Brain Tumour Image Segmentation using Deep Networks

Dr. Chandra Mouli VSA, Prof CSE:BVCE,mouli.ac@yahoo.co.in
Dr. Gunamani Jena, Prof CSE:BVCE, drgjena@gmail.com
Matha Bhargavi Devi, CSE:BVCE
Mattaparthi Lakshmi Gowri, CSE:BVCE
Akula Somesh Sai Chandra, CSE:BVCE
Bonam Sai Varsha CSE:BVCE

Article Info
Page Number: 5263 - 5279
Publication Issue:
Vol 71 No. 4 (2022)

Article History
***Article Received**: 25 March 2022*
***Revised**: 30 April 2022*
***Accepted**: 15 June 2022*
***Publication**: 19 August 2022*

Abstract
Automated segmentation of brain tumours from multimodal MR images is a key part of figuring out how a disease is progressing and keeping track of it. Since gliomas are cancerous and different from one another, efficient and accurate segmentation techniques are used to divide tumours into classes within the tumour. In tasks of semantic segmentation, deep learning algorithms do better than the more traditional, context-based computer vision approaches. Convolutional Neural Networks have made a big difference in the accuracy of brain tumour segmentation. They are used a lot for biomedical image segmentation. In this paper, we propose a group of two segmentation networks, a 3D CNN and a U-Net, that work together in a simple but important way to make predictions that are more accurate. Both models were trained separately on the BraTS-19 challenge dataset and evaluated to produce segmentation maps that were very different from each other in terms of how they divided up tumour sub-regions and how they were put together to make the final prediction.

Keywords: 3D CNN, BraTS-19, U-Net, and Deep Learning

INTRODUCTION:

Accurate segmentation of tumours in medical images is very important because it gives important information for analysing and diagnosing cancer, as well as planning treatment options and keeping track of how the disease is getting worse. Brain tumours are a type of cancer that kills people all over the world. They can be either primary or secondary, depending on where they started [1]. The glioma, which starts in the brain's glial cells [2] and makes up 80% of all malignant brain tumours [3], is the most common type of primary brain cancer. Gliomas can be of the slow-growing low-grade (LGG) subtype, which has a better prognosis for the patient, or they can be the more aggressive and infiltrative high-grade (HGG) or glioblastoma, which needs treatment right away [4]. These tumours cause a lot of suffering. For example, a person with glioblastoma has a median survival time of only 14 months and a near-zero 5-year survival rate, even with the best surgical and medical treatment [5, 6]. For patients to get the best care, they need to be diagnosed as soon as possible.

Magnetic resonance imaging (MRI) is a technique that radiologists prefer and use often to look at and evaluate brain tumours [1]. It gives you a number of different 3D MRI modalities that work well together. These are T1-weighted, post-contrast T1-weighted (T1ce), T2-weighted, and FluidAttenuated Inversion Recovery (FAI) (FLAIR). Different intensities of these sequences [6] show different parts of the tumour. For example, the whole tumour, which includes infiltrative oedema, stands out more on FLAIR and T2 sequences. On the other hand, T1 and T1ce images show the tumour core without any oedema around it [7]. It lets these scans and the information they give that complements each other be used together to find different tumour subregions.

The Multimodal Brain Tumour Segmentation Challenge (BraTS) is a way to test the development of machine learning models for the task of tumour segmentation. Participants are given a large set of 3D MRI images of LGG and HGG gliomas, as well as ground truths that have been annotated by doctors. The provided multimodal scans are used to train and test the neural networks that were made for the segmentation task [6, 8–11].

Manually drawing lines between brain tumour subregions on MRI scans is a subjective task that takes a lot of time and isn't always accurate [12]. Automated segmentation of gliomas from multimodal MRI images can help doctors speed up diagnosis and planning for surgery. It can also provide an accurate, repeatable solution for further analysis and monitoring of tumours [13, 14]. The old ways of automatically separating brain tumours are based on a process called "feature engineering," which involves hand-crafting features from input images and then training a classifier [11, 15]. Unsupervised learning algorithms avoid the difficulty of designing and choosing features by automatically learning a hierarchy of feature representations [16–19]. Deep learning models are especially good at this [11]. Convolutional Neural Networks (CNNs) are thought to be the best way to divide up images of brain tumours because they automatically learn the most useful and important features [6].

But it's hard to get a clear picture of a tumor's shape, size, and appearance because gliomas come in different sizes, shapes, and looks and because the line between cancer and brain tissue is unclear and fuzzy [20]. The fact that the MRI data can vary in how intense they are makes this problem even worse [13]. So, it still has room for improvement and can be used to find better ways to segment and more accurate ways to do so.

1.1 BRAIN AND BRAIN TUMOR

The brain is the most important part of the nervous system. It is in the human head, and the skull covers it. The brain's job is to control all the other parts of the body. It is one kind of organ that helps people adapt to and survive in all kinds of environments. People can act and share their thoughts and feelings because they have brains.

There are two main types of brain tumours: primary brain tumours (also called benign tumours) and secondary brain tumours (malignant tumor).

Gliomas are a type of brain tumour made up of slow-growing cells that are harmless. It comes from brain cells called astrocytes that are not neurons. In general, primary tumours aren't as dangerous, but they put a lot of pressure on the brain, which makes the brain stop working right [6]. The second-stage tumours are more aggressive and spread to other parts of the body more quickly. The second type of brain tumour comes from somewhere else in the body. This kind of tumour is made up of cancer cells that have spread to other parts of the body, like the brain, lungs, etc. This type of brain tumour is very dangerous. Cancer in other parts of the body, such as the lungs, kidneys, bladder, etc., is usually the cause of a second brain tumour.

