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Optimized Deep Neural Networks for Accurate Brain Tumor Image Segmentation

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ABSTRACT_ Automated segmentation of brain tumors from multimodal MR images is essential for disease evaluation and progression monitoring, particularly for gliomas due to their malignant and heterogeneous nature. Efficient and accurate segmentation techniques are crucial for delineating tumors into intra-tumoral classes successfully. Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have demonstrated superior performance in semantic segmentation tasks compared to traditional context-based computer vision approaches. In this study, we propose an ensemble approach combining a 3D CNN and a U-Net segmentation network to improve accuracy and precision in tumor segmentation. Both models are trained separately on the BraTS-19 dataset and evaluated to generate segmentation maps with variations in segmented tumor sub-regions. The ensemble strategy integrates these models effectively to achieve enhanced predictions

1.INTRODUCTION

Accurate segmentation of tumours through medical images is of particular importance as it provides information essential for analysis and diagnosis of cancer as well as for mapping out treatment options and monitoring the progression of the disease. Brain tumours are one of the fatal cancers worldwide and are categorised, depending upon their origin, into primary and secondary tumour types [1]. The most common histological form of primary brain cancer is the glioma, which originates from the brain glial cells [2] and attributes towards 80% of all malignant brain tumours [3]. Gliomas can be of the slow-progressing low-grade (LGG) subtype with a better patient prognosis or are the more aggressive and infiltrative high-grade glioma (HGG) or glioblastoma, which require immediate treatment [4]. These tumours are associated with substantial morbidity, where the median survival for a patient with glioblastoma is only about 14 months with a 5-year survival rate near zero despite maximal surgical and medical therapy [5]. A timely diagnosis, therefore, becomes imperative for effective treatment of the patients. Magnetic Resonance Imaging (MRI) is a preferred technique widely employed by radiologists for the evaluation and assessment of brain tumours [1]. It provides several complimentary 3D MRI modalities acquired based on the degree of excitation and repetition times, i.e. T1-weighted, post-contrast T1-weighted (T1ce), T2-weighted and FluidAttenuated Inversion Recovery (FLAIR). The highlighted subregions of the tumour across different intensities of these sequences [6], such as the whole tumour (the entire tumour inclusive of infiltrative oedema), is more prominent in FLAIR and T2 modalities. In contrast, T1 and T1ce images show the tumour core exclusive of peritumoural oedema [7]. It allows for the combinative use of these scans and the complementary information they deliver towards the detection of different tumour subregions.

2.LITERATURE SURVEY

2.1 Bengio, Y., Lamblin, P., Popovici, D., Larochelle, H.: Greedy layer-wise training of deep networks. Advances in Neural Information Processing Systems 19 (NIPS), 153–160 (2007).

Complexity principle of circuits strongly suggests that deep architectures can be lots extra environment friendly (sometimes exponentially) than shallow architectures, in phrases of computational factors required to characterize some functions. Deep multi-layer neural networks have many tiers of non-linearities permitting them to compactly signify distinctly non-linear and highly-varying functions. However, till these days it used to be now not clear how to teach such deep networks, for the reason that gradient-based optimization beginning from random initialization seems to frequently get caught in bad solutions. Hinton et al. currently brought a grasping layer-wise unsupervised mastering algorithm for Deep Belief Networks (DBN), a generative mannequin with many layers of hidden causal variables. In the context of the above optimization problem, we find out about this algorithm empirically and discover versions to higher recognize its success and prolong it to instances the place the inputs are non-stop or the place the shape of the enter distribution is now not revealing sufficient about the variable to be expected in a supervised task. Our experiments additionally verify the speculation that the grasping layer-wise unsupervised coaching method mainly helps the optimization, by means of initializing weights in a location close to a accurate neighborhood minimum, giving upward push to inner disbursed representations that are high-level abstractions of the input, bringing higher generalization.

