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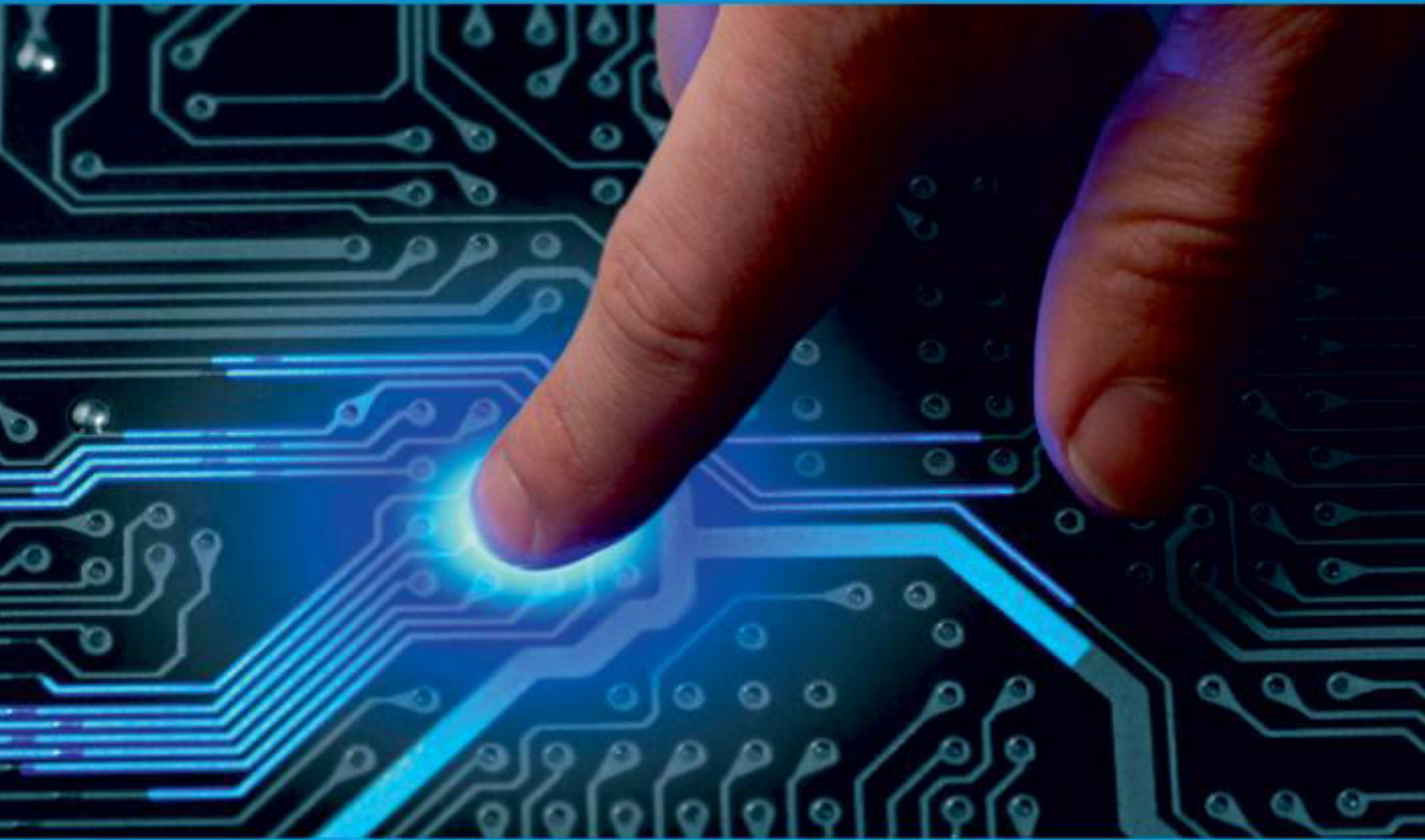

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Brain Tumor Segmentation Using U-NET Based Convolutional Neural Network