1.2 IMAGING WITH MAGNETIC RESONANCE (MRI)

In 1969, Raymond V. Damadian came up with the first magnetic image. In 1977, the first MRI images of the human body were made. This was the best technique at the time. Because of MRI, we can see the details of the brain's internal structure, which lets us see the different kinds of tissues in the body. When compared to X-rays and computer tomography, MRI images are of higher quality. [8]. MRI is a good way to find out if a person has a brain tumour.

1.3 Motivation:

The main goal of this application is to segment brain tumours so that doctors can better plan for diseases and take care of patients. This project is about such a system, which uses Convolution

Neural Network Algorithm for MRI images of different patients to find tumour blocks and classify the type of tumour.

1.4 Problem Statement:

In the field of medical image processing, brain tumour segmentation is a very important task. Brain tumours can be treated better and patients are more likely to live longer if they are found and treated early. Manually separating brain tumours from a large number of MRI images made as part of clinical routine is a hard and time-consuming task that is used to find cancer. There is a need for brain tumour image segmentation that can be done automatically.

1.6 Work Scope:

As deep learning is becoming more popular for efficient semantic segmentation of medical images, the author is combining both 3D CNN and UNET algorithms to automate the process of brain tumour segmentation. The author is using a combination of two deep learning algorithms called CNN and UNET to improve the process of segmentation even more. Both algorithms were trained separately on the BRATS brain tumour dataset, and then the predicted outputs of both algorithms were merged or mapped to make the final segmentation. The final segmentation gave a high dice score after mapping the predicted outputs of both algorithms. The dice score is the number of correctly mapped parts in the image.

In this study, we use CNN, UNet, and ResNet algorithms.

3.1.1 CNN ALGORITHM

The idea behind neural networks: There are three types of layers in a typical Neural Network.

Layers of input: It is the layer where we tell our model what we want it to do. The total number of features in our data is equal to the number of neurons in this layer (number of pixels in the case of an image).

Hidden Layer: The hidden layer then gets the information from the input layer. Depending on our model and the size of our data, there could be a lot of hidden layers. The number of neurons in each hidden layer can be different, but it's usually more than the number of features.

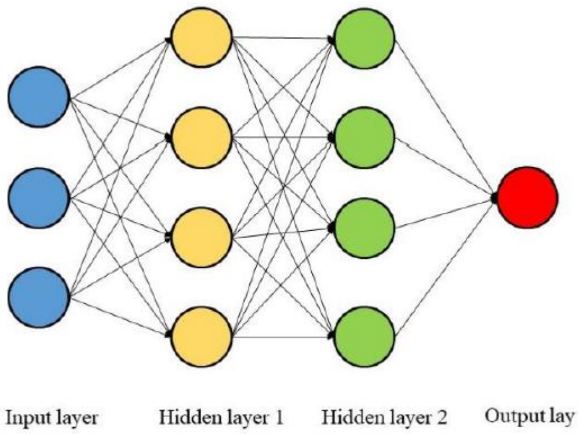

Fig.1 CNN

Output Layer: The output of the hidden layer is then fed into a logistic function like sigmoid or soft max, which turns the output of each class into the probability score of each class.

3.1.2 UNet UNet is a convolutional neural network architecture that grew while the CNN architecture changed only slightly. It was made for biomedical images where the goal is not only to tell if there is an infection or not, but also to find where the infection is.

3.1.3 ResNet

In their paper, Shaoqing Ren, Kaiming He, Jian Sun, and Xiangyu Zhang introduced ResNet, a well-known deep learning model. "Deep Residual Learning for Image Recognition" [1] was the title of the paper in 2015. One of the most popular and successful deep learning models so far is the ResNet model.

In the fields of Deep Learning and Computer Vision, there have been a number of big steps forward. With the help of very deep Convolutional neural networks, these models helped solve problems like image recognition and image classification at the cutting edge of the field.

So, over time, deep learning architectures got deeper and deeper (added more layers) to solve more and more complicated tasks. This also helped improve the performance of classification and recognition tasks and make them more stable.

But as we add more layers to the neural network, it gets harder and harder to train, and the model's accuracy starts to plateau and then get worse. The ResNet saves us from that situation and helps us figure out how to fix this problem.