2.2 Bengio, Y.: Learning deep architectures for AI. Foundations and Trends in Machine Learning 2, 1–127 (2009).

Theoretical effects propose that in order to analyze the variety of elaborate features that can signify high-level abstractions (e.g., in vision, language, and different AI-level tasks), one can also want deep architectures. Deep architectures are composed of a couple of stages of non-linear operations, such as in neural nets with many hidden layers or in elaborate propositional formulae re-using many sub-formulae. Searching the parameter area of deep architectures is a challenging task, however studying algorithms such as these for Deep Belief Networks have these days been proposed to address this trouble with exceptional success, beating the latest in sure areas. This monograph discusses the motivations and standards concerning mastering algorithms for deep architectures, in unique these exploiting as constructing blocks unsupervised mastering of single-layer fashions such as Restricted Boltzmann Machines, used to assemble deeper fashions such as Deep Belief Networks.

2.3 S.-H. Hsu, Q. Peng, and W. A. Tomé, ``on the era of artificial CT for an MRI-only radiation remedy workflow for the abdomen,'' J. Phys., Conf. Ser, vol. 1154, no. 1, Mar. 2019, Art. no. 012011.

The advances in clinical imaging have led to new multi dimensional imaging modalities that have grow to be essential medical equipment in diagnostic radiology. The two modalities succesful of producing multidimensional pix for radiological purposes are Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). Normally the first radiologic examination in suspicion of stroke is talent CT imaging. But MRI gives excessive decision pictures with extremely good gentle tissue characterization capabilities. A comparative analysis for the prognosis of stroke on CT and MRI photographs is presented in this paper. The algorithm proposes the use of Digital Image processing equipment for the identification of infarct and Hemorrhage in human brain. Preprocessing of clinical pics is completed by way of median filtering. Segmentation is finished via Gabor filtering and seeded location developing algorithm. The technique is established on the CT and MRI Genius photos having extraordinary sorts of infarcts. The effects of the approach are evaluated visually. The proposed technique is promising for detection of stroke and additionally establishes that MRI imaging is best to CT imaging in stroke detection.

3.PROPOSED SYSTEM

In the realm of medical image analysis, the integration of deep learning methodologies has become increasingly prevalent, particularly in the segmentation of brain tumors. A novel approach to automating the segmentation process involves combining the strengths of both 3D Convolutional Neural Networks (CNN) and the UNet algorithm. This fusion aims to capitalize on the respective advantages of each method, thereby enhancing the efficiency and accuracy of tumor delineation.

By training separate models on the BRATS brain tumor dataset, which comprises multimodal MRI scans including FLAIR, T1, T2, and T1CE images, significant progress has been made. Each model produces its own segmentation output. The subsequent step involves merging or mapping the outputs of both algorithms to generate a final segmentation. Notably, this combined approach has demonstrated a remarkable improvement in Dice score, indicating a more precise delineation of tumor boundaries.

The dataset utilized in this endeavor is multi-institutional, sourced from 19 different contributors. To ensure consistency and reliability, preprocessing steps include skull-stripping to mitigate any inherent discrepancies in the data. Through this concerted effort, the aim is to develop an automated brain tumor segmentation method that not only achieves superior accuracy but also facilitates the delineation of intra-tumoral classes with enhanced efficiency compared to existing methodologies

4.DATASET

BRATS dataset images are saved inside dataset folder and in below screen you can see dataset content

