Development of Deep Learning Algorithm for Brain Tumor Segmentation

MS. Jyoti Patil, G.Pradeepini

Abstract:*Medical imaging is an emerging field in engineering. As traditional way of brain tumor analysis, MRI scanning is the way to identify brain tumor. The core drawback of manual MRI studies conducted by surgeons is getting manual visual errorswhich can lead toofa false identification of tumor boundaries. To avoid such human errors, ultra age engineering adopted deep learning as a new technique for brain tumor segmentation. Deep learning convolution network can be further developed by means of various deep learning models for better performance. Hence, we proposed a new deep learning algorithm development which can more efficiently identifies the types of brain tumors in terms of level of tumor like T1, T2, and T1ce etc. The proposed system can identify tumors using convolution neural network(CNN) which works with the proposed algorithm "Sculptor DeepCNet". The proposed model can be used by surgeons to identify post-surgical remains (if any) of brain tumors and thus proposed research can be useful for ultra-age neural surgical image assessments. This paper discusses newly developed algorithm and its testing results.*

Index Terms*: *cnn, brain tumor, segmentation, tumor levels, deep learning, post-surgical analysis, feature extraction

I. INTRODUCTION

Segmentation includes a diverse collection of uses starting from scenario recognizing, image analysis for medical field, traffic monitoring etc. Previous solutions which usually depended on poor-intensity perspective signs have quickly been replaced by preferred machine learning (ML) methods. Specifically, deep learning provides enormous accomplishment recently in digital identification, speech, clustering entire graphics and discovering targets through images [1, 2, 3]. In brain tumor segmentation likewise, deep learning technique is said to carry a great opportunity for offering remarkable outcomes above typical solutions. In this analyze, existing methods presented a completelycomputerized brain tumor recognition and segmentation structured on convolution neural network (CNN) [4, 5, 6, 7].

As shown in figure 1, presently there are 3 key measures concerning in deep learning (DL) algorithm. Deep learning-founded segmentation methods for brain MRI are attaining awareness because of their particular self-learning and then capability through significant portions of critical information. As the DL architectures are getting considerably more experienced, these steadily do better than earlier traditional ML algorithms [8, 9].

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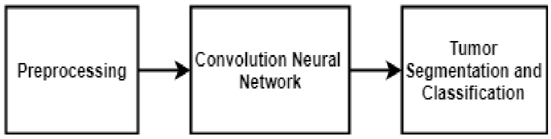

Figure 1- Deep learning brain tumor processing [2]

Also, the deep neural networking, and so the specified convolution neural systems, have got established to become the state of the art in various computing device perspective products [10]. In contrast to typical trivial classifiers [11] in which usually characteristic architectural is important, DL solutions routinely uncover hierarchies of important features straight out of the natural inputs.

CNNs [12, 13, 14, 15, 16] possess the potential of gaining knowledge of a hierarchical manifestation of the input information with noneed of any kind of attempt to layout generate features. Distinct levels of the networking system are in a position of diverse amounts of analysis and so catch several volumes of elements via the patterns available inside the image. Because of the difficulty with the work as well as highly huge amount of networking variables that must definitely be discovered at the time of training, CNNs need a significant quantity of training graphics to be able to achieve viable outcomes [17]. As being an effect, vital effectiveness boost can be attained the moment quicker components and as well, more significant volume of training data turned into obtainable [18]. With study of existing system algorithms and approaches, we propose a deep learning CNN algorithm "Sculptor DeepCNet" for identification/classification and segmentation of brain tumors which is useful for post-surgical analysis. The image analysis is based on 2D slice analysis for representation of neural network. The results are shown with BRATS2017 dataset which is retrieved after legal registration process.

II. PROPOSED METHODOLOGY

The proposed researchintended for classification of different levels of tumor as T1, T2, T1ce and Fluid Attenuated Inversion Recovery (FLAIR) [9]. At the time of MRI accumulation, even though may differ by system to system, about 150 slices of 2D images are actually generated to symbolize the 3D brain volume level. The moment when the slices of the needed typical techniques are put together for analysis of the data becomes somewhat complex. T1 images are actually utilized for differentiating healthier cells, while T2 images are actually utilized to represent the edema area which in turn generates idealistic indication around the image.