3.3 Architecture/Framework:

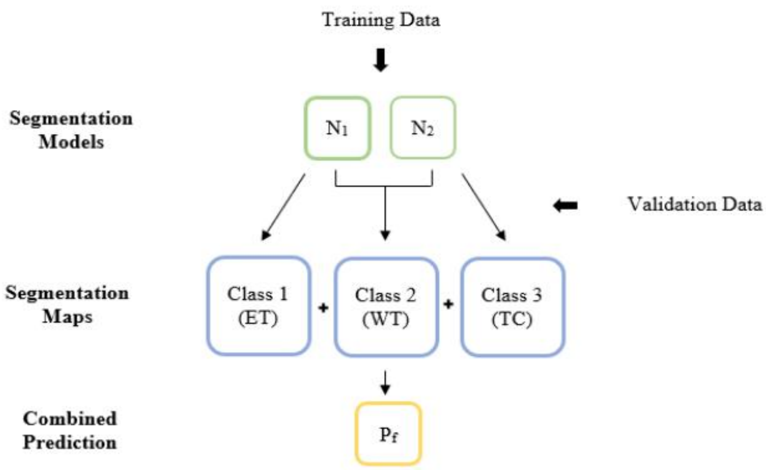

Fig.2. Architecture

3.4 Algorithm and Process Design:

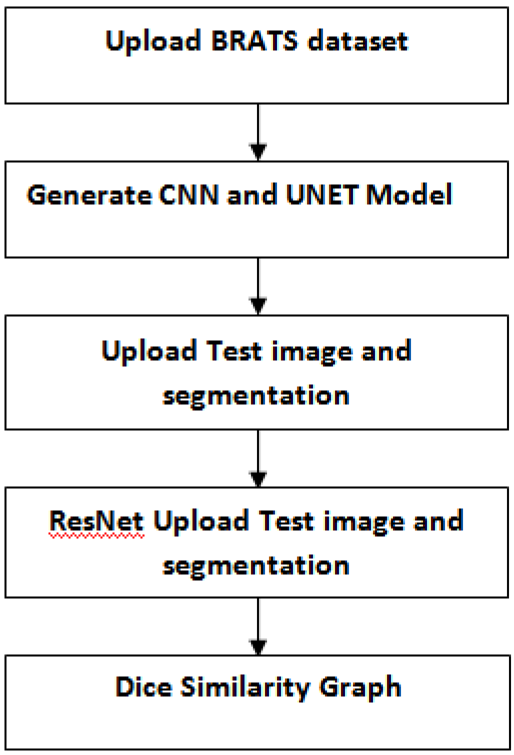

Fig.3 Process Design

Modules

Upload BRATS dataset: We will upload BRATS dataset using this module.

Generate CNN and UNET Models: Using this module, we can see that both models are generated.
Upload Test image and segmentation: We will use this module to upload an image to look for a brain tumour.
Existing UNET algorithms aren't as clear as RESNET algorithms when it comes to separating parts of an image. Because pixels are clear, we can get a high DICE score for how similar the original image and the predicted image are.
Using this module, you can see how dice are alike. We did 50 iterations, or epochs, to build the CNN and UNET models. At each iteration, the DICE score between the training and testing images got better, so the final score was 0.8 * 100 = 80%.

4 How It Was Done and What Happened

4.1 Getting information

We use four different kinds of images to carry out this project. These images are called FLAIR, T1, T2, and T1CE, and the fourth is called a segmented image. The multi-institutional dataset was put together by 19 different institutions. It has multimodal MRI scans of each patient, including T1, T1 contrast-enhanced (T1ce), T2-weighted (T2), and Fluid Attenuated Inversion Recovery (FLAIR), which are used to separate the tumoral subregions. The data is processed to get rid of the differences so that they can't be seen.
Images from the BRATS dataset are saved in the dataset folder**. In the figure below, you can see what's in the dataset**

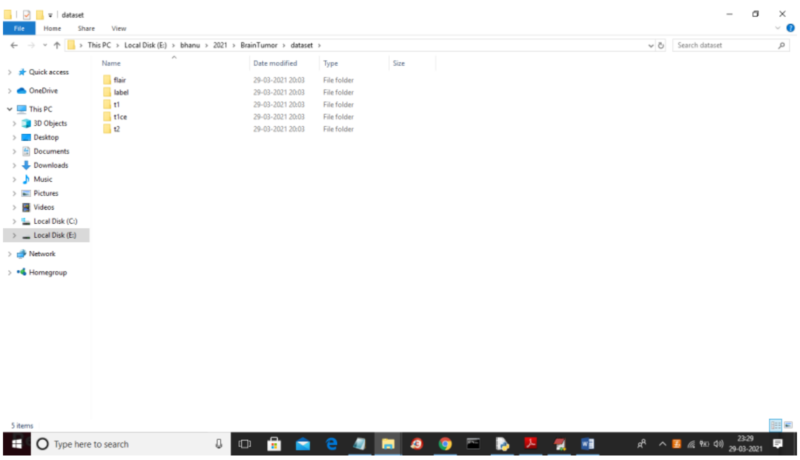

Fig.4. Format Image

In above figure we have different format image and you can go inside any folder to see images

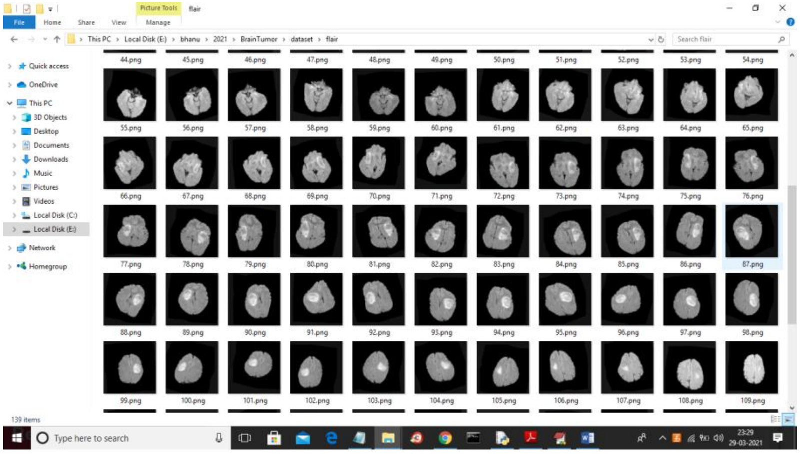

Fig.5. Dataset

Above dataset is used to train CNN and UNET model

4.2 Evaluation Metrics:

We can see both models are generated and we can see below black console to see CNN and UNET layer details