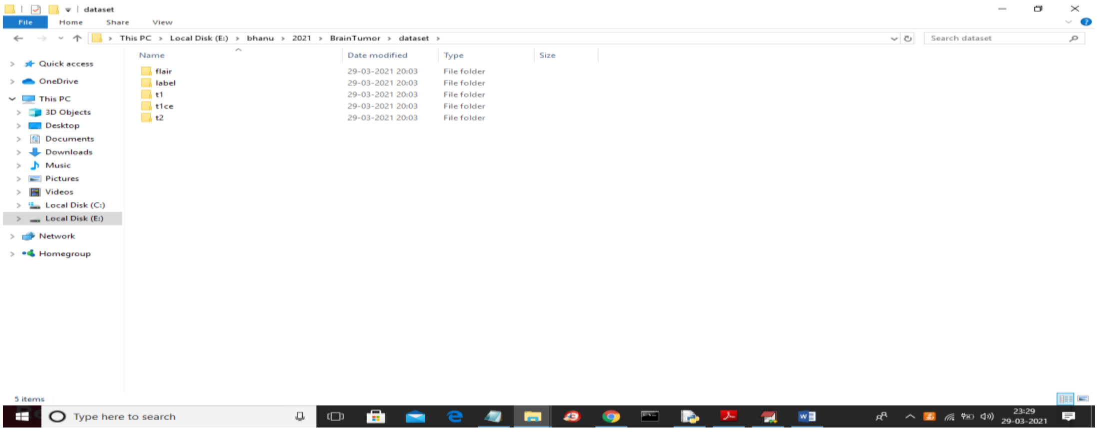

Fig 1:In above screen we have different format image and you can go inside any folder to see images

Fig 2:Above dataset is used to train CNN and UNET model

After building UNET and CNN model we will upload test images from ‘testSamples’ folder and then UNET model will give us segmented image. Below screen shots showing testSamples image

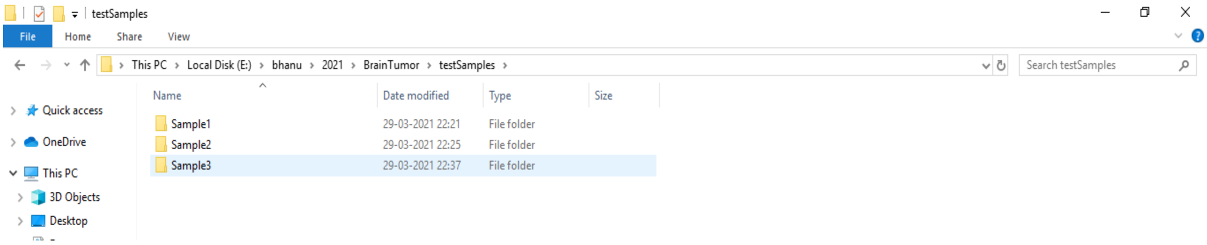

Fig 3:In above screen we have 3 samples images and now go inside any folder to get below images

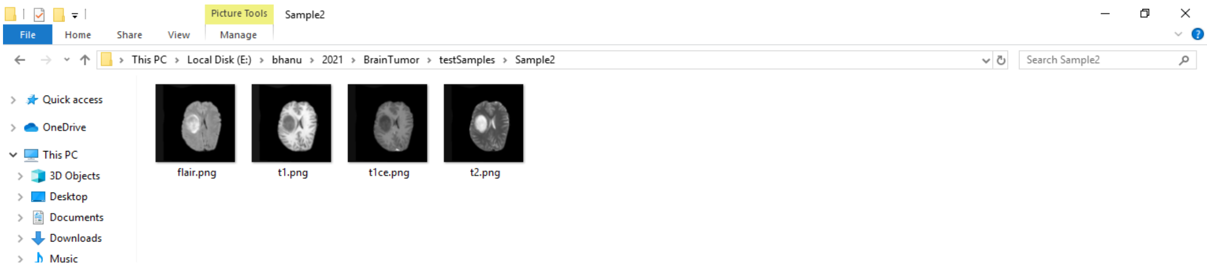

Fig 4:In above screen we have FLAIR, T1, TICE and T2 images but we don't have segmented label image and after applying model on above images then we will get segmented label image

