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BRAIN TUMOUR IMAGE SEGMENTATION USING DEEP NETWORKS

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Abstract

Automated segmentation of brain tumour from multimodal MR images is pivotal for the analysis and monitoring of disease progression. As gliomas are malignant and heterogeneous, efficient and accurate segmentation techniques are used for the successful delineation of tumours into intra-tumouralclasses.Deeplearningalgorithmsoutperformontasksofsemanticsegmentationasopposed to the more conventional, context-based computer vision approaches. Extensively used forbiomedical image segmentation, Convolutional Neural Networks have significantly improved thestate-of-the-art accuracy on the task of brain tumour segmentation. In this paper, we propose anensemble of two segmentation networks: CNN and a U-Net, in a significant yet straightforwardcombinative technique that results in better and accurate predictions. Both models were trainedseparately on the BraTS-19 challenge dataset and evaluated to yield segmentation maps whichconsiderablydifferedfromeachotherintermsofsegmentedtumoursub-regionsandwereensembled variably to achieve the final prediction. The suggested ensemble achieved dice scores of0.750, 0.906 and 0.846 for enhancing tumour, whole tumour, and tumour core, respectively, on the validation set, performing favourable in comparison to the state-of-the-art architectures currentlyavailable.

Keywords—Deeplearning,BraTS,Medicalsegmentation,U-Net,CNN,ensembling.

1. INTRODUCTION

Accurate segmentation of tumours through medical images is of particular importance as it providesinformation essential for analysis and diagnosis of cancer as well as for mapping out treatmentoptions and monitoring the progression of the disease. Brain tumours are one of the fatal cancersworldwide and are categorised, depending upon their origin, into primary and secondary tumourtypes. The most common histological form of primary brain cancer is the glioma, which originates from therainglialcells andattributestowards80%ofallmalignant braintumour.Gliomas can be of the slow-progressing low-grade (LGG) subtype with a better patient prognosis orare the more aggressive and infiltrative high-grade glioma (HGG) or glioblastoma, which requireimmediate treatment. These tumours are associated with substantial morbidity, where the mediansurvival for a patient with glioblastoma is only about 14 months with a 5-year survival rate near zerodespite maximal surgical and medical therapy. A timely diagnosis, therefore, becomes imperative foreffective treatment of the patients. Magnetic Resonance Imaging (MRI) is a preferred techniquewidely employed by radiologists for the evaluation and assessment of brain tumours. It providesseveral complimentary 3D MRI modalities acquired based on the degree of excitation and repetitiontimes,i.e.T1-weighted,post-contrastT1-weighted(T1ce),T2-

weightedandFluidAttenuatedInversion Recovery (FLAIR). The highlighted sub regions of the tumour across different intensities ofthese sequences, such as the whole tumour (the entire tumour inclusive of infiltrative oedema), ismore prominent in FLAIR and T2 modalities. In contrast, T1 and T1ce images show the tumour core exclusive of peritumouraloedema. It allows for the combinative useofthesescansandthecomplementary information they deliver towards the detection of different tumours sub regions.