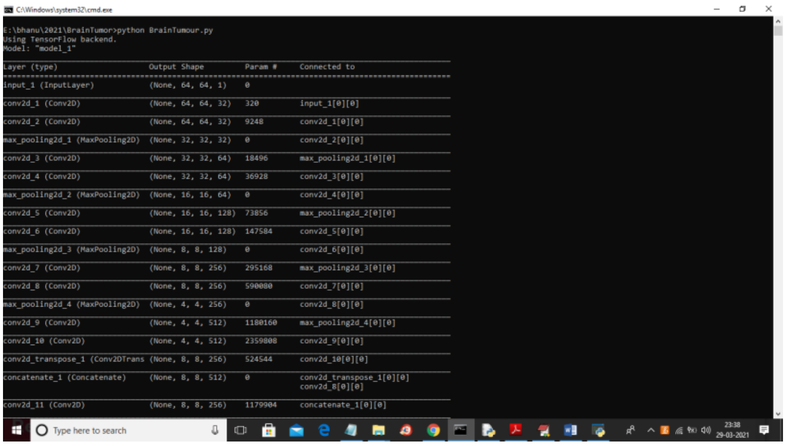

Fig.6 different type images

In above figure we can see models are using different size images to filter them and to get best features from it to build efficient model and now model is generate

4.3 Outcome:

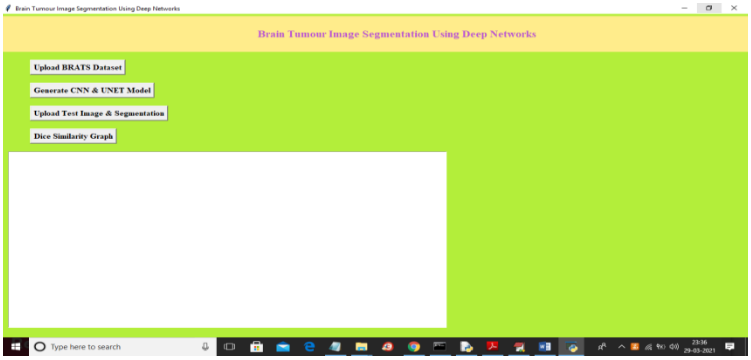

Fig.7

In above figure click on 'Upload BRATS Dataset' button to upload dataset

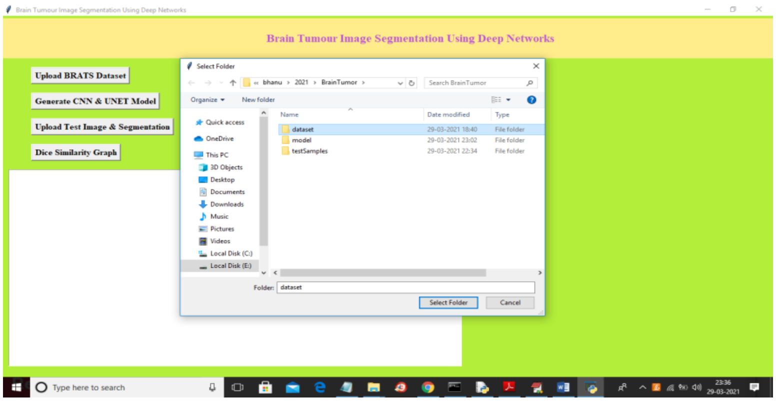

Fig.8

In above figure selecting and uploading 'dataset' folder and then click on 'Select Folder' button to load dataset and to get below figure

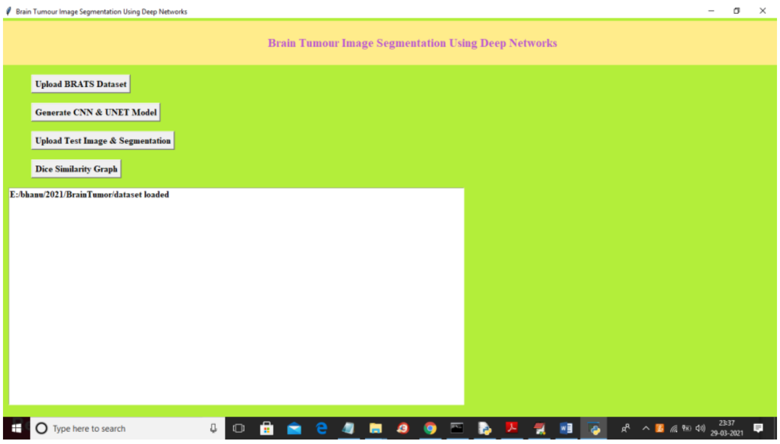

Fig.9

In above figure dataset loaded and now click on 'Generate CNN & UNET Model' button to generate models and to get below figure

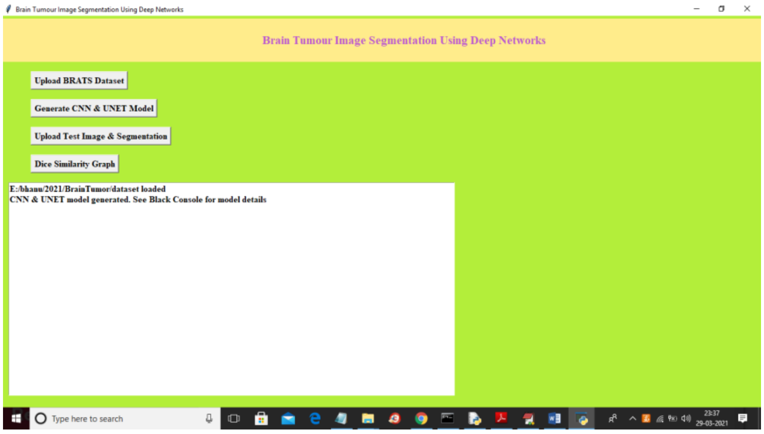

Fig.10

In above figure we can see both models are generated and we can see below black console to see CNN and UNET layer details

