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Research Article

Feature classification and Segmentation of MRI Brain ROI into Edema or Enhancing and Non-Enhancing Tumour using Hybrid U-NET based Convolutional Neural Networks

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ABSTRACT

Utilizing Convolutional Neural Networks (CNNs),Feature Classification and Segmentation of Brain Tumor we can parse several phases of tumor as well as identify and visualise the Hybrid U-Net in adopting to arrive at realistic results and accurate analysis of tumor ROI by using the state-art-of the approaches. With the help of robust Feature Classification and Segmentation Methods we can assess the whole tumor ROI along with the identification of intra tissue tumor and the effected tissues of an brain MRI. To assess these parameters in an normal brain scan is a tedious work hence Magnetic Resonance Imaging is the modality used for efficient studies on identification, diagnosis and prognosis of brain tumor. The concept of Medical Imaging Analysis is quantitative in nature by predicting clinical sequelae like detection of tumor core, tissues associated with the tumor region and differences between affected tissues and normal tissues. In the field of Pathology, analysis and visualising the tumor by feature classification and segmentation methods is critical approach in the pipeline.With the help of Medical Imaging Deep Transfer Learning Pipelines, we could resolve the issues involved in manual feature classification and segmentation which varies vividly different from observers so the pipelines will help us identify the region of interest required for the analysis of brain tumor. In the field of Medical Informatics, the clinical personnel's need to assess the patient by indexing databases based on location of image, size of tumor and related aspects of brain tumor using Magnetic Resonance Imaging. So, the approach utilised here can aid them and minimise the risk associated with it like processing the data which is computationally challenging intensive work. The Magnetic Resonance Imaging modality is chosen for detection and prediction of brain tumor since it provides accurate information on position, size and its type which is later assessed to identify purpose of diagnosis, monitor treatment clinical outcomes in pre-surgery and post-surgery. The feature classification of brain tumor is size, texture, shape and other factors are included whereas segmentation can cluster pixels into a salient image, region correspondence to surfaces etc are analysed quantitively. .The paper gives a view on how MRI Brain Images is reviewed and how hybrid U-Net Method gives analysis on the approaches utilised to identify the required ROI of brain image which could be edema, enhancing tumor or non-enhancing tumor. In the end we have also discussed the recent trends and cutting-edge approaches in image feature classification and segmentation in Brain MRI images.

Keywords: Edema, Enhancing Tumor, Non-Enhancing Tumor, U-NET, T1CE, Magnetic Resonance Imaging, Medical Imaging Deep Transfer Learning.

Introduction

The most common type of cancers are brain tumors which has alarming rate of mortality. Tumors are originated from cells of brain mainly neoplasms. The brain is a soft, delicate, non-replaceable and spongy mass of tissue. It is a stable place for patterns to enter and stabilize among each other. A tumour is basically a mass of tissue that grows out of control of the normal forces that regulates its growth. Brain tumour is a group of abnormal cells that grows either inside the brain or around the brain. Tumours can directly destroy all healthy brain cells. It can also indirectly damage healthy cells by crowding other parts of the brain and causing inflammation, brain swelling and pressure within the skull. The most common types of brain tumors are Glioma, Meningioma and Pituitary tumor. Early detection of tumor cells plays a major role in treatment and recovery of patient. Diagnosing a brain tumor usually undergoes a very complicated and time-consuming process. The MRI images of various patients at various stages can be used for the detection of tumors. There are various types of feature extraction and classification methods which are used for detection of brain tumor from MRI images.

Magnetic Resonance Imaging (MRI) is the common type of imaging modality utilised to assess brain tumors because it gives accurate tissue contrast and the data availability is in 3D. Though labelling each voxel manually leads to delineation of volumetric analysis and rough estimations by physicians arises infeasible practice of clinical medicine. From this estimation it is prone to have a variability varying from intra to inter rater sub optimally details provided from MRI Image. Hence it has become the need of the hour to have reliable and semiautomated feature extraction and segmentation methods.

Though it is difficult to identify the tumor because of variable shape, size or location tissue content is heterogenous. The segmentation, detection, and extraction of infected tumor area from magnetic resonance (MR) images are a primary concern but a tedious and time taking task performed by radiologists or clinical experts, and their accuracy depends on their experience only. So, the use of computer aided technology becomes very necessary to overcome these limitations.

Materials and Methods

Hybrid U-Net Architecture

The Hybrid U- Net Architecture is comprised of Up sampling and down sampling along connections of residual to concatenate variable spatial scales into feature maps. The network is trained by using P100 NVIDIA Tesla so that there is no validation plateau loss up to set of 200 epochs.

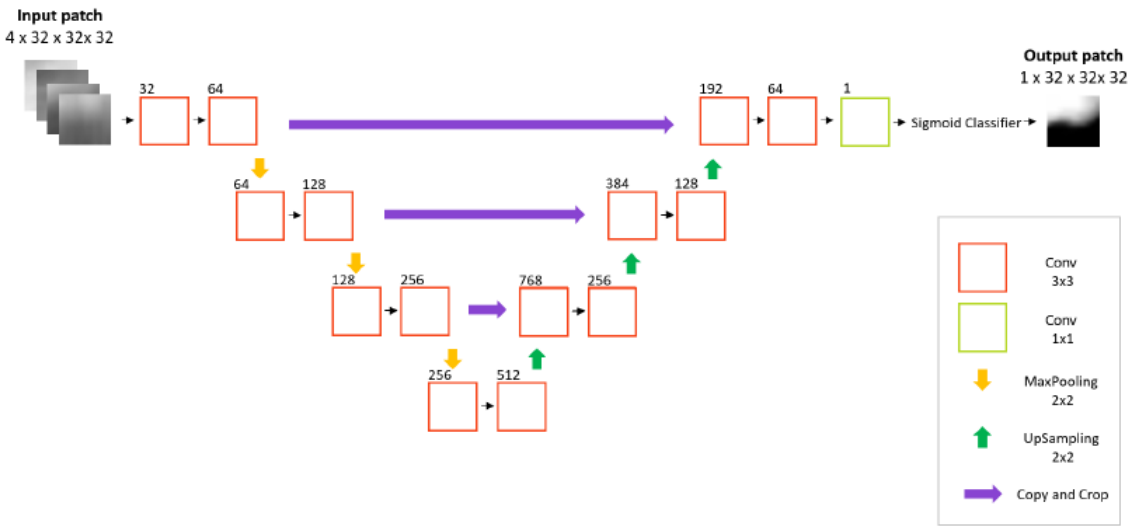


Fig 1: Representation of the Hybrid U-Net Architecture Network.

To an input patch of size 32 x 32 x 32 voxels with four set of channelsT1, T1-post, T2 and FLAIR. Every layer of convolutional network is regularised for batch normalisation. Except for the finalised sigmoid output, every layer is activated through Rectified Linear Unit (ReLU). Through the approach of Nestorov Adaptive Moment Estimation (NAdam) the Hybrid U-NET is trained at a learning rate of 10-6 so as to minimise dice loss functions.

Augmentation and Extraction of Patches

The set of T1, T1-post, T2 and FLAIR volumes are normalised with unit variance and zero mean. The following ratio was followed for sampling of patches 70% of Tumor, 29% of normal brain and rest 1% is background. For a total of 60 patches, each subject was augmented and extracted by doubling the size of train set with the help of sagittal flips.

During the time of interference, each volume is grid into 32 X 32 X 32 voxel patches at 16 possible different offsets starting from the upper most corner of MRI image. The model predicts the patches having each probability maps and prediction of voxel due to multiple overlapping of the patches has led to averaged labels which are binarized at chosen level of threshold.

Whole tumor

Whole tumor comprises of all the sets of Edema, Enhancing Tumor and Non-Enhancing tumor. Initially to obtain the whole tumor core we need to pre process data by down sampling of isotropic 2mm voxels trained with Hybrid U-Net Model along with input patches. These patches are converged and fed back to probability map with a resolution of 2mm.

Enhancing Tumor and Non-Enhancing Tumor

Two Hybrid U-Net Model was used for training two different patches which have MR channels of four and ground truth map labelled as Whole tumor as fifth channel. During the interference time, the ground truth is visualised using the prediction of Whole Tumor. From this visualisation we can arrive at the boundaries of tumor to predict about Edema , Enhancing and Non Enhancing Tumors.

Network Post Processing

The Network Post Processing is done with the help of morphological operation like dilation, erosion and withdrawing of connected small components. We have additionally tweaked three predictions i.e., is Edema, Enhancing Tumor and Non-Enhancing Tumor into Hybrid U-Net Architecture. So, all input patches have seven layers in which four MR are anatomical and rest labels are Edema, Enhancing Tumor and Non-Enhancing Tumor.