In T1ce graphics, the tumor boundary can simply be recognized through white-colored signal from the accrued distinction element inside the effective cell area of the tumor cells. As necrotic microscopic cells usually do not have interaction with the entire comparison agent, these may be noticed by extreme component of the tumor foremost developing it feasible to conveniently segment all of them by the productive cell areas within the comparable pattern. In FLAIR images, indication of water compounds are covered up which usually assists in differentiating edema area through the Cerebrospinal Fluid (CSF).

The proposed research methodology is a simulation development. Convolution Neural Networks (CNN) is amongst the alternatives of neural systems utilized intensely in the discipline of Computer system Vision. It was introduced their identity by the variation of obscured layers that is composed of the obscured layers of the CNN ordinarily comprise of convolution and pooling layers. Right here it basically suggests that rather of applying the typical initialization features described earlier, convolution and as well, pooling features are actually employed as acceleration operates.

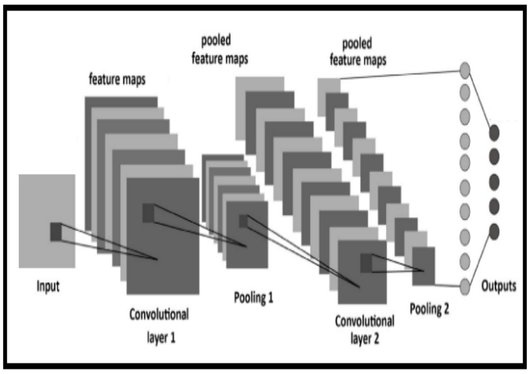

Figure 2–Block diagram of deep learning layers

Convolution works upon pair of images in case of 2D image where 1 considered as the "input" graphic and so the rest as a "filters" for the input image, generating a result graphic so convolution requires pair of images as input and so delivers a final as end result. Pooling is usually a group-centered discretization procedure. The goal is always to reducing-group an input manifestation minimizing its proportions and enabling for presumptions to become relating to features comprised within the sub-areas. Therefore since one can easily observe Convolution Neural Networking i.e. CNN is fundamentally a deep neural networking which generally is composed of covered layers keeping convolution and so pooling capabilities in companion to the initial function for producing nonlinear output.

Proposed Algorithm: Sculptor DeepCNet

Data: X: the number of convolution layers, Y: deconvolution layers, $P\{0, 1\}$: pooling layers

Assumption: $X_{cl} = 0$ for initial run, X_{cl}: the number of concatenated convolution layers (if running second time)

Result: Incr_algo_npz: a CNN trained and tested model for selected batch task

1. Select hyper-parameter 'task'=(all | enhance | edema | necrotic)

    If batch batch _task==all
    Else if batch_task==enhance
    Else if batch_task==edema
    Else batch_task== necrotic

2.Create$Incr_algo_batch_0\ (X\ , P)$:
$Incr\_algo\_\ batch\_n\ (X, P) +\ X_{cl}$# Creating the first batch
Where, $X_{cl}\ = 0$

3.$Incr\_algo\_batch\_n\ =\ (Incr\_algo\_0\ (X, P) +$ ConcatLayer)
Run the training using ConcatLayertoidentify dice loss, Sensitivity etc.
Where, $X_{cl}! = 0$

4. while$(X_{cl}\ ! = 0)$ **do**

5. AddConcatLayer
$Incr\_algo\_\ batch\_n = X_{cl} + Incr\_algo\_\ batch\_n(X, P) -$ $losses$# connects all layers and removes losses for prediction
while$(X_{cl}\ ! = 0\ \&\&\ Y! = 0)$ **do**

6. Activaterectified linear unit$Incr_algo_n_{relu\,()}$

7. Adding a new batch (X , P) withX_{cl} and Y:
$Incr_algo_$batch$_n$(X, P)+$X_{cl} + Y$

8. $Incr\_algo\_$ batch $(0\ to\ n) = \sum_0^n Incr\_algo\_n_{relu\,()} + X_{cl} + Y$

9. end while

The proposed algorithm can be utilized for normal tumor identification and for post-surgery analysis i.e. post-surgical MRI is used to identify left over part of tumor after surgery.