2. RELATED WORK

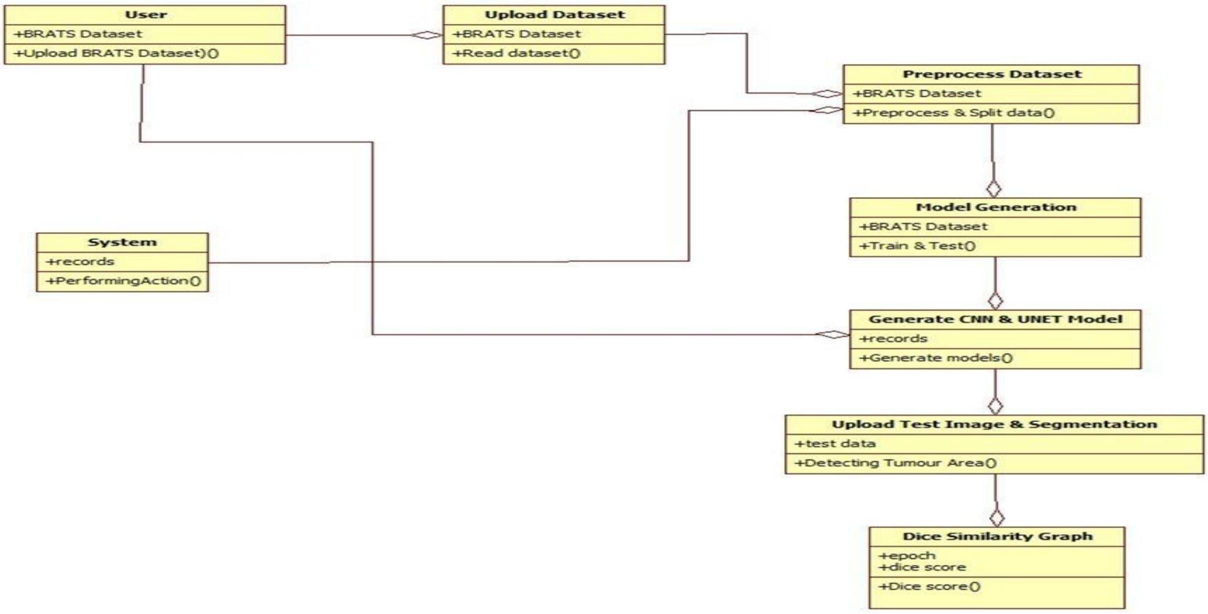
Inthisprojectwereporttheset- upand results of the Multi modal Brain Tumor ImageSegmentationBenchmark(BRATS)organizedinconjunctionwiththeMICCAI2012and2013conferences. Twenty state-of-the-art tumor segmentation algorithms were applied to a set of 65multi-contrast MR scans of low- and high-grade glioma patients – manually annotated by up to fourraters–and to 65 comparable scans generate dusing tumor image simulation software. Quantitative evaluationsrevealedconsiderabledisagreementbetweenthehumanratersinsegmenting various tumor sub-regions (Dicescores in the range 74-85%), illustrating the difficultyof this task. We found that different algorithms worked best for different sub-regions (reachingperformance comparable to human inter-rater variability), but that no single algorithm ranked inthetopforallsubregionssimultaneously.

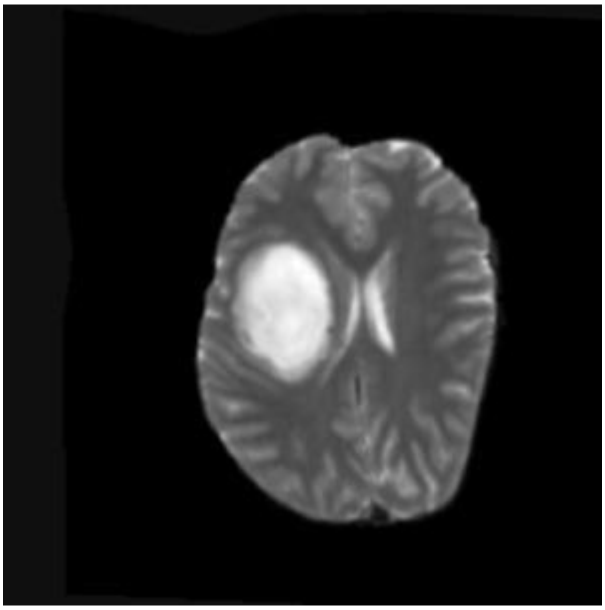
3. PROPOSED FRAMEWORK

In this paper we report the set-up and results of the Multimodal Brain Tumor Image SegmentationBenchmark (BRATS) organized in conjunction with the MICCAI 2012 and 2013 conferences. Twentystate-of-the-art tumor segmentation algorithms were applied to a set of 65 multi-contrast MR scansof low- and high-grade glioma patients –manually annotated by up to four raters –and to 65comparablescansgeneratedusingtumorimagesimulationsoftware.Quantitativeevaluationsrevealed considerable disagreement between the human raters in segmenting various tumor sub-regions (Dice scores in the range 74-85%), illustrating the difficulty of this task. We found thatdifferent algorithms worked best for different sub-regions (reaching performance comparable tohuman inter-rater variability), but that no single algorithm ranked in the top for all subregionssimultaneously.