Proposed Approach

With the help of Network, were Tensor Flow and Keras at the backend, we then used the training and test data sets for validating purpose. Then set of T1, T1-post, T2 and FLAIR volumes of every subject with pre-operative scans was obtained.

All the pre-operative scan datasets are registered as intra-subject and skull stripped. We obtained the whole training set (n = 60) of images where the test images (n = 35) and trained images (n = 25) for optimisation of parameters and training purposes.

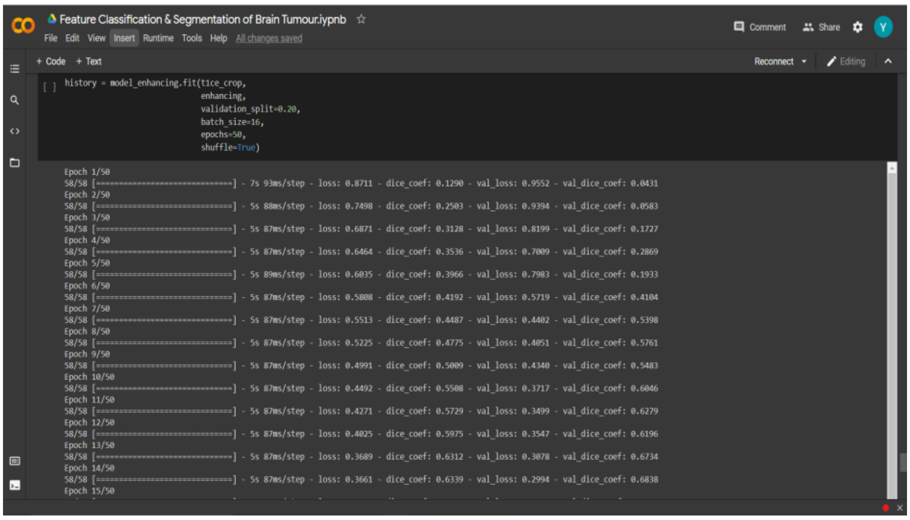


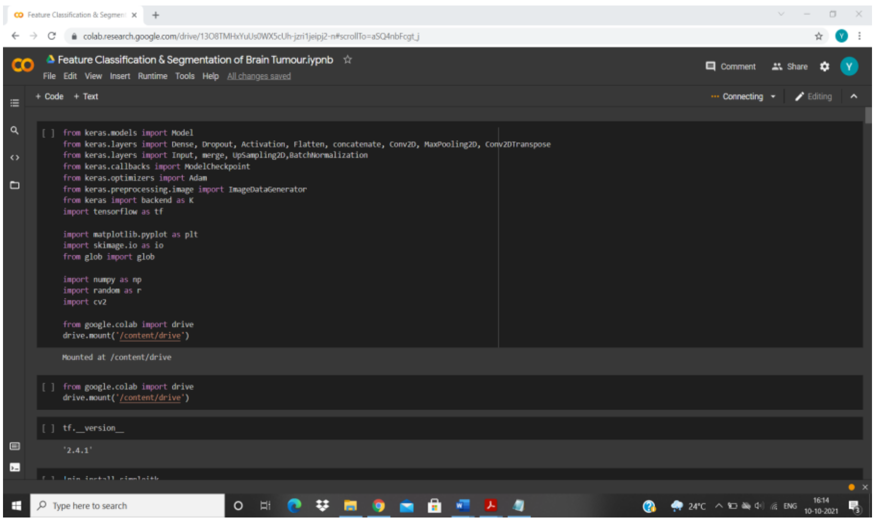
Fig 2: Visualisation of the epochs which is trained and provides accurate information on validation loss and dice coefficients.

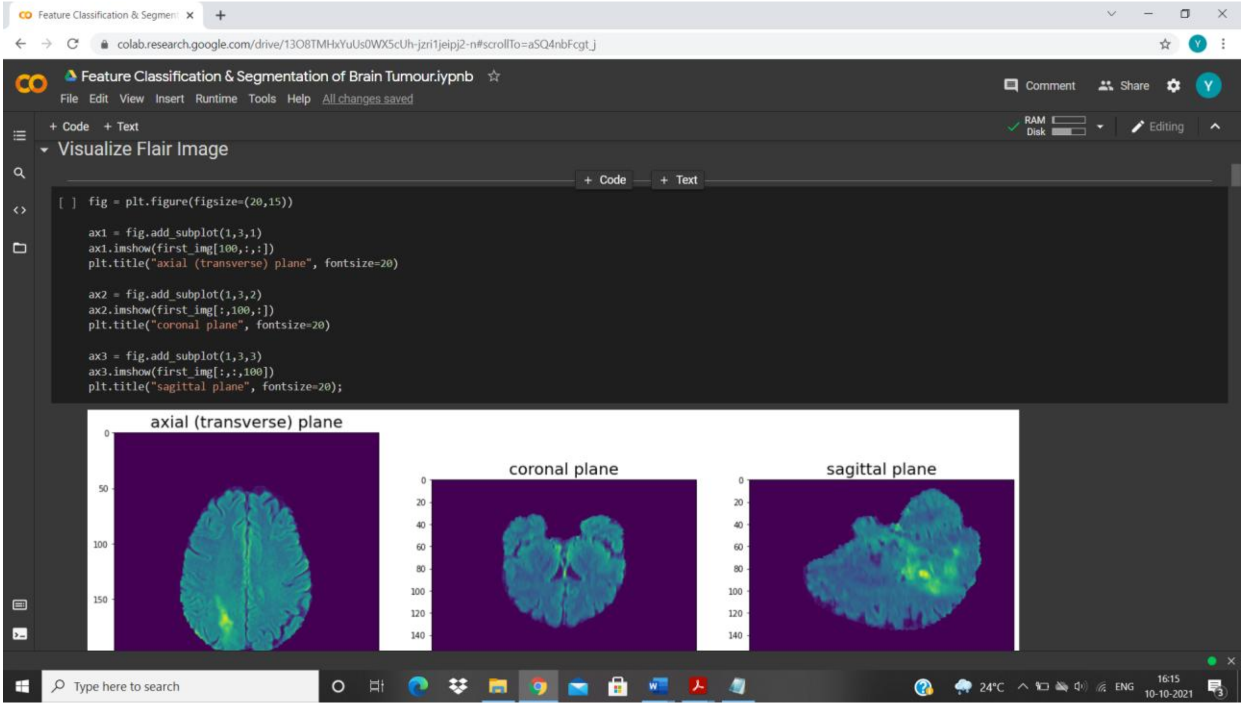
The Ground truth labels was not present hence we validated Dice Scores, loss, specifities and sensitivities were obtained through the Epochs training methods.

Empirical Setup

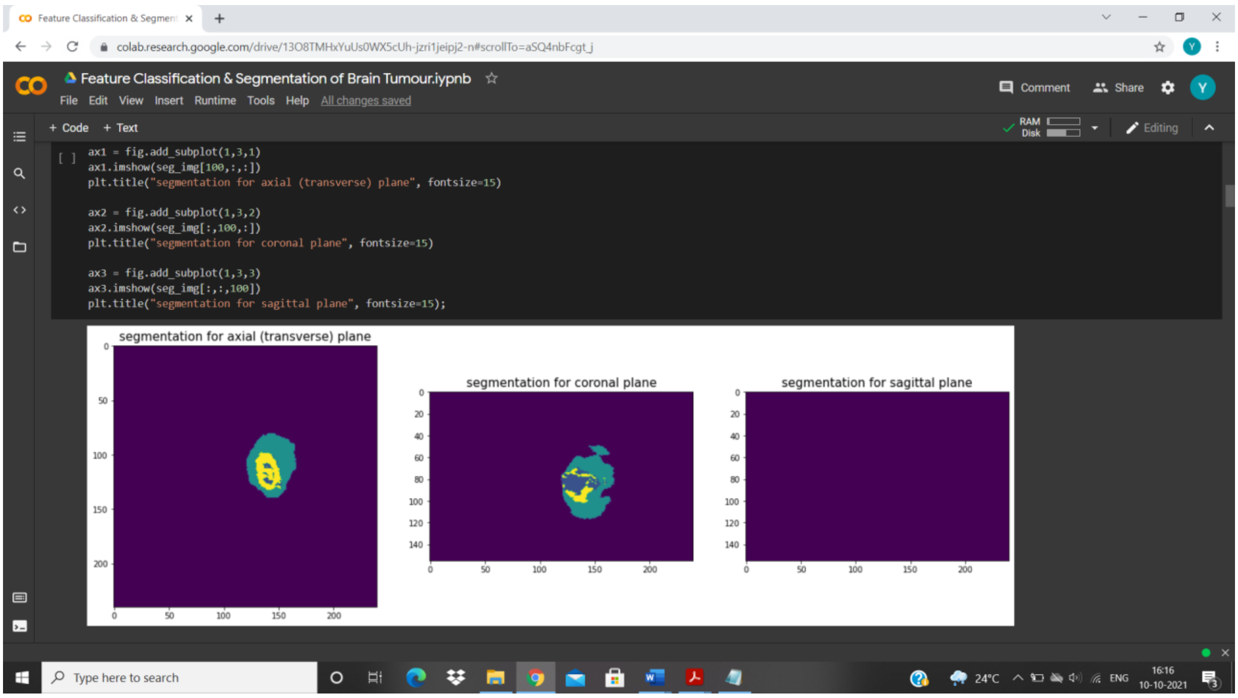
In the Empirical Setup tests are executed by using customized Windows® laptop having an Intel Core (TM) i7-7700 CPU with a 3.60GHz processor storage of 1 TB HDD with 64 GB RAM, CUDA-envised Nvidia GTX storage of 1060 6GB along with Graphical Processing Unit (GPU), Python 3 version of 3.6.7, Keras version of 2.2.4 with TensorFlow version of 1.12.0 backend and Google Colab Integration Tools.