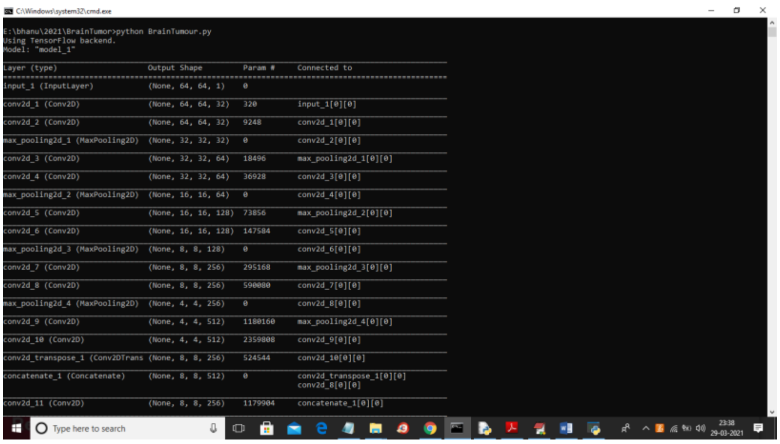

Fig.11

In above figure we can see models are using different size images to filter them and to get best features from it to build efficient model and now model is generate and now click on 'Upload Test Image & Segmentation' button and then upload test samples to get segmented output

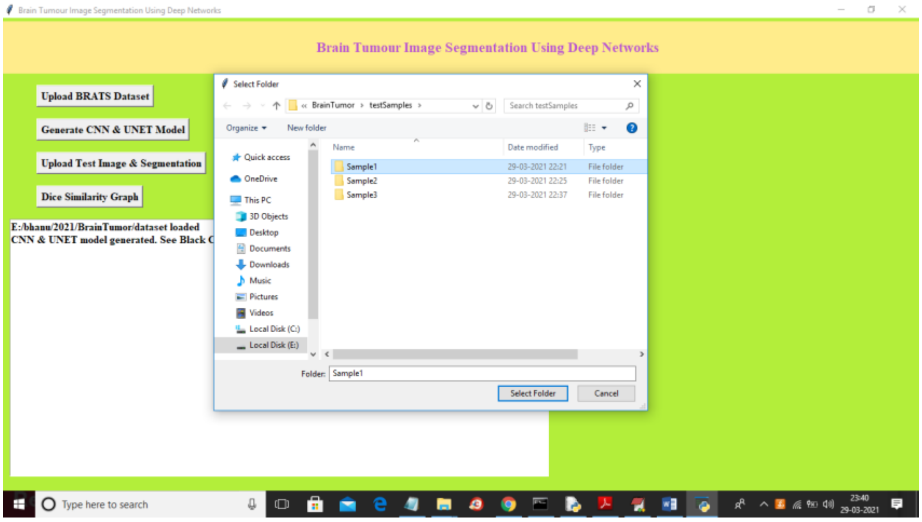

Fig.12

In above figure selecting and uploading ‘Sample1’ folder and then click on ‘Select Folder’ button to get below output

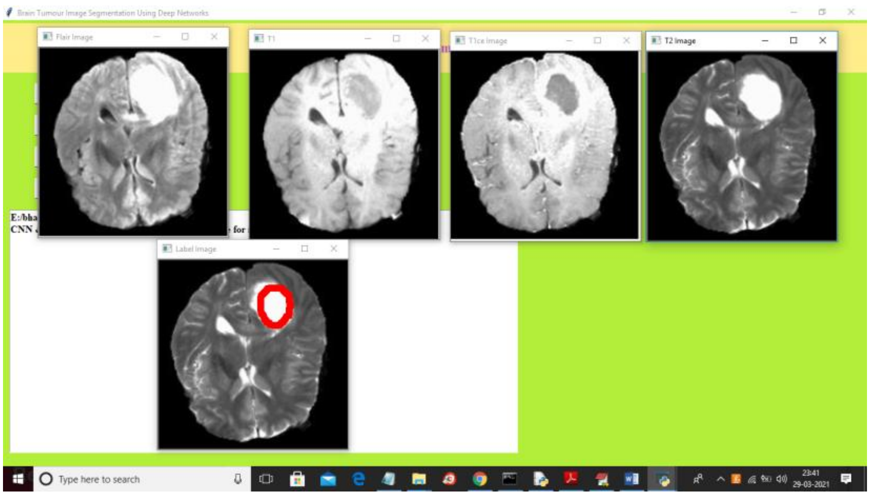

Fig.13

In above figure top 4 images are the input images such as FLAIR, T1, T2 and T1CE and 5th image is the predicted image with segmented part showing in red colour and this algorithm correctly detecting and marking tumour area and now test with other image

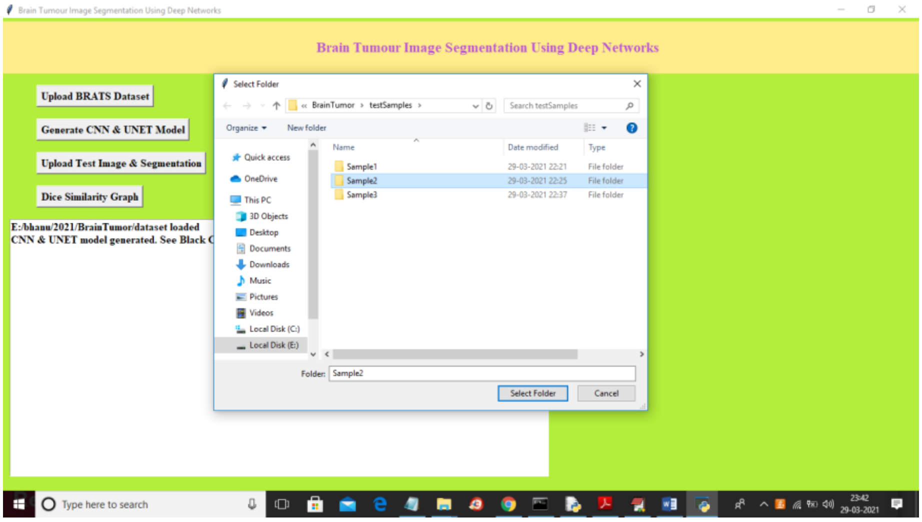

Fig.14

In above figure I am selecting and uploading ‘Sample2’ folder and then click on ‘Select Folder’ button to load images and to get below output