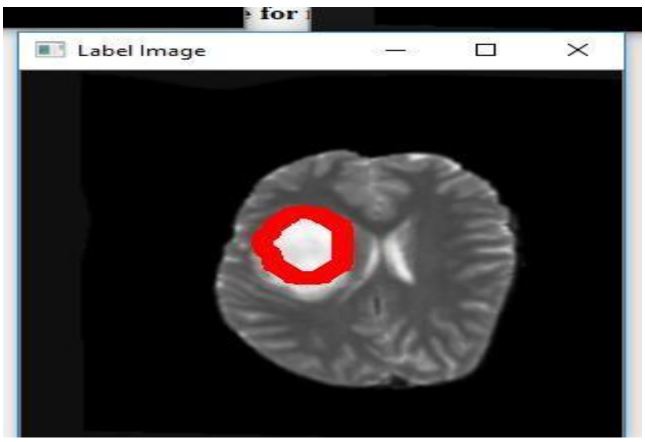
CONVOLUTIONAL NEURAL NETWORKS(CNN)

To demonstrate how to build a convolutional neural network based image classifier, we shall build a6 layer neural network that will identify and separate one image from other. This network that weshallbuildisaverysmallnetworkthatwecanrunonaCPUaswell.Traditionalneuralnetworksthat are very good at doing image classification have many more parameters and take a lot of time iftrained on normal CPU. However, our objective is to show how to build a real-world convolutional neural network using TENSOR FLOW. Neural Networks are essentially mathematical models to solve an optimization problem. They are made ofneurons,the basic computation unit of neural networks.A neuron takes an input (say x), do some computation on it (say: multiply it with a variable w andadds another variable b) to produce a value (say; z= wx+b). This value is passed to a non-linearfunction called activation function (f) to produce the final output(activation) of a neuron. There aremany kinds of activation functions. One of the popular activation function is Sigmoid. The neuron which uses sigmoid function asanactivationfunction will be called sigmoidneuron.





WITHOUTIDENTIFYINGBRAINTOMOUR



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4. METHODOLOGY

MODULES:

- **UploadBRATSDataset:**

In thismoduleuser uploaddataset ofBRATS.

- **GenerateCNN&UNETModel**

We can see models are using different size images to filter the mand to get best features from it to build efficient model and now model is generate.

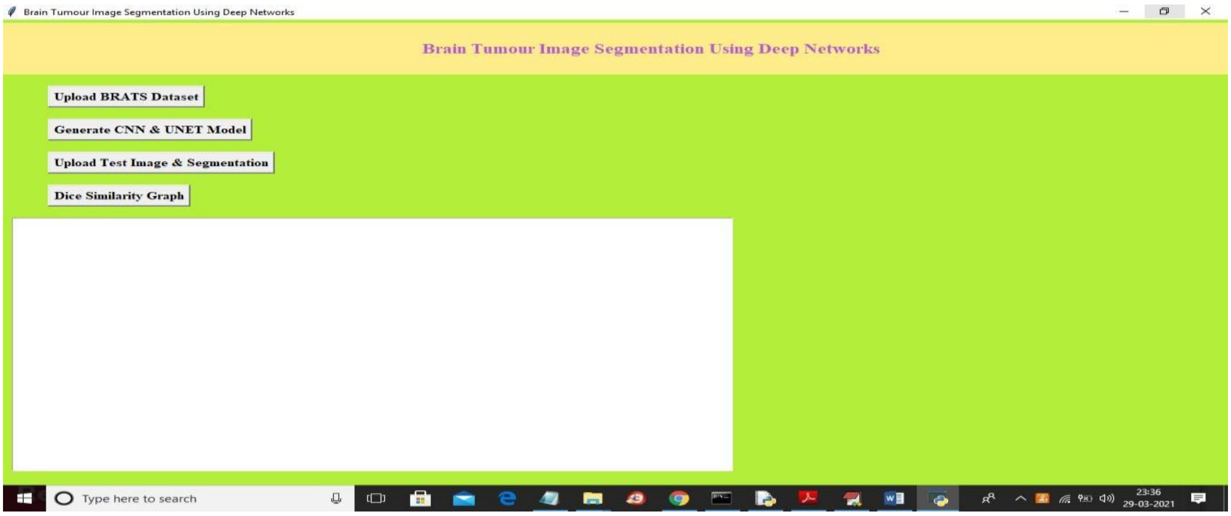
- **Upload Test Image & Segmentation**

In this module user upload test image andtop 4 images are the input images such as FLAIR, T1, T2and T1CE and 5th image is the predicted image with segmented part showing in red colour and this algorithm correctly detecting and marking tumour area.