Procedural Step 1: To import the necessary libraries and networks required for the Feature Classification and Segmentation of Brain Tumor.

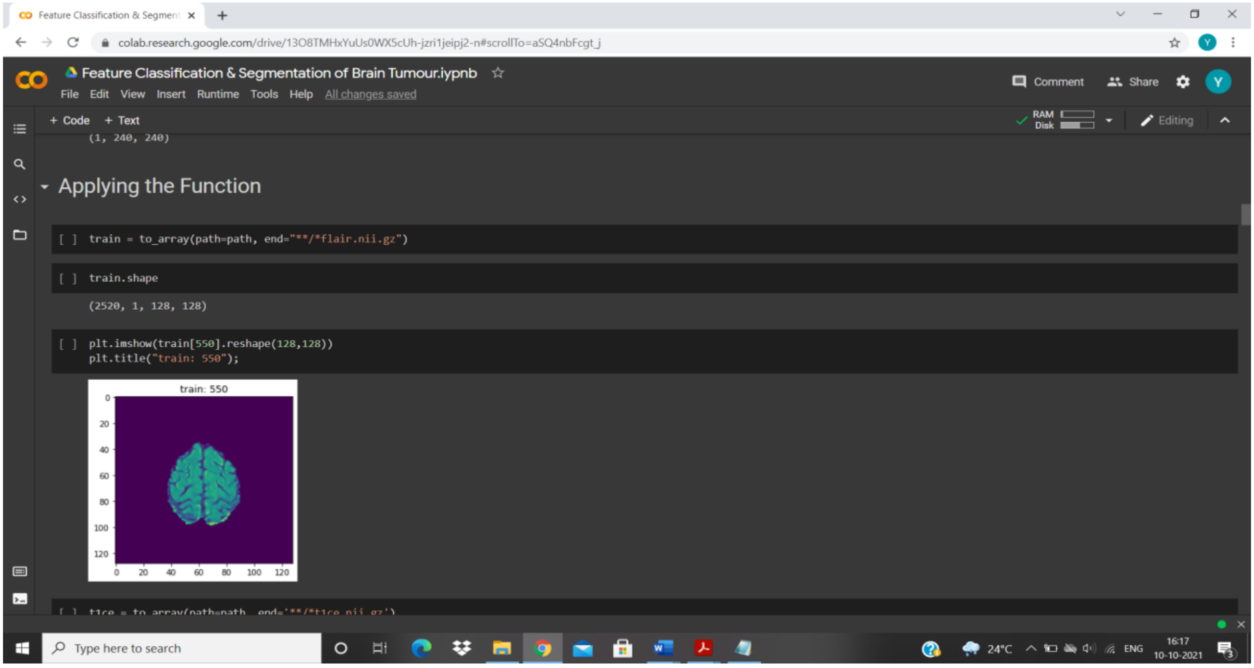




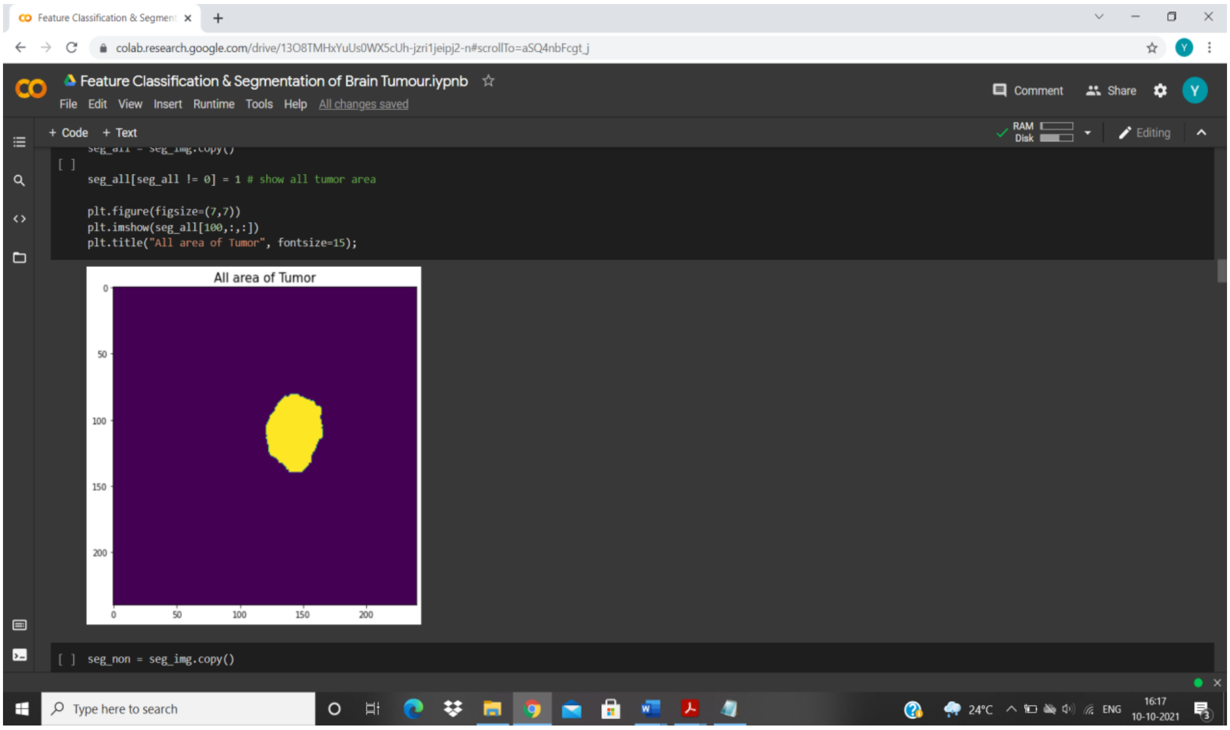
Procedural Step 2: Visualising the images in Axial, Coronal and sagittal planes required for the Feature Classification and Segmentation of Brain Tumor.