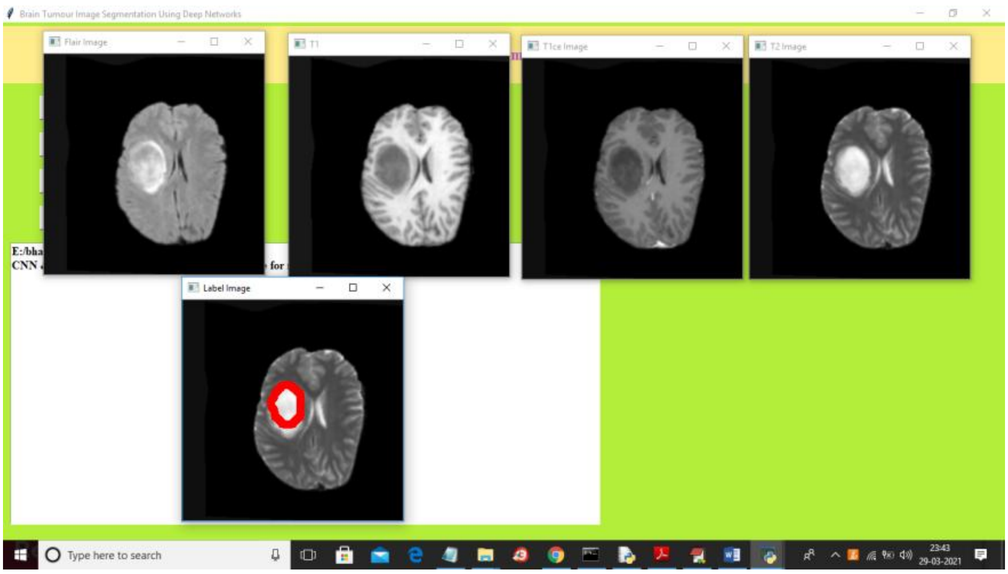

Fig.15

In above figure first 4 images are the input images and fifth image is the predicted label image with segmented parts around tumour area. Now click on ‘Dice Similarity Graph’ button to get below graph

Fig.16

To build CNN and UNET model we took 50 epoch or iterations and at each iteration DICE score between training and testing images get better and better and we get final dice score as 0.8 * 100 = 80%. In above graph x-axis represents epoch and y-axis represents dice score

Extension Outcomes:

In this project as extension we have added RESNET algorithms which can extract segmented part from image with more clarity compare to existing UNET algorithms. Due to pixel clarity we can get high DICE score similarity between original and predicted image.

Run project as per previous steps and I added extra button to apply RESNET on input image and then show segmented UNET and RESNET image and between this two images you can see RESNET with more clarity

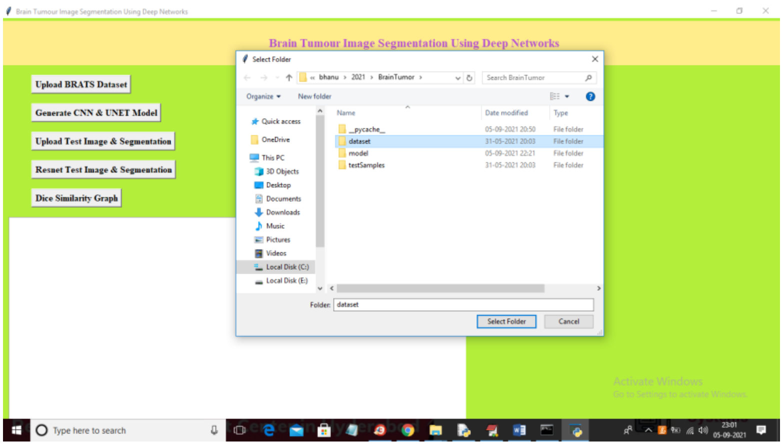

Fig.17.

In above figure uploading dataset folder and then click on 'Generate CNN & UNET Model' button to load UNET model and to get bellow figure