5.RESULTS AND DISCUSSION

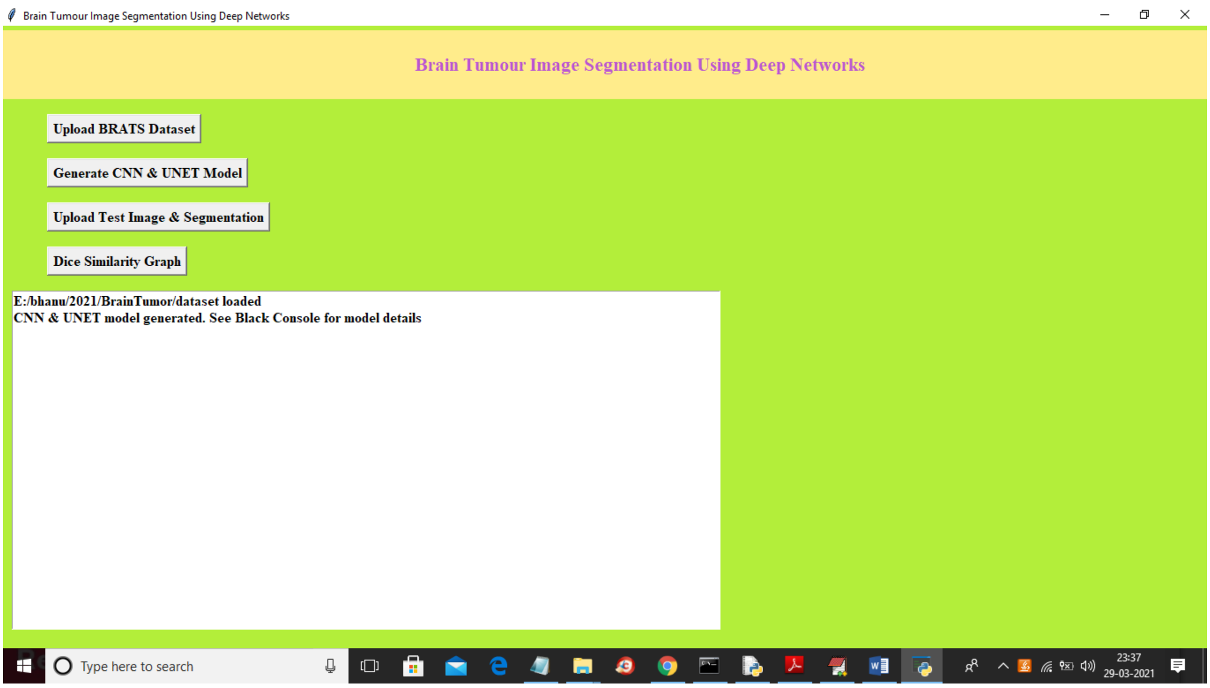

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Fig 5: In above screen we can see both models are generated and we can see below black console to see CNN and UNET layer details