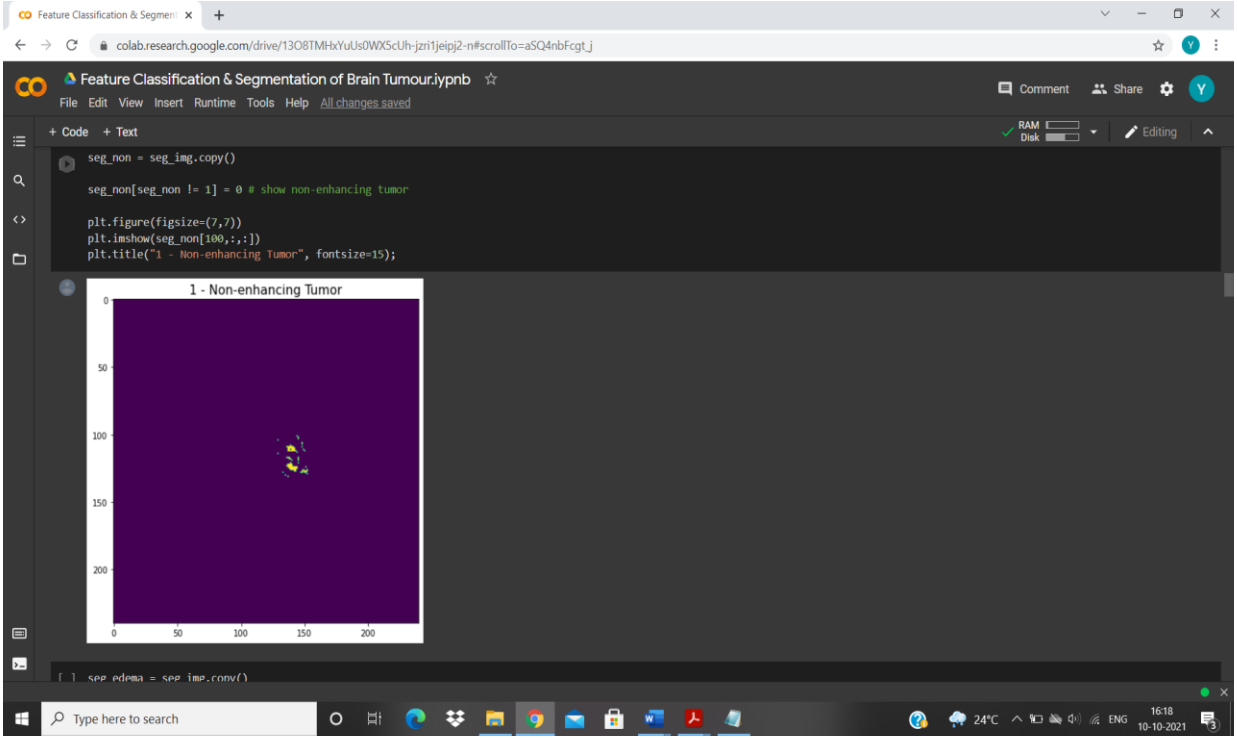
Procedural Step 3: Visualising the segmented images in Axial, Coronal and sagittal planes required for the Feature Classification and Segmentation of Brain Tumor.



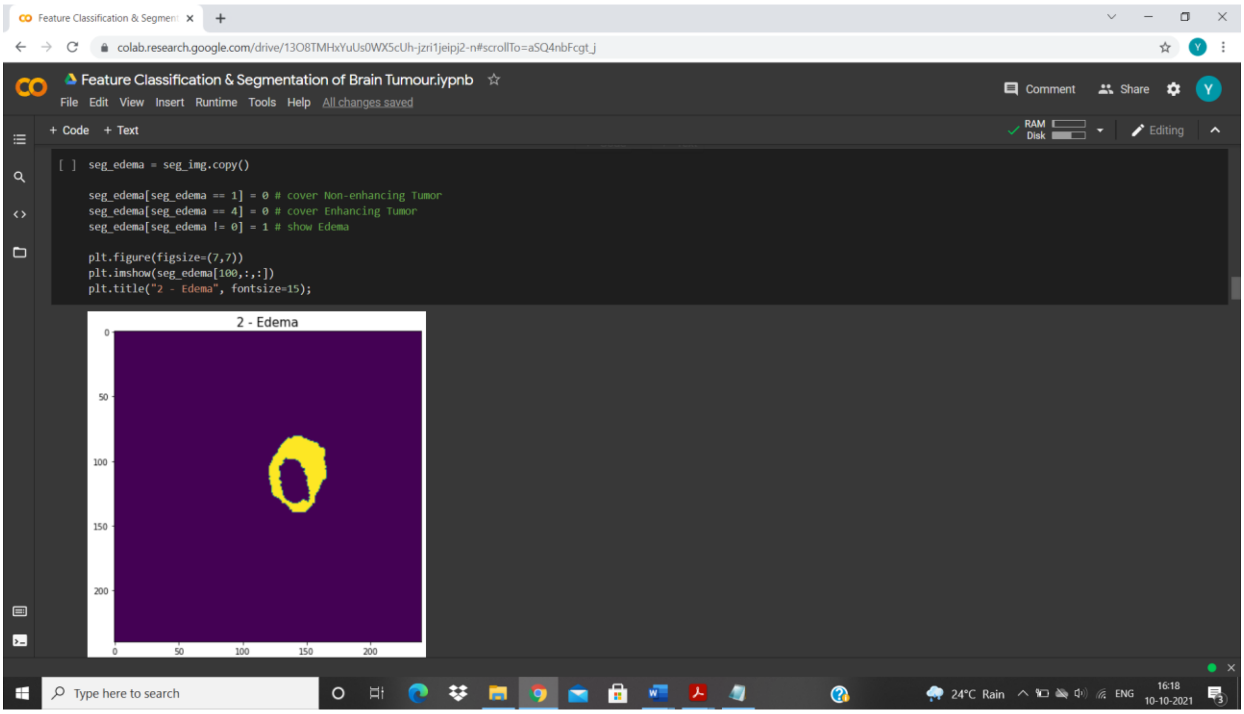
Procedural Step 4: Analysing the segmented images by applying the trained dataset functions which is required for the Feature Classification and Segmentation of Brain Tumor.



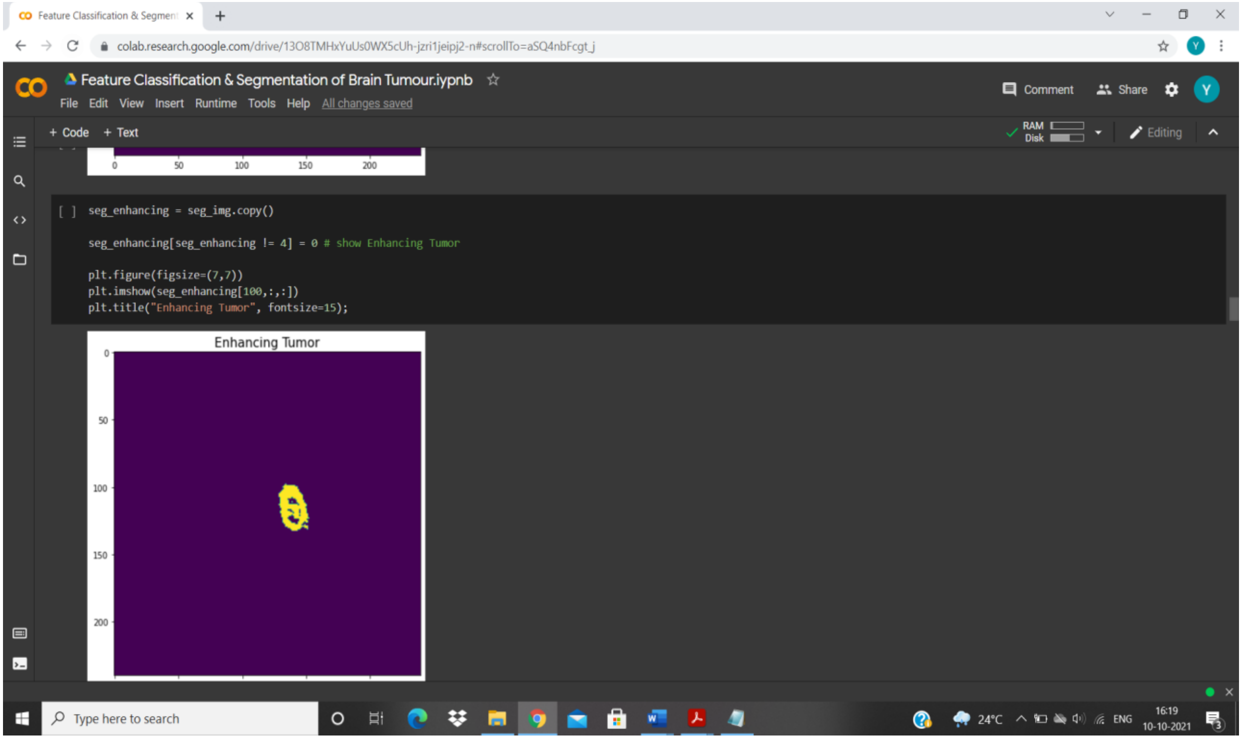
Procedural Step 5: Analysing the all area of tumor image by applying the trained dataset functions which is required for the Feature Classification and Segmentation of Brain Tumor.