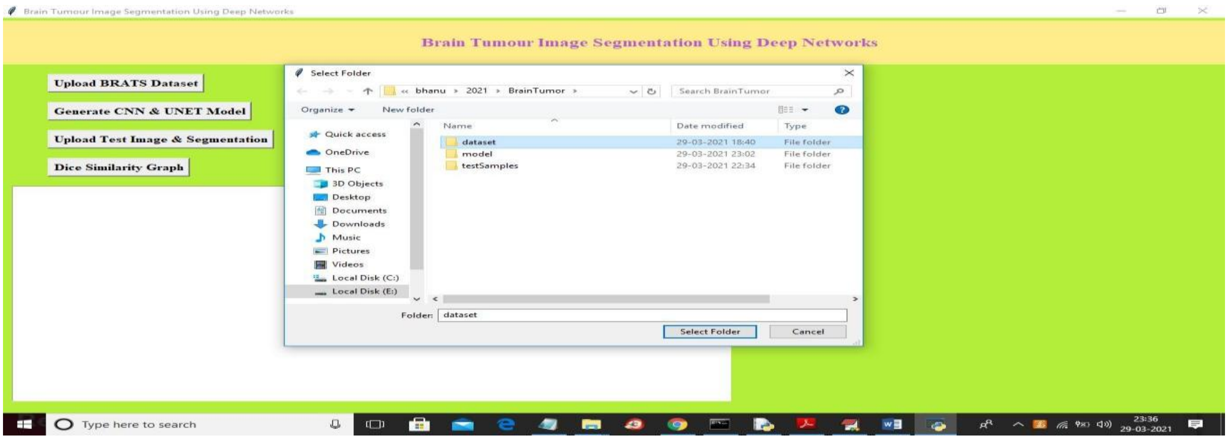
- **Dice Similarity Graph**

In this Module, we get final dice score as 0.8 * 100 = 80%. In above graph x-axis represents epochandy-axis represents dicescore.

