor was considered as effective image processing approach that is proficient of identifying any irregularities in the brain parts predominantly at small patches.

Table .1 CURRENTLY DEVELOPED FILTERS/ARCHITECTURE AND TRAINING/EFFICIENCY/LIMITATION

S. No	Author	Datasets	Filters	Architectures	Training	Effectiveness/Efficiency	Limitations
1	Havaei, M, 2017	(BRATS) 2013 dataset	Convolution of kernels, Valid-mode	Two-pathway and Cascaded	Stochastic gradient descent	Improved accuracy and speed	1st phase caused some false positives, 2nd phase it over came
2	Dou, Q, 2017	3D CT scan of Abdomen & Heart Segmentation	3D kernels	Deep Supervised Network (3D)	Gaussian distribution	High-quality score volumes (3D DSN)	Deep network trained by limited training data
3	Zhao, X, 2018	BRATS (2013, 2015 and 2016)	Kernel	Fully convolutional neural networks	Gaussian	Achieved computational efficiency	Relationship among image patches is typically lost
4	Karimaghaloo, Z, 2016	Multi-center clinical trials	Kernel-based classifier: Relevance Vector Machine	Not Applicable	Kappa or Dice coefficient	Offer a fast and accurate solution	Effects of limited parameters

5	Mohsen, H, 2017	Fuzzy C-means	Cascaded and Convolution filters	Deep Neural Network classifier	Discrete wavelet transforms	Performance measures were quite good	Not Applicable
6	Xie, Y, 2018	Four microscopy image datasets	Convolution kernels	Fully convolutional networks-based cell counting	Hungarian algorithm	Detection accuracy and running time superiority	Sample size
7	Kamnitsas, K, 2017	Traumatic Bra in Injury	Small kernels	3D Convolutional neural networks	Stochastic Gradient Descent	Computationally efficient	Memory limitations.
8	Wan, S, 2017	UIUCTex, CUReT, UMD, ALOT, KTHTIPS2b and Outex	Gabor filters	K-nearest neighbors (KNN) and neural network	HOG (Histogram of Oriented Gradients)	Able to achieve more accurate image	Frequent patterns are limited
9	Hor, S, 2016	Alzhemer's Disease	Multi-kernel with support vector machine	Single modal tree	Scandent tree	Discriminative image power transferred efficiently	Small genomic data set and MR image in testing phase.
10	Drozdzal, M, 2018	Electron Microscope	Median filter	FCN and ResNets	Watershed algorithm	Accurate segmentations was successful by using Flexible Framework	Expanding to 3D FCN – Model has more advantage.
11	Arabi, H and Zaidi, H, 2016	Co-registered atlas dataset	Gradient anisotropic diffusion filtering	Sorted atlas pseudo-CT (SAP)	Gaussian kernel	PET quantification accuracy – Results was good	Computational time reduced and further improvement
12	Wenzel, F, 2018	Model-based segmentation	Conjugate gradient	Convolutional neural networks, shape-constrained deformable	Gauss-Newton optimization	Accuracy rate improved in test-retest stability of Segmentation method approach	< 0.5 mm – Average Segmentation error seen.
13	Irving, B, 2016	Rectal DCE-MRI dataset	1D Gaussian filter	Automated DCE-MRI	Perfusion-super voxel	0.63 and 0.71 was reached successfully by DSC (Dice similarity coefficient)	Linear discriminant analysis limited the number of parameters

X. CONCLUSION

This retrospect paper done with deliberate motive contemplated several techniques that were used to detect brain tumors from MR Images. Comparing results with other machine learning methods, deep learning methodology/technique reported best results and considered to be robust for brain tumor segmentation and classification compared with other machine learning classifiers. Research work started with current usage of techniques in image pre-processing, image segmentation, common feature extraction and classification recently used were analyzed and studied. Finally, current trends in deep learning with various techniques recently used in medical image processing analyzed in-depth on the accuracy of classification. Based on other research works this review paper is prepared and listed various techniques and efficiency in achieving high accuracy rate were significantly studied. As end note the current method Deep learning model can be used for Automatic Brain tumor segmentation and classification for better diagnosis compared with other models.

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