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ABSTRACT: Brain tumor segmentation can be used to separate healthy tissues from cancerous tissues accurately. Usually, in clinical settings, a brain MRI (Magnetic Resonance Imaging) scan is used to detect tumors, but manually segmenting out a tumor is a time-consuming process and requires highly skilled and experienced radiologists. If a malignant tumor is not detected in the early stages of cancer, it can cost a life. Hence, early detection of tumors in a short amount of time would be a great boon to humanity. This paper proposes a brain tumor segmentation technique using a Deep Convolutional Neural Network (CNN). The type of Convolutional Neural Network proposed is called U-NET. The U-NET architecture uses semantic segmentation that labels every pixel of an image rather than just detecting objects. So, if we can segment out an image, we would know which pixel belongs to what part of a human's anatomy. It can help us efficiently detect all types of tumors and irregularities, which would help the radiologists and surgeons with detection and surgery.

KEYWORDS: Deep Learning, CNN, U-NET, Brain Tumor, Segmentation

I. INTRODUCTION

Meningioma, Glioma, and Pituitary tumor are some of the most precarious types of brain tumors.
Glioma is the most common type of adult brain tumor, accounting for 80% percent of malignant brain tumors. The mortality rate is higher in adults than children, according to the World Health Organization [1]. According to a survey published by cancer.net, an estimated 24,530 adults and 3,460 children in the United States will be diagnosed with primary cancerous tumors of the brain in this year alone.
MRI (Magnetic Resonance Imaging) is a technique very widely used for scanning brain images. It detects the size, shape of the tumor without exposing the patient to high ionization radiation. Several modalities such as T1-weighted (T1), T1-Post contrast-enhanced (T1ce), T2-weighted (T2), and T2-weighted fluid-attenuated inversion recovery (Flair) can be captured using MRI scanning. T1 is mainly used for the segmentation of tumors from healthy brain tissues. T1ce is used for enhancing tumor borders. T2 is used to focus on the edema region, and Flair is significant for differentiating the edema region from cerebrospinal fluid [2].
Precise detection of brain tumors using MRI scans is an arduous and time-consuming task which can also lead to many errors. Cancer patients have a minimal period within which the tumor has to be detected and treated, or else it can cost them their lives. Manually dissecting the MRI scans usually takes a very long time for even experienced radiologists. Automatic brain tumor detection can fasten the process, and we can detect cancer at an early stage and save the patient's life.
In recent years, Artificial Intelligence in the field of medicine has gained much momentum. The field of Deep CNN has especially made an enormous amount of progress in image segmentation. CNN is a neural network that feeds images as input and extracts all the vital details from the images. An MRI scan image fed to a CNN would help us determine the tumor's shape, size, and texture with well-defined boundaries to differentiate the healthy brain tissues from the cancerous ones.
In this paper, we have proposed a type of CNN architecture named U-NET. U-NET was first designed and applied in 2015 to process biomedical images. In biomedical cases, the prediction for the presence of disease and the localization of abnormality is essential. U-NET solves this problem by localizing and distinguishing borders by classifying every pixel, so the input and output share the same size [3].

II. LITERATURE SURVEY

Segmentation of brain tumors is typically complex due to the variety of ever-changing factors like the shape, size, location, boundaries that vary from person to person. Hence, various approaches have been tried, but they typically are built with some of the other limitations. Let us look at some of the approaches tested and tried for automatic brain segmentation using MRI scans.