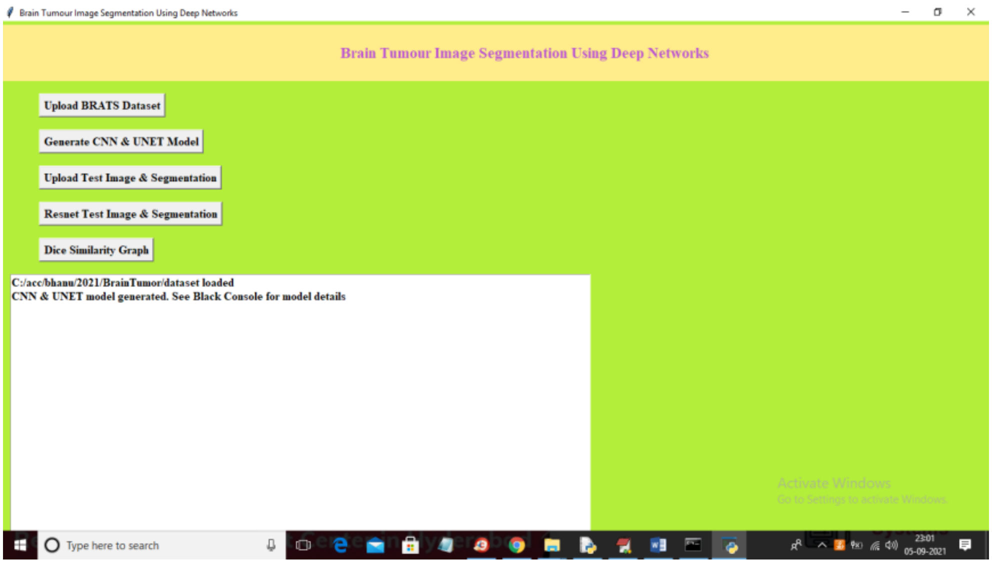

Fig.18

In above figure UNET model is loaded and now click on 'Upload Test Image & Segmentation' button to perform segmentation using UNET and to get below figure

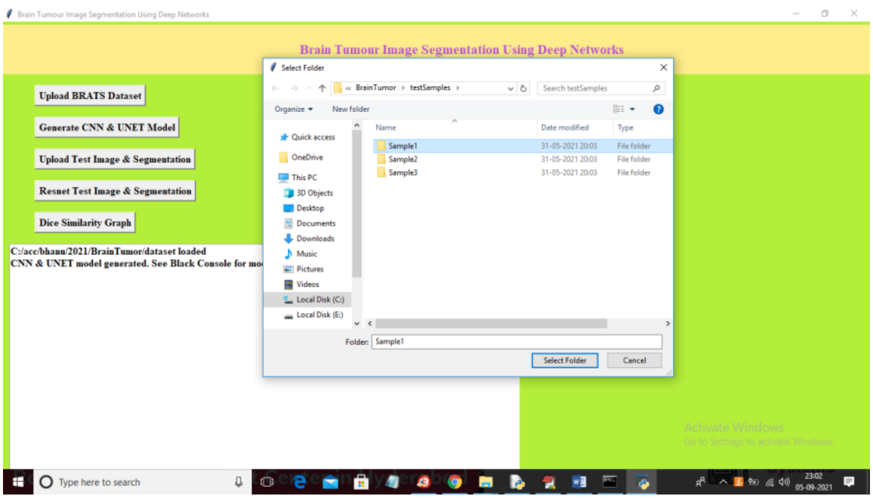

Fig.19

In above figure selecting and uploading 'Sample1' folder and then click on 'Select Folder' button to get below output

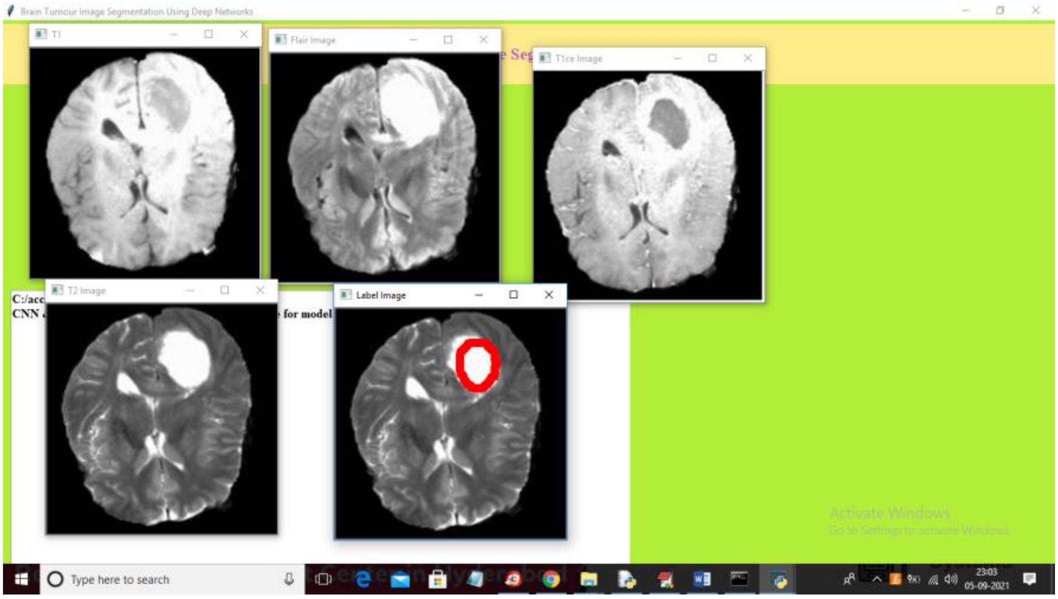

Fig.20

In above figure we can see UNET extracted segmented part and then put bounding box around it and now click on 'Resnet Test Image & Segmentation' button to get segmented image with RESNET and then we can see difference between UNET segmented and Resnet segmented image