For the implementation of our models (Sculptor DeepCNet), we used and Tensorflow as a backend. Further we used Keras deep learning library for convolution step execution. For identification of application performance we considered number of convolution layers required to get results. More the number of convolution layers, more the gpu processing time required and consequently memory usage increases.

The proposed model flow is shown in figure 3. Finally, the initial stage turned out to be preprocessing procedure, where the graphic was segmented applying pixels and then collected right into identical pixels by the distinct image techniques. The secondary stage concerned the CNN training is a monitored method. During the last stage, the likelihood mapping of tumor area is produced through the qualified CNN and the complete tumor area is determined. In comparison to computer system vision which in turn executes DL upon 2D photos, medical graphics frequently cope with the quantities obtained by using scanning devices just like MRI. As per existing systems, the majority of techniques include persisted functioning in 2D by getting close to 3D verification in a slice-by-slice manner. The benefit is substantial swiftness, poor memory space usage and so the capability to employ pre-qualified data.

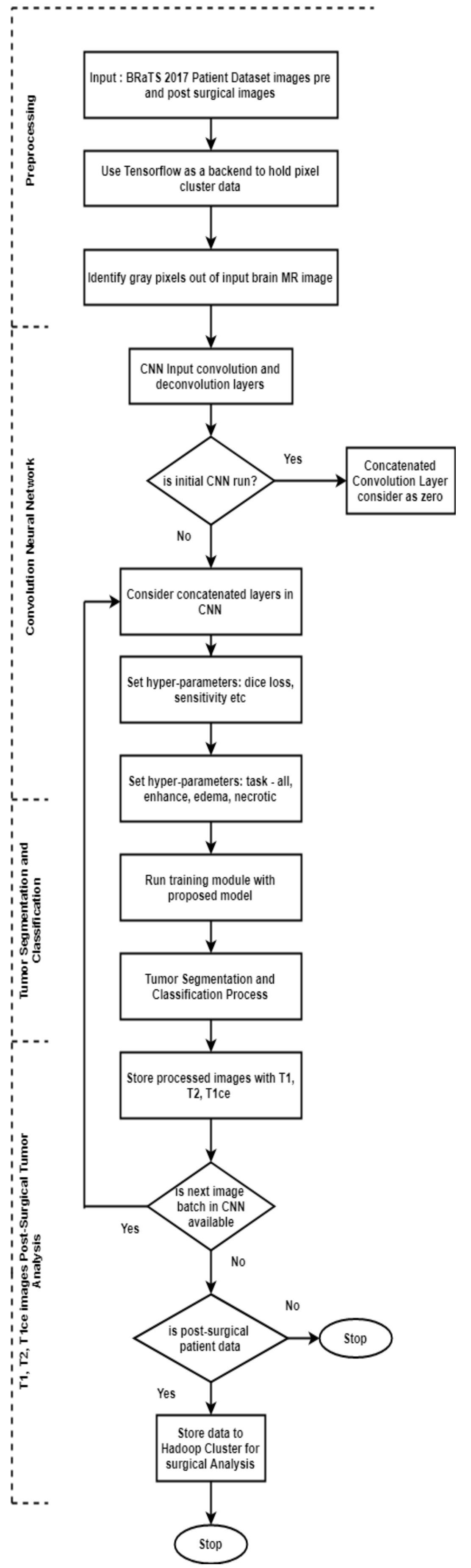

Figure 3 - Proposed Algorithm Flowchart

For comparison of results, we considered the hyper-parameters as dice loss and sensitivity. The comparison of existing and proposed model result is discussed in the next section of this paper.