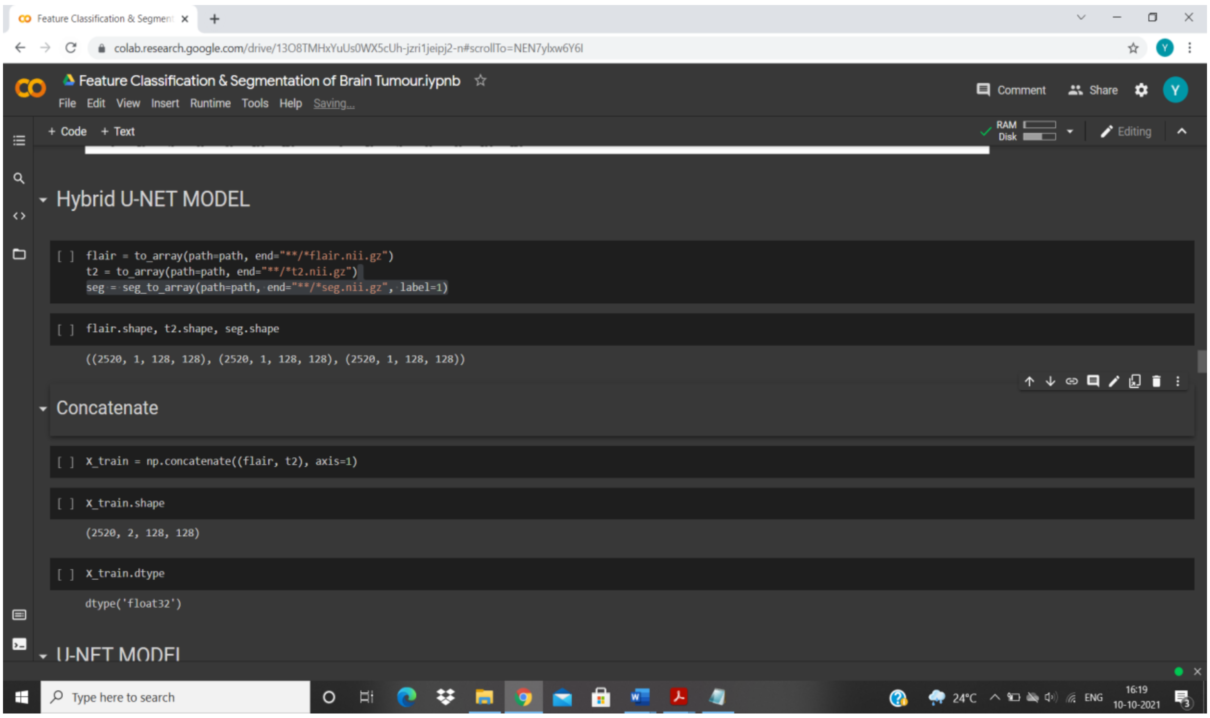
Procedural Step 6: Analysing the Non enhancing tumor image by applying the trained dataset functions which is required for the Feature Classification and Segmentation of Brain Tumor.



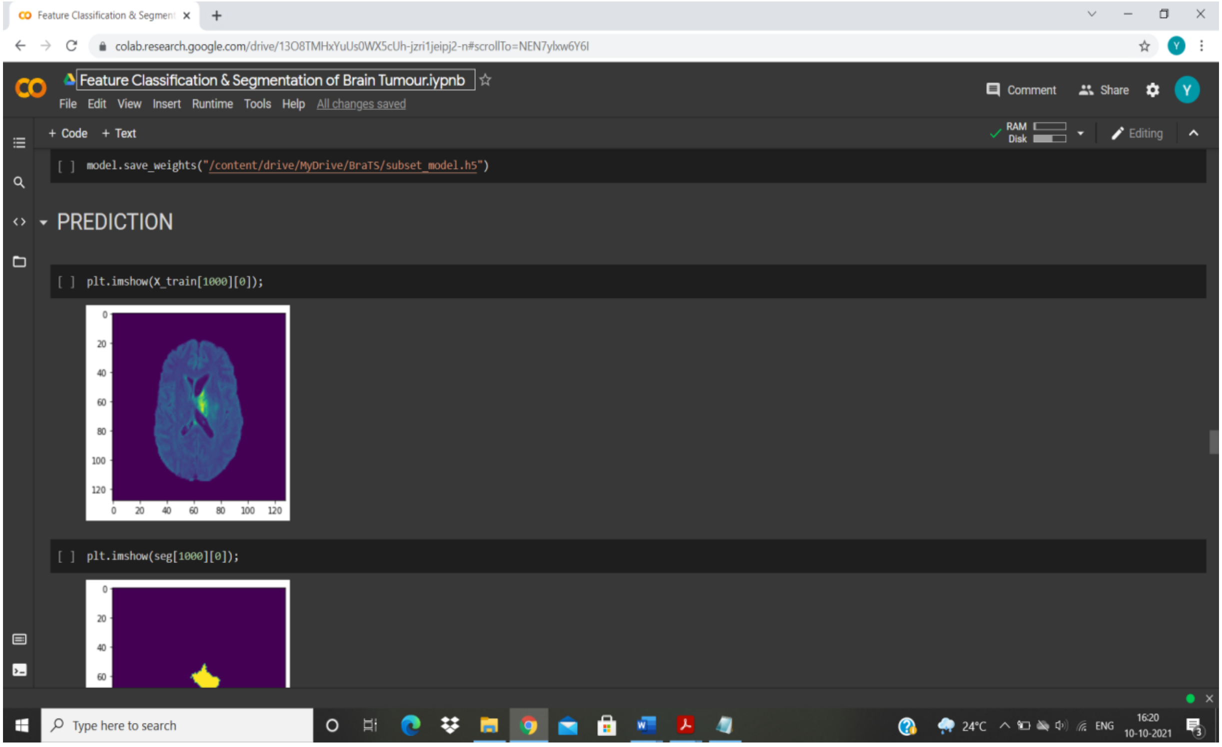
Procedural Step 7: Analysing the Non enhancing tumor image by applying the trained dataset functions which is required for the Feature Classification and Segmentation of Brain Tumor.



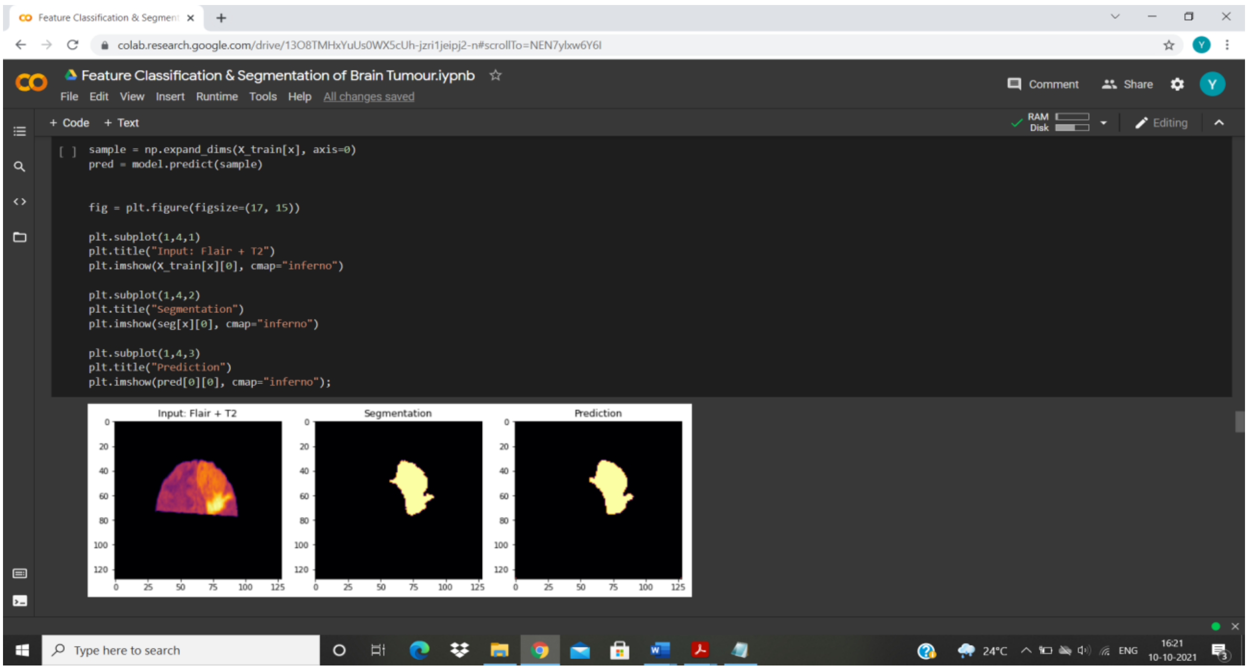
Procedural Step 8: Analysing the Enhancing tumor image by applying the trained dataset functions which is required for the Feature Classification and Segmentation of Brain Tumor.