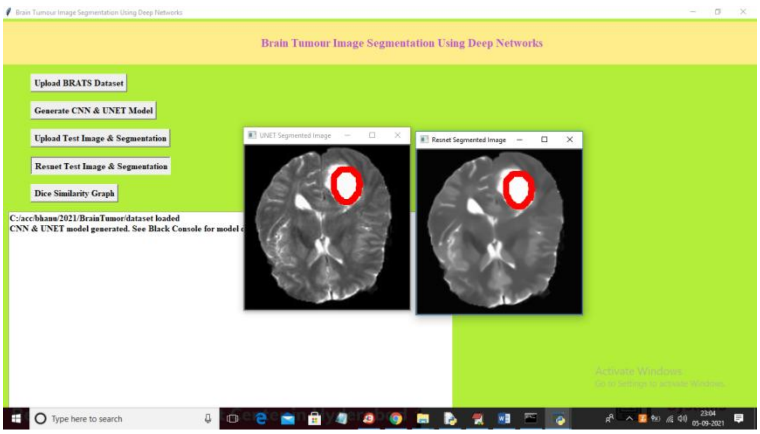

Fig.21

In above figure first image is the UNET segmented image and second one is the RESNET segmented image and in second image we can see little clarity in pixels as in first UNET image there are little black dots in pixels and this dots are removed in RESNET and similarly you can upload other images and test. Now click on 'Dice Similarity Graph' button to get below graph

Fig.22

In the above graph, the x-axis shows the number of epochs or iterations used to train both models. As the number of epochs increases, we can see that the similarity between the original and predicted images increases for both models, but Resnet has a higher score than UNET because its predicted and original images are more similar. The green line in the graph above shows the UNET score, and the blue line shows the RESNET score.

CONCLUSION

In this work, we talked about a group of two networks, each of which is often used on its own to segment biomedical images. CNN, UNET, and Resnet are able to create highly accurate segmentations of brain tumours from the multimodal MRI scans given by the BraTS 2019 challenge. This is better than what other state-of-the-art models can predict.

REFERENCES

[1] S. Bauer, R. Wiest, L. P. Nolte, and M. Reyes. (2013). A Survey of MRI-Based Medical Image Analysis for Brain Tumour Studies. [Online]. Available: http://www

[2] R. Leece, J. Xu, Q. T. Ostrom, Y. Chen, C. Kruchko, and J. S. Barnholtz-Sloan, ''Global incidence of malignant brain and other central nervous system tumors by histology, 2003–2007,'' NeuroOncology, vol. 19, no. 11, pp. 1553–1564, Oct. 2017.

[3] T. A. Dolecek, J. M. Propp, N. E. Stroup, and C. Kruchko, ''CBTRUS statistical report: Primary brain and central nervous system tumours diagnosed in the United States in 2005–2009,'' Neuro. Oncol., vol. 14, no. 5, pp. v1–v49, 2012.

[4] D. N. Louis, A. Perry, G. Reifenberger, A. von Deimling, D. Figarella-Branger, W. K. Cavenee, H. Ohgaki, O. D. Wiestler, P. Kleihues, and D. W. Ellison ''The 2016 World Health Organization classification of tumours of the central nervous system: A summary,'' Acta Neuropathol., vol. 131, no. 6, pp. 803–820, 2016.

[5] R. Stupp et al., ''Radiotherapy plus concomitant and adjuvant temozolomide for glioblastoma,'' New England J. Med., vol. 352, no. 10, pp. 987–996, 2005.

[6] S. Bakas et al., ''Identifying the best machine learning algorithms for brain tumor segmentation, progression assessment, and overall survival prediction in the BRATS challenge,'' 2018, arXiv:1811.02629. [Online]. Available: https://arxiv.org/abs/1811.02629

[7] B. H. Menze, K. van Leemput, D. Lashkari, M.-A. Weber, N. Ayache, and P. Golland, ''A generative model for brain tumor segmentation in multimodal images,'' in Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent., 2010, pp. 151–159.

[8] S. Bakas, H. Akbari, A. Sotiras, M. Bilello, M. Rozycki, J. S. Kirby, J. B. Freymann, K. Farahani, and C. Davatzikos, ''Advancing the cancer genome atlas glioma MRI collections with expert segmentation labels and radiomic features,'' Sci. Data, vol. 4, no. 1, Dec. 2017, Art. no. 170117.

[9] S. Bakas et al., ''Segmentation labels and radiomic features for the preoperative scans of the TCGA-LGG collection,'' Cancer Imag. Arch., vol. 286, 2017.

[10] S. Bakas, H. Akbari, A. Sotiras, M. Bilello, M. Rozycki, J. Kirby, J. Freymann, K. Farahani, and C. Davatzikos ''Segmentation labels and radiomic features for the pre-operative scans of the TCGA-GBM collection. The cancer imaging archive,'' Nat. Sci. Data, vol. 4, 2017, Art. no. 170117.

[11] B. H. Menze et al., ''The multimodal brain tumor image segmentation benchmark (BRATS),'' IEEE Trans. Med. Imag., vol. 34, no. 10, pp. 1993–2024, Oct. 2015.

[12] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, ''Brain tumor segmentation using convolutional neural networks in MRI images,'' IEEE Trans. Med. Imag., vol. 35, no. 5, pp. 1240–1251, May 2016.

[13] M. B. Naceur, R. Saouli, M. Akil, and R. Kachouri, ''Fully automatic brain tumor segmentation using end-to-end incremental deep neural networks in MRI images,'' Comput. Methods Programs Biomed., vol. 166, pp. 39–49, Nov. 2018.

[14] M. Goetz, C. Weber, F. Binczyk, J. Polanska, R. Tarnawski, B. Bobek-Billewicz, U. Koethe, J. Kleesiek, B. Stieltjes, and K. H. Maier-Hein, ''DALSA: Domain adaptation for supervised learning from sparsely annotated MR images,'' IEEE Trans. Med. Imag., vol. 35, no. 1, pp. 184–196, Jan. 2016.

[15] K. Farahani, B. Menze, and M. Reyes. (2014). Brats 2014 Challenge Manuscripts (2014). [Online]. Available: http//www. braintumoursegmentation.org