III. RESULT ANALYSIS

The proposed Sculptor DeepCNet is tested using the BraTS 2017 dataset. The gpu is considered for proposed analysis. The dataset contains 210 patient's impressions with HGG and 75 patient's impressions with LGG. Each image is processed for identification of tumor types T1, T1c, T2, flair and ground truth as shown in figure 4 below.

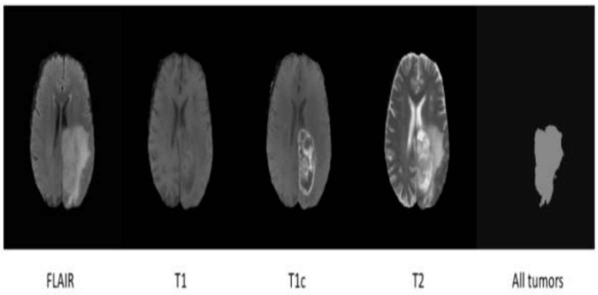

Figure 4- Identified tumor types

Further, as per considered hyper parameters, the proposed CNN model Sculptor DeepCNet is tested and compared with existing system 2CNet.

Table 1- Proposed Segmentation Results Comparison

WT, TC, ET depict Whole Tumor (complete), Tumor Core, Enhancing Tumor core

Methods	**Dice**			**Sensitivity**		
	WT	TC	ET	WT	TC	ET
Sculptor DeepCNet	0.90	0.83	0.85	0.88	0.87	0.80
2CNet	0.88	0.80	0.83	0.88	0.86	0.78

The results shown in table-1 depict that proposed Sculptor DeepCNet performance is better than existing system.

Further, post surgical images are tested to identify the left over part of tumor as shown in figure 5 below.

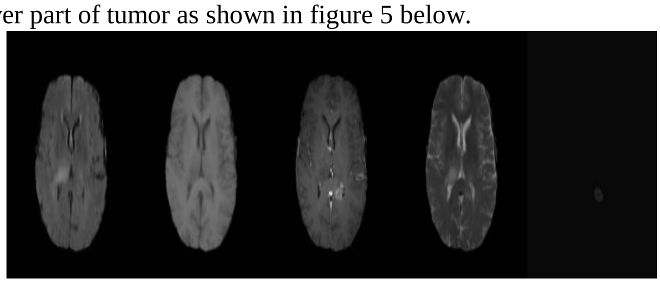

Figure 5- Post surgical left over tumor identification

As brain is a very important and complex system, a single tissue is on great importance. So, surgeons often clean affected area carefully to avoid more damage to healthy tissues. But, in attempt to save healthy tissues sometimes affected tumor remains at pixel level which surgeon comes to know only after pathological tests.

So, proposed algorithm can be used for post surgical analysis of MRI. Such post surgical manual observations and processed observations are depicted in table-2.

Table 2- Post Surgical Analysis

PatientID (Epoch-1)	Manual Post Surgical Image Analysis Approx. Accuracy (%)	Proposed Post Surgical Image Analysis Accuracy (%)
Brats2017_6_1	15	16.5%
Brats2017_7_1	10	10.8
Brats2017_8_1	20	21.8
Brats2017_9_1	10	11.4
Brats2017_10_1	15	14.8

When manual MRI carried out by doctors, they always consider approximate rounded-off readings whereas with proposed system more accurate readings can be acquired.

IV. CONCLUSION

In this paper we discussed the need of deep learning image processing in medical imaging. Also, proposed Sculptor DeepCNet deep learning algorithm is shown by means of flowchart for better understanding. The convolution and deconvolution layers are formed to get the evaluation parameters. The BraTS2017 dataset is most authentic dataset of brain tumor patients worldwide so proposed algorithm is tested on BraTS2017 dataset. The analysis is conducted for pre-surgical and post-surgical brain images. Also, the various types of tumor as t1, t2, t1ce and flair are classified. The post surgical analysis proves that proposed algorithm gives more accurate results over manual observation. As a future development processed images can be stored on Hadoop cluster to provide facility for doctors to access patient data more efficiently instead of manual paper handling.

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