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In 2014, a 3D convolutional neural network for automatic brain tumor detection was proposed by Urban, G [4]. The dataset consisted of multi-modality MRI images. The 3D inputs were piled into a 4D volume where the four dimensions represent the height, width, channels, and modalities. It consisted of 3x3x3 filters with rectified linear unit (ReLU) activation layers and 3D max-pooling layers. The model achieved 73% and 87% accuracy for an active and whole tumor, respectively. The high computation time for the model was a bottleneck, but it was attributed to the usage of 3D images, which made the job of radiologists much easier.
In 2016, Pereira introduced an approach that required building a deep neural network using small convolution filters of size 3x3 to enhance the depth and retrieve more features about the tumor [5]. It had 11 layers comprised of 6 convolutional layers, two max-pooling layers, and three fully-connected layers at the end. The authors performed pre-processing to normalize the images for better accuracy. The model obtained an accuracy of 77% for an active tumor and 88% for the whole tumor.
In 2019, Salma Alqazzaz proposed an automatic brain tumor segmentation approach using the SegNet architecture [6]. The images were pre-processed for normalization. The network was used to classify four different modalities of the tumor. The architecture consisted of an encoder and a decoder. The encoder had 13 convolutional layers with 3x3 filters followed by ReLU activation layers and max-pooling layers. The decoder had 13 convolutional layers, and the extracted features were fed to the SoftMax function for classification. The model obtained an accuracy of 85% for the whole tumor.

III. PROPOSED METHOD

The usage of Deep CNN to solve critical medical use-cases has increased exponentially over the last decade, thanks to the colossal increase in the computational power of the processors and the staggering amount of data present with us today for processing and doing research.
Deep CNN does the job of taking an image as an input and passing it through various filters(kernels), pooling layers, activation functions such as "ReLU" followed by fully connected layers, and SoftMax function. An extensive, deep convolutional neural network can achieve record-breaking results on a highly challenging dataset using purely supervised learning as well [7].

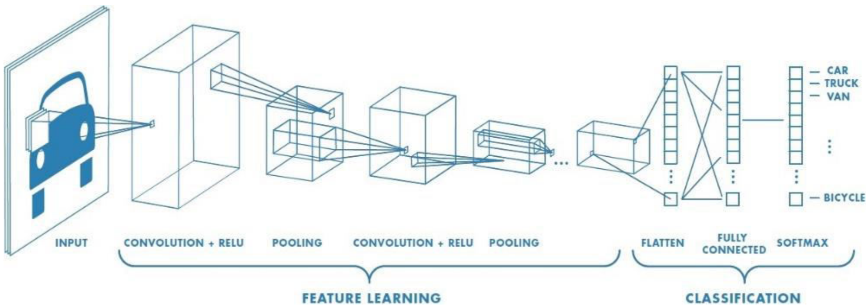

Fig 1. Convolutional Neural Network.

U-NET, over the years, has become one of the most widely used architectures of Deep CNN. It incorporates the usage of Image Segmentation. Segmenting labels every pixel of an image and then uses the labels to determine the tumors or any irregularities. A segmentation map is generated in U-NET, where every pixel is appropriately labeled. In a standard deep CNN network, the number of channels increases as the network gets deeper, and the image's width and height go down. However, in U-NET, after enough details pertinent to the features are extracted, the number of channels decreases, and the image starts going back to the original shape and size. The overall architecture diagram seems to be of 'U' shape, and hence, it is called 'U-NET architecture.'

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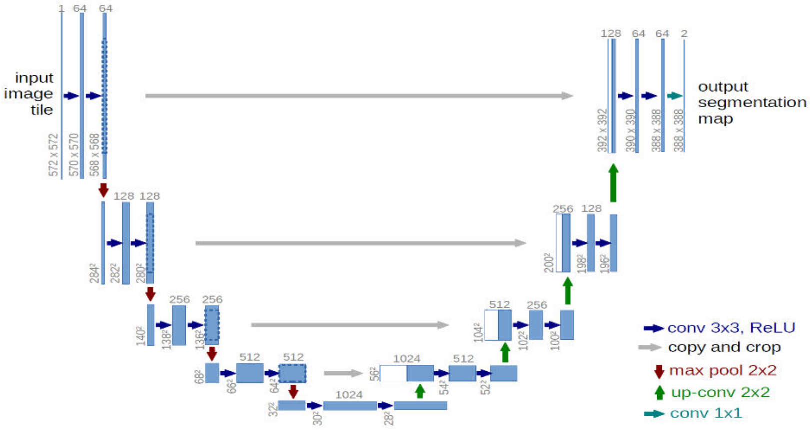

Fig 2.U-NET model by Olaf Ronneberger et. el.