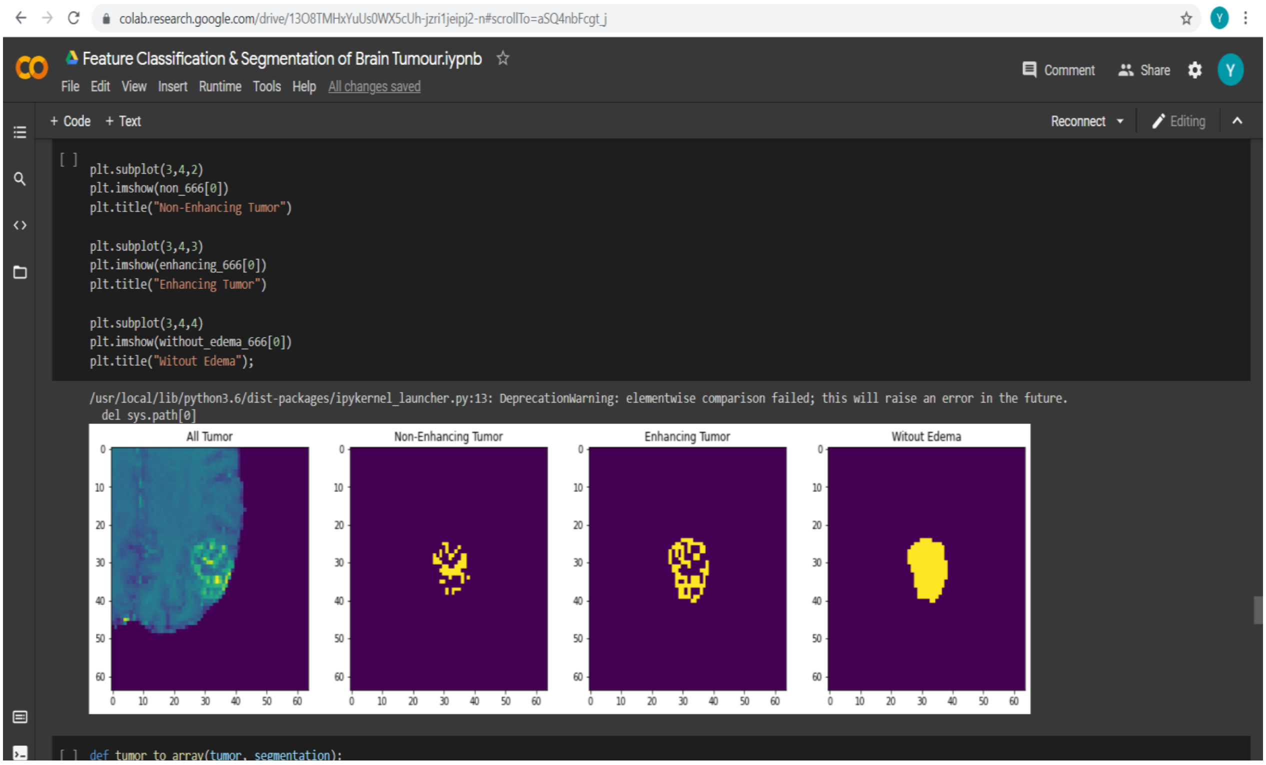
Procedural Step 9: Utilising the Hybrid U-Net Model on the test dataset functions which is required for the Feature Classification and Segmentation of Brain Tumor.



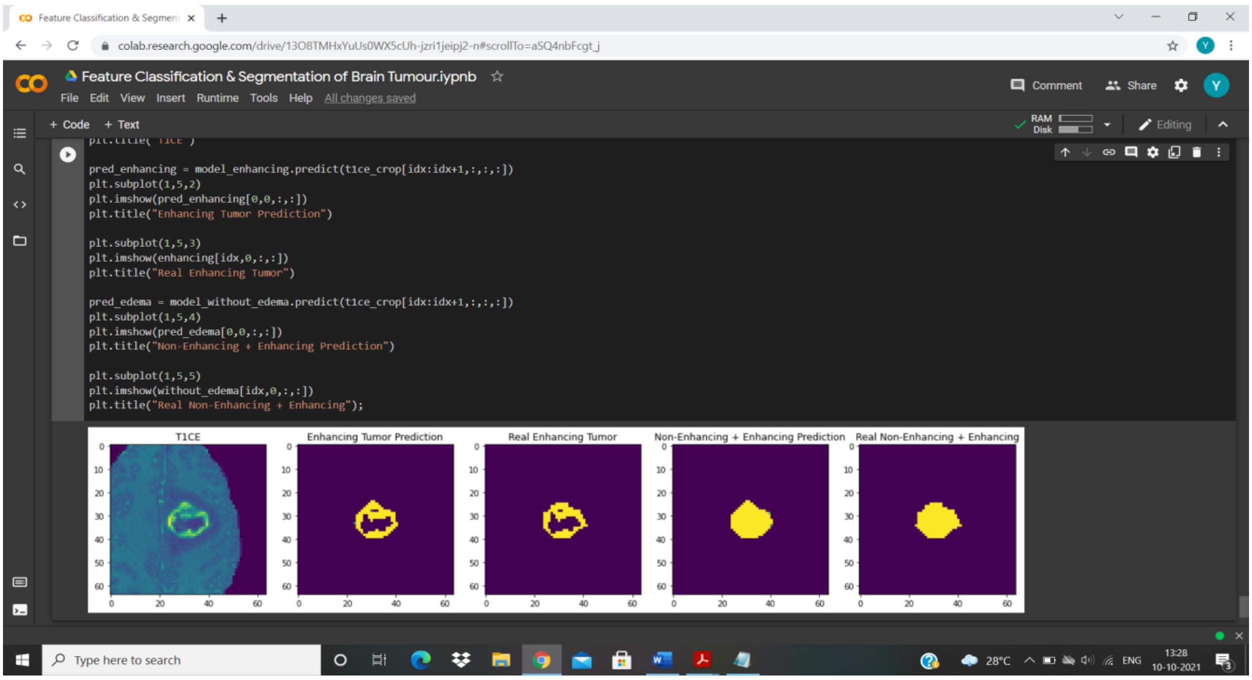
Procedural Step 10: Prediction of the test dataset imagesfor analysing tumor region which is required for the Feature Classification and Segmentation of Brain Tumor.



Procedural Step 11: Visualising the input test dataset images for segmentation and prediction which is required for the Feature Classification and Segmentation of Brain Tumor.



Procedural Step 12: Visualising the input test dataset images as All Tumor, Non-Enhancing Tumor , Enhancing Tumor and without edemawhich is required for the Feature Classification and Segmentation of Brain Tumor.



Procedural Step 13: Visualising the input test dataset images as T1CE ,Enhancing Tumor Prediction , Real Enhancing Tumor, Non Enhancing along with Enhancing Prediction and Real Non Enhancing along with Enhancing image which is required for the Feature Classification and Segmentation of Brain Tumor.

Discussion

In Quantitative image analysis, the clinical sphere of Brain tumor Feature Classification and Segmentation plays a dominant role since traditionally Brain tumors were analysed qualitatively manually through inspection which led to a clinical astray in the field of Medical Imaging Deep Transfer Learning which mainly focuses on feature quantitative analysis of classification and segmentation along with this it also focuses about voxel extraction ,volumetric feature of habitat tumor along with prediction of clinical outcomes which could be grading tumor and other outcomes.

Either in the field of Radiomics or Medical Imaging Deep Transfer Learning novelty to predict clinical outcomes and translation of segmentation methods to analysable analysis like the feature classification as texture, Intensity, shape and patterns of tumor core and its tissues are studied and also in segmentation process filtration matrices etc are applied to get outcomes. Analysis of tumor core into edema, enhancing tumor and non-enhancing tumor patterns and tissues associated with it. To arrive at the prediction of results because of the by utilising Hybrid U-Net Segmentation method to arrive at impact of clinical practices.

Because of Deep Transfer Learning, Medical Imaging has led to automated quantitative image analysis. The area to be investigated is done through segmentation translation features extraction and modelling into clinical radiomic outcome. To arrive at these outcomes, dataset is trained for extracting features where necessary parameters are fixed to obtain a set of trained datasets. Later the test sets are fused with these trained sets to analyse the outcomes followed by multiple iterations and manipulation methods based on voxel.

Results

The main aim of brain surgery is to perform the re-sectioning of tumors more accurately and preserve normal brain cells for the patient. The development of label-free and non-contact methods and frameworks is necessary to support the reliable resection of the tumor in real-time.