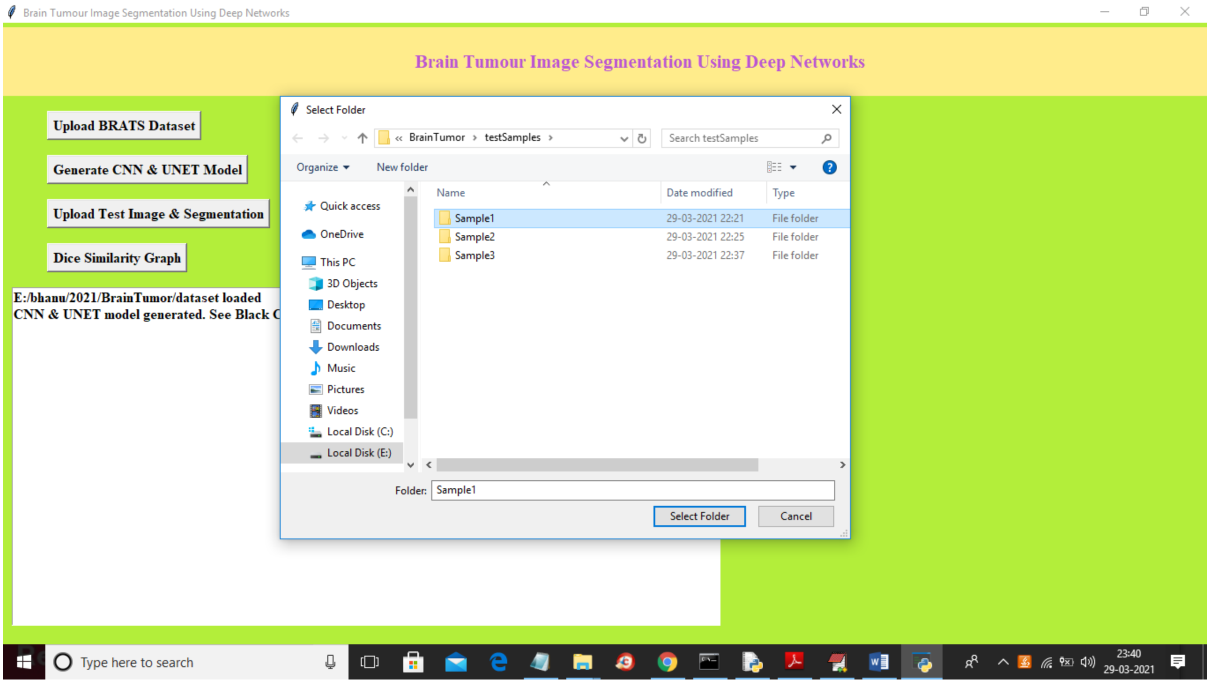

Fig 6:In above screen selecting and uploading 'Sample1' folder and then click on 'Select Folder' button to get below output