5. RESULTSANDDISCUSSION



5.1 MAINACTIVITY



5.2 UPLOADTHEDATASET

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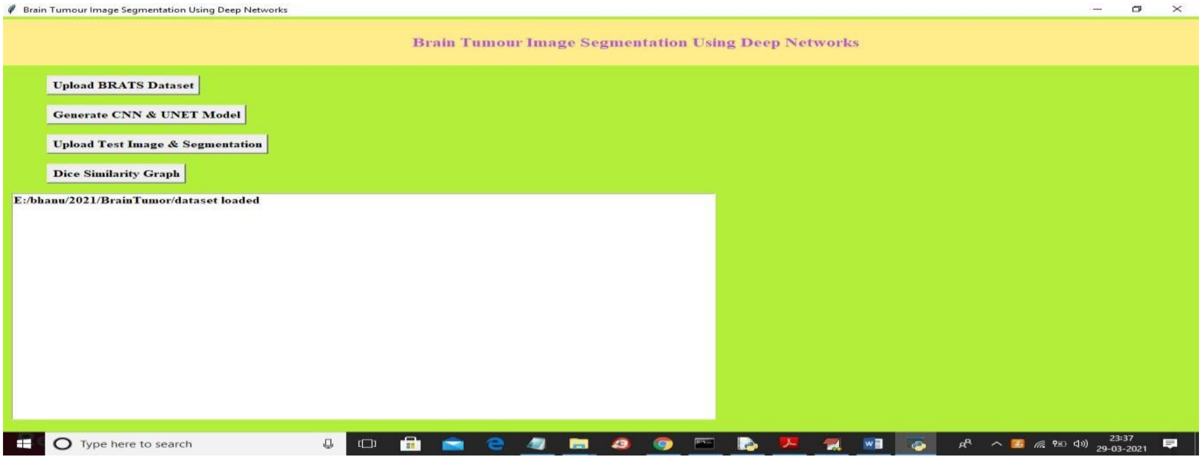
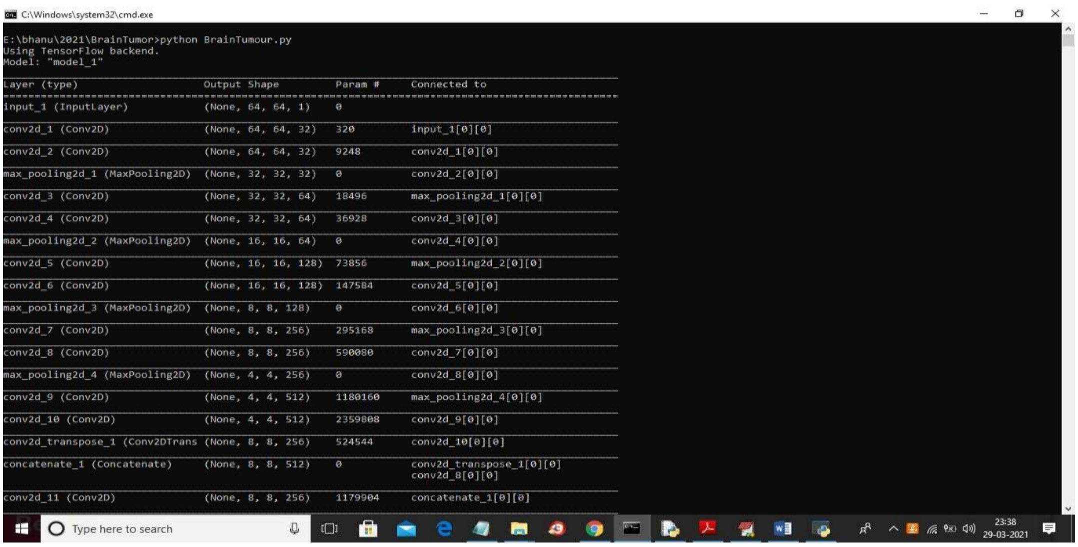
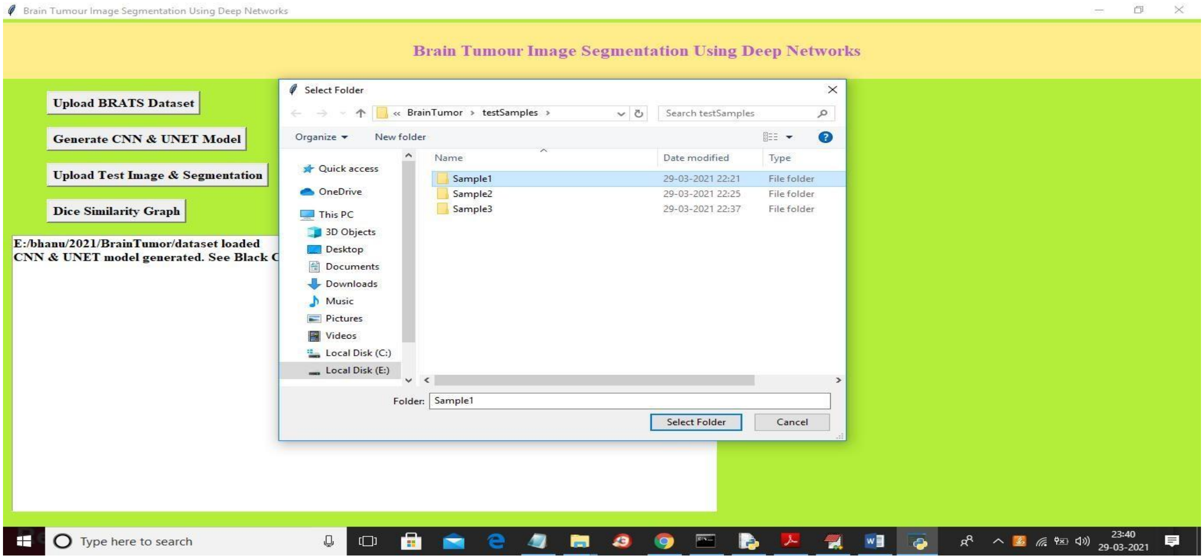