Hyperspectral imaging is non-ionizing, label-free and non-contact. The Medical Imaging deep-learning framework pre-processes the hyperspectral images in vivo brain tissues. The framework generates a thematic map that shows the parenchymal area of the brain and the location of the tumor is identified that helps the surgeon in successful and precise tumor resection.

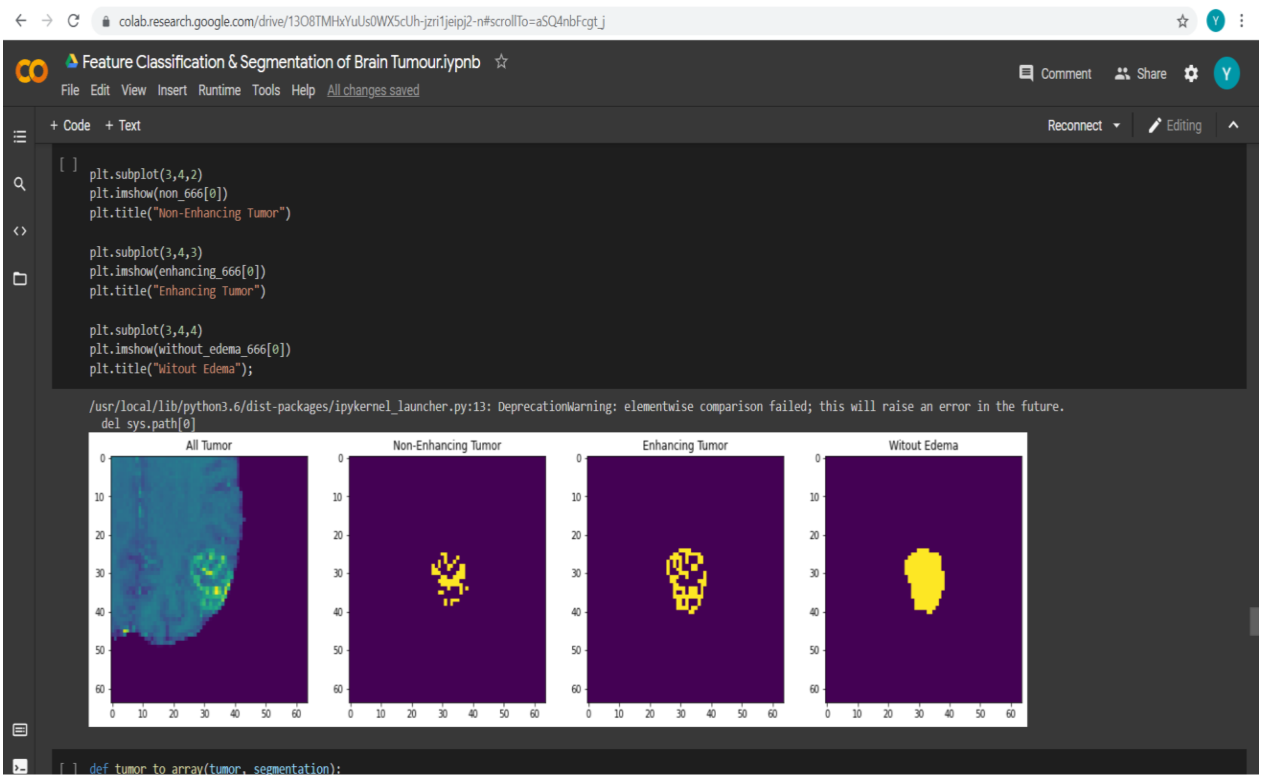


Fig 3: Visualising the input test dataset images as All Tumor, Non-Enhancing Tumor, Enhancing Tumor and without edema as the final output of test dataset.

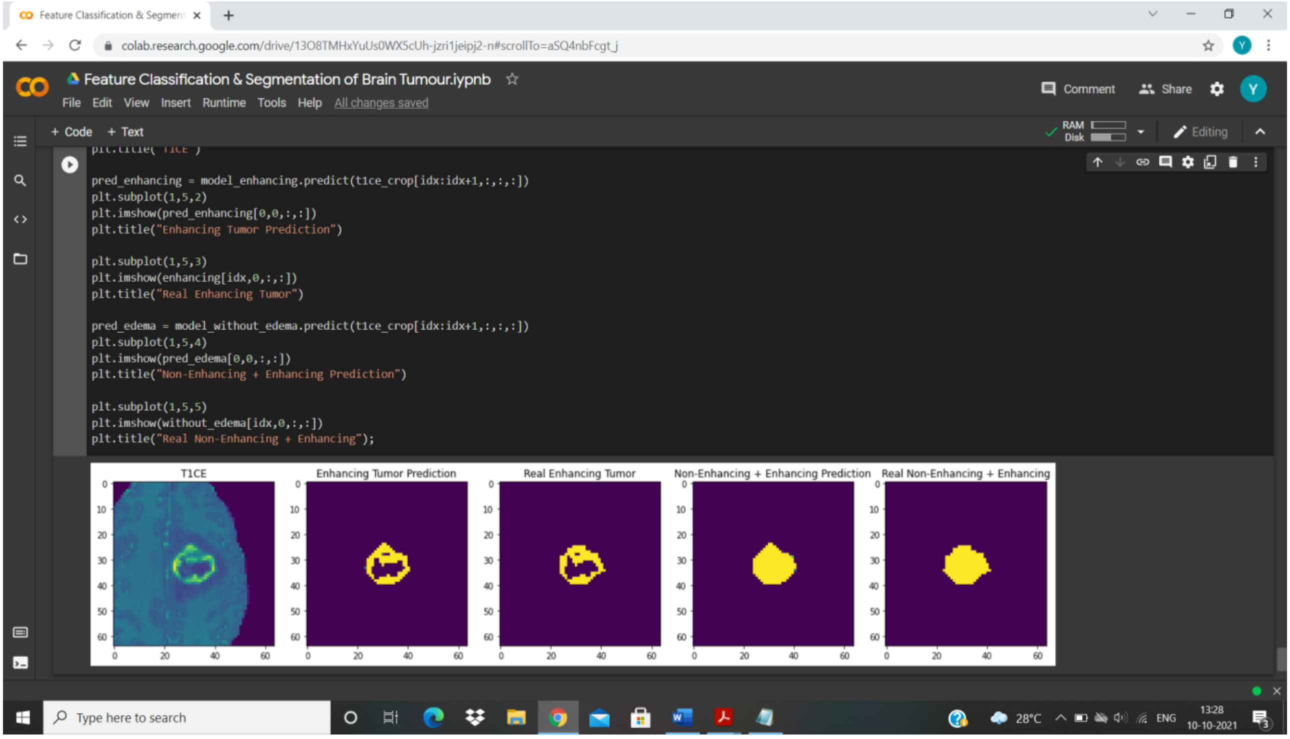


Fig 4:Visualising the input test dataset images as T1CE, Enhancing Tumor Prediction, Real Enhancing Tumor, Non-Enhancing along with Enhancing Prediction and Real Non-Enhancing along with Enhancing image as the finalised output of the test dataset.

Conclusion

In the field Medical Imaging Deep Transfer Learning Analysis, Brain tumor feature classification and segmentation is considered as multi-class problem because it requires accurate analysis to distinguish whole tumor and the sub tissues associated with the tumor. With the methodological context, Deep Transfer Learning Convolutional Neural Network, uses feature classification methods based on machine learned and texton which classifies the Brain Magnetic Resonance Imaging voxel image converted to visualise normal brain tissues along with different parts of tumor like edema, enhancing tumor and non-enhancing tumor.

The methodological approach anatomises the whole tumor is segmented binarily and subdivided to segment to full patch to arrive at proper regularisation and also delineation of tumor core along with enhancing and non-enhancing tumor. Since the Hybrid U-Net Method has no complicated pre-processing and postprocessing techniques and significant use of perfusion techniques like Dynamic Susceptibility Contrast approach to identify the complete and core of enhancing tumor. Basically, Hybrid U-Net is outlined to obtain compact image representations and batch loss to adjust weight of the classes.

Over the decades in the field of Medical Imaging Deep Transfer Learning Image, Feature Classification and Segmentation is the latest trend though there is availability of wide-ranging cutting-edge methods for MRI brain segmentation is still a sturdy and requires scope for further improvision of precision and accuracy of Feature Classification and Segmentation Methods. Hence in this paper, we have combined the different methods to arrive at Hybrid U-Net Model which is the future improvement in the field of Feature Classification and Segmentation Methods in tumors as there is increasing knowledge about the anatomical deviation, Feature Classification and Segmentation is considered as first tool for analysing and visualising computational study.The approach utilised in the paper is the newest approach of Feature Classification and Segmentation for better validated accuracy and fidelity of precision of outcome.