In order to scale the image back to its original dimensions, we used transpose convolution. It is an integral building block of the U-NET architecture that takes a small set of activations and blows them up to a bigger set. In a transpose convolution, if we take a 2x2 activation and convolve it with a 3x3 filter, we might have a 4x4 output, which is bigger than the original input. In transpose convolution, the matrix is placed on the output rather than the input image, which allows us to scale the image and give effective results.

As depicted in figure 3, the first part of the architecture uses normal convolutions hence reducing the scale of the image, so we lose all the spatial information, but the contextual information is gathered as the network is much deeper. The second part of the architecture uses transpose convolutions and blows the representation size of the image back to its original shape and size. The chief building block behind this process is the usage of ‘skip connections’ that takes earlier blocks of activations and copy them directly to the later blocks. It helps the blocks get high-level contextual information from the previous layers while retaining the high-level spatial information to identify what pixels represent the tumor.

Fig 3. Contraction &Expansion process of the U-NET architecture by Olaf Ronneberger et. el.

IV. RESULTS

The experimentation consists of U-net architecture implementation for brain tumor segmentation. U-NET model is provided with input images of resolution 256 x 256 and 3 (red, green, blue) channels. A standard feed-forward neural network is used for the first part of the architecture. It consists of two 3 x 3 unpadded convolutions, each followed by ReLU and a 2 x 2 max pooling operation with stride 2 for down-sampling. Every time we down-sample, the number of channels are doubled. In the later part of the architecture, transpose convolutional layers build the dimensions backup and perform up-sampling. In detail, each step in the expanding path up-samples the feature map, followed by a 2 x 2 transposed convolution. It helps us scale the image while halving the no of filters. Next is a concatenation with the correspondingly cropped feature map from the contracting path and two 3 x 3 convolutions, each followed by a ReLU. Cropping is performed to handle the loss of border pixels in every convolution. In the final layer, a 1x1 convolution maps each 64-component feature vector to the desired number of classes. Skip connections are used to carry the

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activations from the previous blocks to the current blocks. Thus, semantic image segmentation allows us to predict a precise mask for each object by labeling each pixel in the image with its corresponding class.
We have carried out quantitative and qualitative analyses. For quantitative analysis, the performance evaluation in terms of numbers is explained. For qualitative examination, the visual quality of the results is examined.
For evaluating the performance of U-Net, we have used the Dice score as the figure of merit. The Dice coefficient is utilized extensively to calculate the similarity between two images. In 2016, itwas adapted as a loss function known as Dice Loss [8].

$$DL(y,\hat{p}) = 1 - \frac{2y\hat{p}+1}{y+\hat{p}+1}$$

The model was tested on the dataset from the 'figshare'website. It had 3046 images. 80% of the data was used for training and the rest for testing. The intensity of the images was changed in order to normalized them during pre-processing. The images were rotated, flipped to incorporate images with different irregularities as we see in MRI scans of different individuals. The model was trained for over 55 epochs. Dice loss metric was used to compare the loss against the accuracy. The results have been depicted through figure 4.