5.3 DATASETLOADED

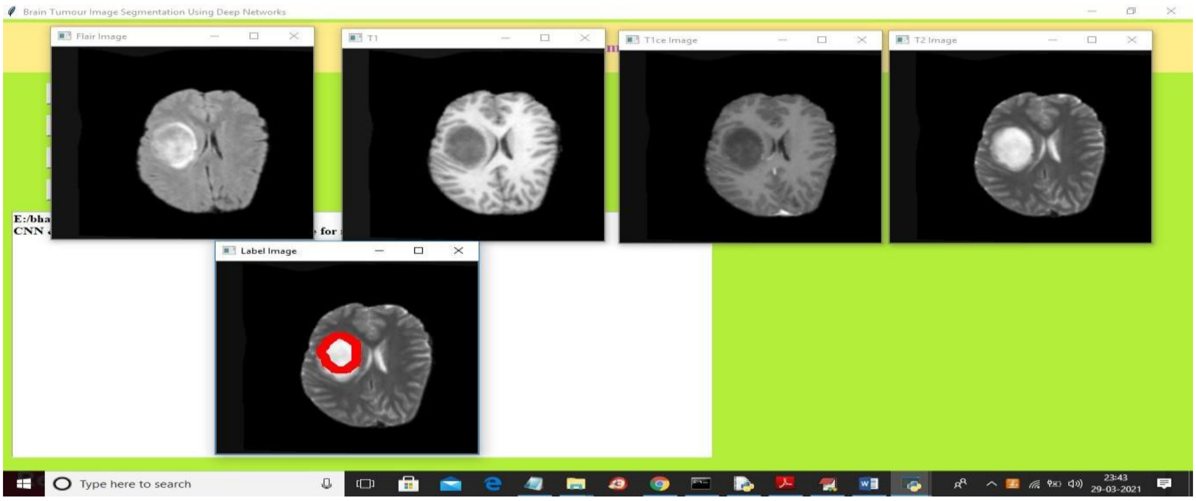
5.4 BOTHCNNANDU-NETMODELSAREGENERATED



5.5 MODELSAREUSING DIFFERENTSIZEIMAGES



5.5 SELECTINGANDUPLOADINGSAMPLE1FLODER



5.6 In above screen first 4 images are the input images and fifth image is the predicted label image with segmented parts around tumour area

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5.7 ACCURACYGRAPH

6. CONCLUSIONANDFUTUREWORK

InthispaperweareusingImageSegmentationmethod.Wehaveusedahybridoftwodifferenttechniques,i.e. Watershedand Contrast Technique. Thistechnique is well suited for detection of tumorin the image. This segmentation methodgives highaccuracyascomparetoother methods. MRI images are best suitable for brain tumor detection. In this study Digital Image Processing Techniques are important for brain tumor detection by MRI images. The pre processingtechniques include different methods like Filtering, Contrast enhancement, Edge detection is used for image smoothing. The preprocessed imagesareusedforpostprocessingoperationslike;threshold,histogram,segmentationandmorphological,whichisusedtoenhancetheimages.

7. REFERENCES

J.Vijay et.al [3], propose the work on automated brain tumor detection by using segmentation by k-means algorithm and object labeling algorithm. They identified that a well known segmentationproblem within MRI is the task of labeling the tissue type which include White Matter (WM), GreyMatter (GM), Cerebrospinal Fluid (CSF) and sometimes pathological tissues like tumor. S.Koley et.al[4], propose the efficient work on tumor detection and segmentation of brain MRI for the purposeof determining the exact location of brain tumor using CSM based partitioned K-means clusteringalgorithm. CSMhas attracted much attention as it has given efficient result as aself mergingalgorithmcomparedtoothermergingprocessesandtheeffectofnoiseisalsolessandtheprobability of obtaining the exact location of tumor is more. Their approach is much simpler andcomputationallylesscomplexandcomputationtimeisvery less.