Future Clinical Prevalence

The applicability of Clinical Prevalence of Brain Tumor Feature Classification and Segmentation is the most important stride in utilising prognostic features or segmentation as quantitative image analysis. In the field Medical Imaging Deep Transfer Learning Analysis which is rapidly expanding, these methods will help clinical practisers and radiologists to provide precise care for the patients. So, the basic outline of how the Hybrid U-Net is being utilised for identifying tumor and its tissues are presented in the paper. It's very critical for clinical practisers and radiologists to understand and functioning knowledge about the methods and architectures used in Deep Transfer Learning Convolutional Neural Networks so as to be in a position to deploy the tools for further practices of clinical applications.

Declaration of Competing Interest

The Authors certifies that they have NO affiliations with or inclusion in any Association or entity with any monetary interest (such as honoraria; educational awards; cooperation in speakers' bureaus; enrolment of membership, employment , consultancies, stock possession, or then again other value interest and expert declaration or patent-permitting license plans), or non-monetary interest (like individual or proficient connections, affiliations, information or convictions) in the topic or materials talked about in this original copy.

Important Notice

This paper publishes preliminary scientific reports that are not peer reviewed and, therefore, should not be regarded as conclusive, guide clinical practice/health related behaviour, or treated as established information.

Conflict of Interest

The authors announce or proclaim no irreconcilable interests with respect to the current examination and results.

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References

[1] Bakas, S., Akbari, H., Sotiras, A., et al.: Segmentation labels for the pre-operative scans of the tcga-gbm collection (2017)

[2] Bakas, S., Akbari, H., Sotiras, A., Bilello, M., Rozycki, M., Kirby, J., Freymann, J., Farahani, K., Davatzikos, C.: Segmentation labels and radiomic features for the pre-operative scans of the tcga-lgg collection. The cancer imaging archive 286 (2017)

[3] Bakas, S., Akbari, H., Sotiras, A., Bilello, M., Rozycki, M., Kirby, J.S., Freymann, J.B., Farahani, K., Davatzikos, C.: Advancing the cancer genome atlas glioma MRIcollections with expert segmentation labels and radiomic features. Scientific data 4, 170117 (2017)

[4] Bakas, S., Reyes, M., Jakab, A., Bauer, S., Rempfler, M., Crimi, A., Shinohara, R.T., Berger, C., Ha, S.M., Rozycki, M., et al.: Identifying the best machine learn- ing algorithms for brain tumor segmentation, progression assessment, and over- all survival prediction in the BRATS challenge. arXiv preprint arXiv:1811.02629 (2018)

[5] Fu, J., Liu, J., Tian, H., Li, Y., Bao, Y., Fang, Z., Lu, H.: Dual attention network for scene segmentation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 3146–3154 (2019)

[6] Jia, H., Xia, Y., Cai, W., Huang, H.: Learning high-resolution and efficient non- local features for brain glioma segmentation in mr images. In: International Con- ference on Medical Image Computing and Computer-Assisted Intervention. pp. 480–490. Springer (2020)

[7] Jiang, Z., Ding, C., Liu, M., Tao, D.: Two-stage cascaded u-net: 1st place solutionto brats challenge 2019 segmentation task. In: International MICCAI Brainlesion Workshop. pp. 231–241. Springer (2019)

[8] Kamnitsas, K., Ledig, C., Newcombe, V.F., Simpson, J.P., Kane, A.D., Menon,D.K., Rueckert, D., Glocker, B.: Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. Medical image analysis 36, 61–78 (2017)

[9] Li, X., Zhong, Z., Wu, J., Yang, Y., Lin, Z., Liu, H.: Expectation-maximizationattention networks for semantic segmentation. In: Proceedings of the IEEE Inter- national Conference on Computer Vision. pp. 9167–9176 (2019)

[10] Menze, B.H., Jakab, A., Bauer, S., Kalpathy-Cramer, J., Farahani, K., Kirby, J.,Burren, Y., Porz, N., Slotboom, J., Wiest, R., et al.: The multimodal brain tumor image segmentation benchmark (BRATS). IEEE transactions on medical imaging 34(10), 1993–2024 (2014)

[11] Myronenko, A.: 3D MRI brain tumor segmentation using autoencoder regular-ization. In: International MICCAI Brainlesion Workshop. pp. 311–320. Springer (2018)

[12] Pohlen, T., Hermans, A., Mathias, M., Leibe, B.: Full-resolution residual networksfor semantic segmentation in street scenes. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 4151–4160 (2017)

[13] Saxena, S., Verbeek, J.: Convolutional neural fabrics. In: Advances in Neural In-formation Processing Systems. pp. 4053–4061 (2016)

[14] Sudre, C.H., Li, W., Vercauteren, T., Ourselin, S., Cardoso, M.J.: Generalised dice overlap as a deep learning loss function for highly unbalanced segmentations. In: Deep learning in medical image analysis and multimodal learning for clinical decision support, pp. 240–248. Springer (2017)

[15] Sun, K., Zhao, Y., Jiang, B., Cheng, T., Xiao, B., Liu, D., Mu, Y., Wang, X.,Liu, W., Wang, J.: High-resolution representations for labeling pixels and regions. arXiv preprint arXiv:1904.04514 (2019)

[16] Wang, X., Girshick, R., Gupta, A., He, K.: Non-local neural networks. In: Pro-ceedings of the IEEE conference on computer vision and pattern recognition. pp. 7794–7803 (2018)

[17] Wu, Y., Xia, Y., Song, Y., Zhang, Y., Cai, W.: Multiscale network followed networkmodel for retinal vessel segmentation. In: International Conference on Medical Im- age Computing and Computer-Assisted Intervention. pp. 119–126. Springer (2018)

[18] Zhao, H., Zhang, Y., Liu, S., Shi, J., Change Loy, C., Lin, D., Jia, J.: Psanet: Point- wise spatial attention network for scene parsing. In: Proceedings of the European Conference on Computer Vision (ECCV). pp. 267–283 (2018)

[19] H. Zhao, J. Shi, X. Qi, et al., "Pyramid scene parsing network," 2016.

[20] G. Lin, A. Milan, C. Shen, and I. Reid, "Refinenet: Multi-path refinement networks for high-resolution semantic segmentation," 2016.

[21] L. C. Chen, G. Papandreou, F. Schroff, et al., "Rethinking atrousconvolution for semantic image segmentation," 2017.

[22] O. Ronneberger, P. Fischer, and T. Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation. Springer International Publishing, 2015.

[23] B. H. Menze, A. Jakab, S. Bauer, et al., "The multimodal brain tumor image segmentation benchmark (brats)," IEEE Transactions on Medical Imaging, vol. 34, no. 10, p. 1993, 2015.

[24] K. Kamnitsas, C. Ledig, V. F. Newcombe, et al., "Efficient multiscale 3d cnn with fully connected crf for accurate brain lesion segmentation," Medical Image Analysis, vol. 36, p. 61, 2017.

[25] S. Pereira, A. Pinto, V. Alves, et al., "Deep convolutional neural networks for the segmentation of gliomas in multi-sequence mri," in International Workshop on Brain lesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries, 2015, pp. 131–143.

[26] J. Long, E. Shelhamer, and T. Darrell, "Fully convolutional networks for semantic segmentation," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 4, pp. 640–651, 2017.

[27] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classificationwith deep convolutional neural networks," Communications of theAcm, vol. 60, no. 2, p. 2012, 2012.

[28] "Fluid attenuation inversion recovery," https://radiopaedia.org/articles/fluid-attenuation-inversion-recovery.

[29] P. T. D. Boer, D. P. Kroese, S. Mannor, et al., "A tutorial on the crossentropymethod," Annals of Operations Research, vol. 134, no. 1, pp.19–67, 2005.

[30] "Pytorch," http://pytorch.org/blog/.

[31] K. He, X. Zhang, S. Ren, and J. Sun, "Delving deep into rectifiers: Surpassing human-level performance on imagenet classification," pp. 1026–1034, 2015.

[32] M. Kistler, S. Bonaretti, M. Pfahrer, et al., "The virtual skeletondatabase: an open access repository for biomedical research and collaboration." Journal of Medical Internet Research, vol. 15, no. 11, p. e245, 2013.

[33] N. J. Tustison, K. L. Shrinidhi, M. Wintermark, et al., "Optimalsymmetric multimodal templates and concatenated random forestsfor supervised brain tumor segmentation (simplified) with antsr,"Neuroinformatics, vol. 13, no. 2, p. 209, 2015.