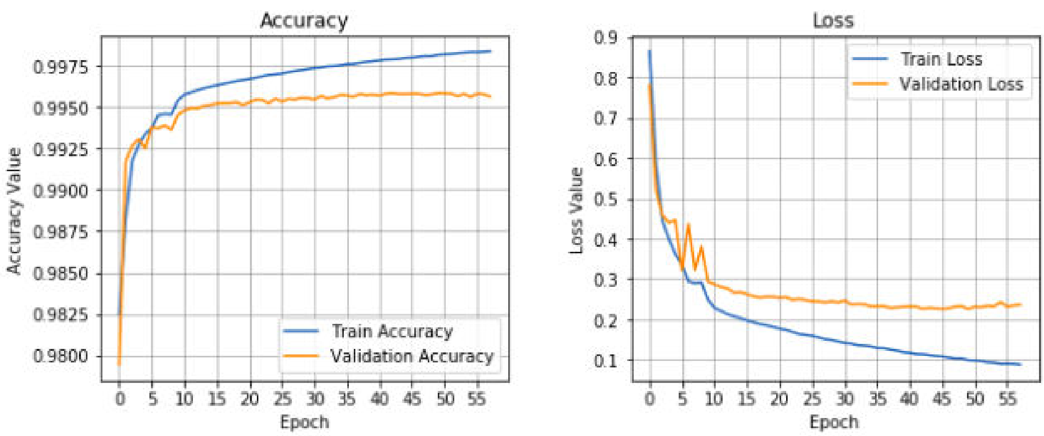

Fig 4. Accuracy and loss results.

Qualitative analysis matters as much as quantitative analysis; hence, we have performed it.
Figure 5 demonstrates the visual comparison between the ground truth and the predicted segmented region using U-Net for an MRI image; as can be seen, the predicted regions by U-Net show a high resemblance with the ground truth. The high resemblance between the original and predicted mask speaks about the high quality of U-Net architecture. At the end of 55 epochs, the accuracy of the U-net was observed to be 95.7%.

Fig 5. Comparison of the original and predicted result of the MRI image.

V. CONCLUSION AND FUTURE SCOPE

U-NET architecture is one of the promising architectures of deep CNN, especially in the MRI segmentation of medical use-cases. It can be compared with the performance of other architectures like VGG, ResNET18, and SegNet. Also, additional techniques like increasing the brightness, zooming/cropping the images can be used to get a mixed set of

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data and thus, get better accuracy. The future study would incorporate building an architecture that is an ensemble of different combinations of the existing Deep CNN architectures and then identifying which combinations work the best and provide the highest accuracy.Also, in the future, working with 3D MRI images instead of 2D would yield exciting results and detailed analysis.

REFERENCES

1. Louis, David N and Perry, Arie and Reifenberger, Guido and Von Deimling, Andreas and Figarella-Branger, Dominique and Cavenee, Webster K and Ohgaki, Hiroko and Wiestler, Otmar D and Kleihues, Paul and Ellison, David W. (2016) “The 2016 World Health Organization classification of tumors of the central nervous system: a summary.” Acta neuropathologica131 (6): 803–820.
2. Bauer, Stefan and Wiest, Roland and Nolte, Lutz-P and Reyes, Mauricio. (2013) “A survey of MRI-based medical image analysis for brain tumor studies.” Physics in Medicine & Biology58 (13): R97.
3. “UNET: Convolutional Networks for Biomedical Image Segmentation”, Olaf Ronneberger, Philipp Fischer, and Thomas Brox, Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. MICCAI 2015. Lecture Notes in Computer Science, vol 9351. Springer Cham.
4. Urban, Gregor and Bendszus, M and Hamprecht, F and Kleesiek, J (2014),“Multi-modal brain tumor segmentation using deep convolutional neural networks”, MICCAI BraTS (Brain Tumor Segmentation) Challenge. Proceedings, winning contribution31: 35.
5. Pereira, Sergio and Pinto, Adriano and Alves, Victor and Silva, Carlos A. (2016) “Brain tumor segmentation using convolutional neural networks in MRI images.” IEEE transactions on medical imaging35(5): 1240–1251.
6. Alqazzaz, Salma and Sun, Xianfang and Yang, Xin and Nokes. (2019) “Automated brain tumor segmentation on multi-modal MR image using SegNet.” Len,Computational Visual Media1: 11.
7. Alex Krizhevsky, Ilya Sutskever, Geoffrey E, “ImageNet Classification with Deep Convolutional Neural Networks (2012)”, Conference on Neural Information Processing Systems.
8. Carole H Sudre, Wenqi Li, Tom Vercauteren, Sebastien Ourselin, and M Jorge Cardoso. 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, pages 240–248. Springer, 2017.