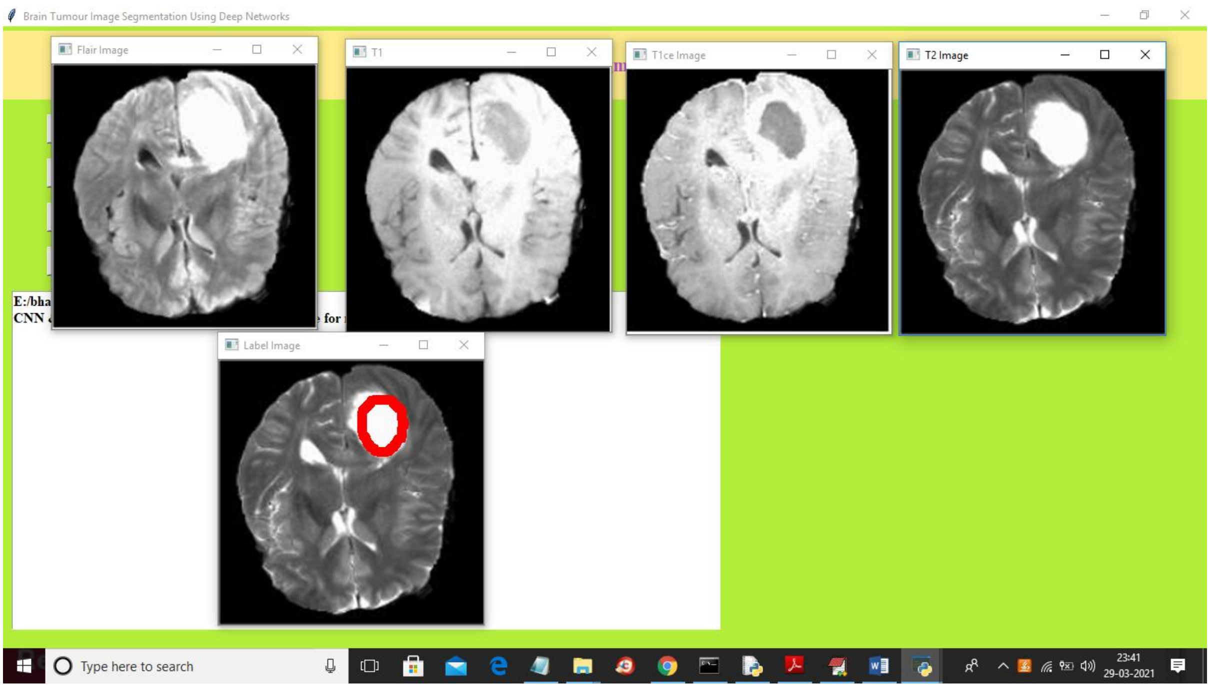

Fig 7:In above screen top 4 images are the input images such as FLAIR, T1, T2 and T1CE and 5th image is the predicted image with segmented part showing in red colour

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and this algorithm correctly detecting and marking tumour area and now test with other image

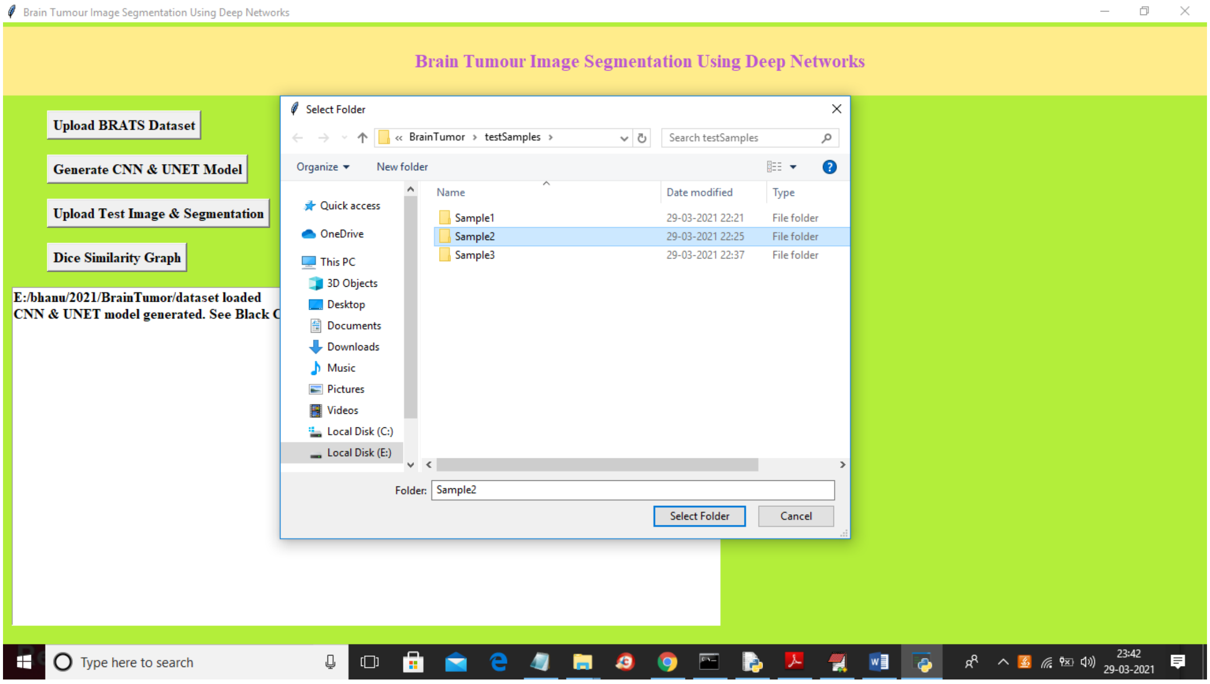

Fig 8: In above screen I am selecting and uploading 'Sample2' folder and then click on 'Select Folder' button to load images and to get below output

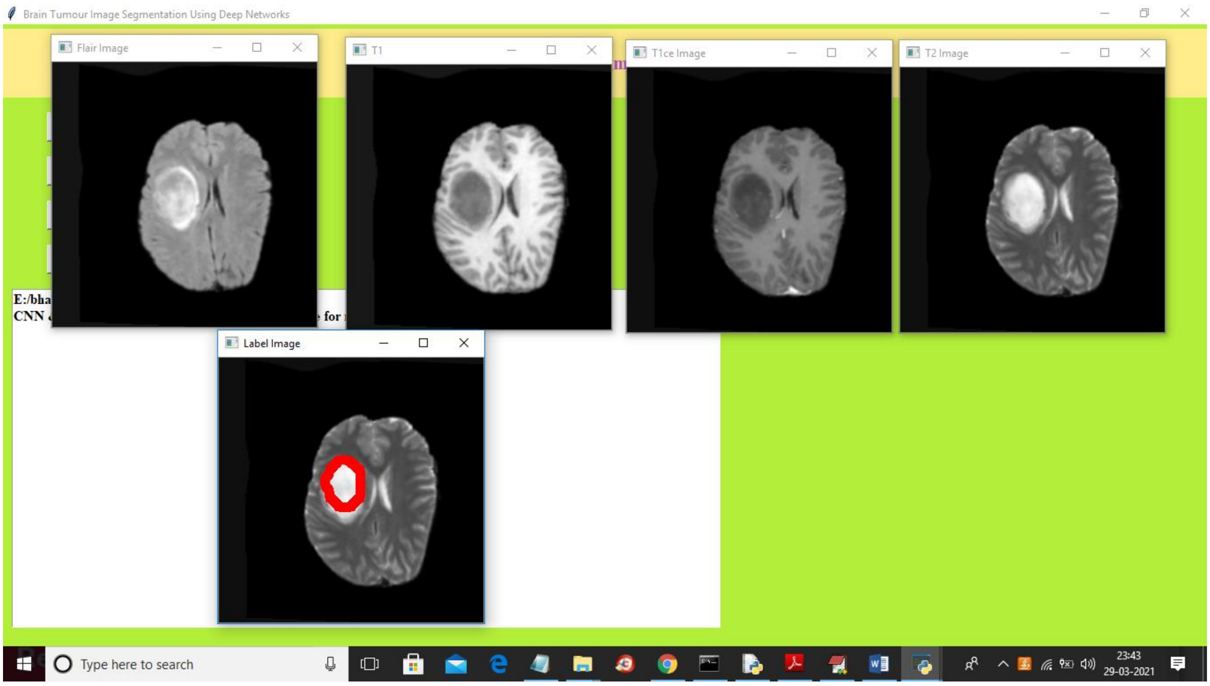

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Fig 9:In above screen first 4 images are the input images and fifth image is the predicted label image with segmented parts around tumour area. Now click on 'Dice Similarity Graph' button to get below graph

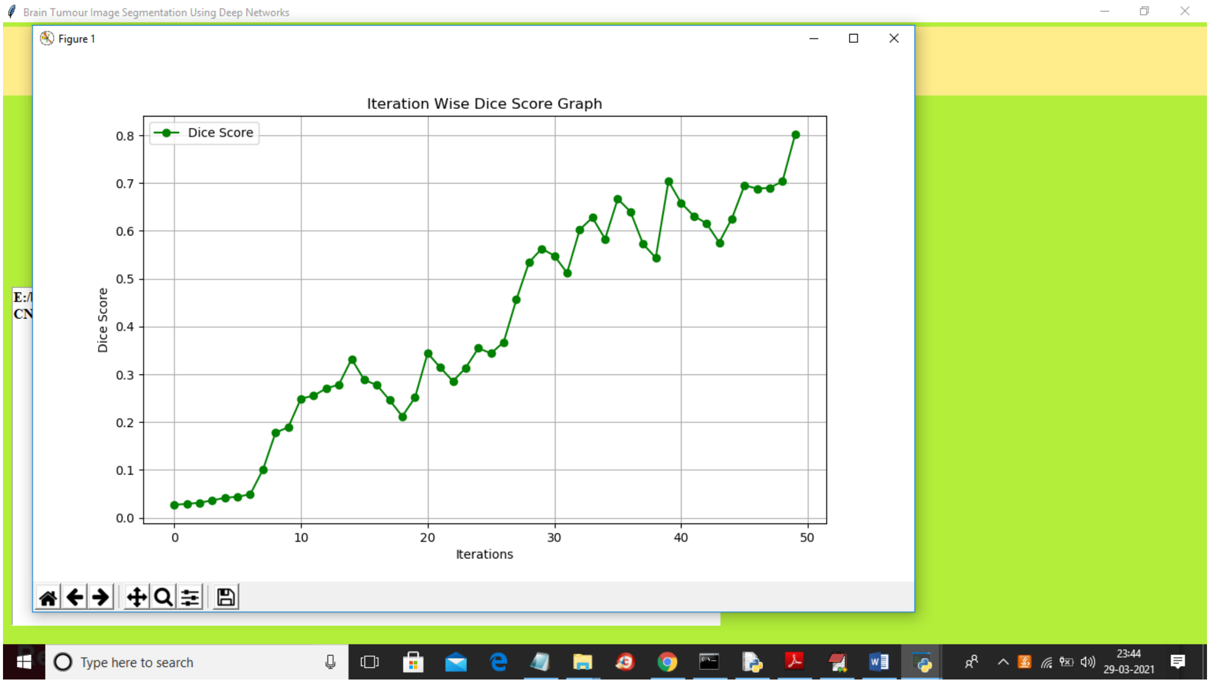

Fig 10: To build CNN and UNET model we took 50 epoch or iterations and at each iteration DICE score between training and testing images get better and better and we get final dice score as 0.8 * 100 = 80%. In above graph x-axis represents epoch and y-axis represents dice score

6.CONCLUSION

In this paper, we use the image segmentation approach. We employed a combination of two unique approaches, Watershed and Contrast Technique. This approach works well for detecting tumors in images. When compared to other methods, this segmentation methodology is extremely accurate. MRI pictures are ideal for detecting talent tumors. In this article, we will learn about Digital Image Processing Techniques, which are vital for detecting tumors using MRI pictures. Preprocessing procedures include unique approaches such as filtering, contrast enhancement, and edge identification, which are used to smooth pictures. The preprocessed snapshots are utilized for publish processing operations such as threshold, histogram, segmentation, and morphological, which are used to improve the images.

REFERENCES

[1] N. Nandha Gopal, "Dr. Karnan,Diagnose Brain Tumor Through MRI using Image Processing Algorithm such as Fuzzy C Means Along with Intelligent Optimization Techniques", journal of IEEE 2010.

[2] Ehab F. Badran, Esraa Galal Mahmoud, and Nadder Hamdy, "An Algorithm for Detecting Brain tumors in MRI Images", journal of IEEE 2010.

[3] K.S Angel Viji, Dr. J.Jayakumari, "Automatic Detection of Brain Tumor based on MRI Using CAD system and watershed segmentation", Proceeding International conference on Signal processing, communication, and Networking technology, 2011.

[4] M. Usma aka Ana Usma, "Computer Aided Brain Tumor Detection and Segmentation", Journal of IEEE, 2011.

[5] R.B.Dubey, M.Hanmandlu, Sr. Member, Shantaram Vasikarla, "Evaluation of three Methods for MRI Brain Tumor Segmentation", Eighth International Conference on Information Technology, 2011.

[6] Natranjan.p, Krishnan.N, Natasha Sandeep Kenkre, Shraiya Nancy, Bhuvanesh Pratap singh, "Tumor Detection using threshold operation in MRI Brain Image", IEEE International Conference on Computational Intelligence and Computing Research, 2012

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