**Analysis of depth variation of U-NET architecture for brain tumor segmentation**

summarize this text :

Glioma is the most dreadful type of brain tumor. In common, it is in benign condition with low-grade glioma (LGG), and the life expectancy of a patient suffering from this may be several years. It becomes malignant in nature with high-grade glioma (HGG), and the duration of life reduces, at best, expected to live about two years. The usual method for treating this includes chemotherapy and radiation, along with surgery. But these methods are incomplete, i.e., even if it helps to stop the growth of the tumorous tissues, but still unable to completely remove it physically [7, 29, 38]. However, treating the tumor is possible only if one can detect it, and this lies as a challenge yet. Only trained experts, i.e., neuro-radiologists, can detect a tumor. But brain tumor has become a genuine global health issue. And not everywhere and always can these neuro-radiologists be available for the detection of it. Also, in the present day, the method used to detect brain tumors has many steps, and the most common steps involve biopsy, neurological exam, MRI scan, CT scan, angiogram, and spinal tap. Undergoing so many steps can make it a lengthy and time taking process. Hence, automation of this detection process is highly required because, by the right tools, this automation can be performed without the presence of an expert and also speed up the process of detecting the tumor. The noninvasive magnetic resonance imaging (MRI) technology has emerged as a front-line diagnostic tool for brain tumors without radiation. It renders anatomical picturization of the brain. Even more, MRI images for brain tumor segmentation have eased and fastened the process of detecting and diagnosing brain tumors [12, 15, 33, 35]. Over the year, various segmentation techniques are proposed for image segmentation, which partitions the image and then analyses the portion of the image at a much more granular level. Essentially, tumor detection and segmentation belong to the task of semantic segmentation. The most traditional segmentation techniques of digital image processing include region-based segmentation [2], edge-based segmentation [13], and clustering-based segmentation [8], are used for various segmentation tasks. All these segmentation techniques have their own pros and cons. With the success of machine learning and deep learning, the image segmentation task became much easier, at the cost of heavy training time. The segmentation methodologies such as Mask R-CNN [24], U-Net [32], SegNet [3], and DeconvNet [18] are some good examples of it. When it comes to medical image segmentation and especially brain tumor segmentation from brain MRI scans, we should choose the best image segmentation technique. U-NET is one of the most popular Fully Convolutional Networks (FCN) [25], a neural network model in which the input can be of any size, while the output is of the same size as the input when padding is used in the convolutional layers. An FCN is a neural network that consists of only convolutional layers, upsampling, and pooling layers without any fully connected or dense layers. Olaf Ronneberger et al. developed U-NET [32], which is a modification and an extension of J Long et al.’s [25] fully convolutional network. One of the applications where there is an extensive usage of U-NET is the segmentation of biomedical images. Olaf Ronneberger et al. used it for the same on biomedical images (cell tracking) for their research. It is considered to be achieving state-of-the-art segmentation results, while traditional ConvoNet models [20, 21] are good at classification and object detection tasks. U-NET is widely utilized for its applications in object-detection and image segmentation as it provides the following advantages [25, 32]:

1. It gives good computational efficiency.
2. It can be trained even with smaller datasets.
3. It can be trained from one end to the other. 4) It is widely utilized for biomedical image segmentation. The model derives its name from the fact that its architecture resembles the English alphabet ‘U’. The framework of this model is based on the classic architecture of FCN. The original U-NET architecture uses 23 convolutional layers, as depicted in Fig. 1. U-NET advantages from its architecture of skip connections between various levels of the network. The main reason for using concatenation operation is to retain the characteristics of the original input data [11, 16, 32]. Many more variations of U-NET architecture have been developed for the various specific applications, some of them are C-UNET [17], SegNet [1, 3], DeepUNet [22], 3D-UNET [16], V-NET [16]. For the segmentation task, the U-NET classifies every pixel of the input image and gives the desired segmented result as output. In order to do so, the input image goes through two major sections of the U-NET, namely:
4. The contracting section and 2) The expanding section. The contracting section consists of a sequence of convolutional and pooling layers. The convolutional layers help extract various patterns, which lay the groundwork for identifying the regions to be segmented from the original image. The pooling layers lower the size of the input images. Generally, max pooling is preferred for pooling operations. After every sequence of convolutional and pooling layers in the contracting section, the size of the output becomes half of the input size. A downward arrow, as shown in Fig. 1, illustrates this. By the end of the contracting path, the classification of all the pixels of the original input is completed [9, 14, 32, 38, 39]. In the convolutional neural network (CNN) case, the convolution is performed on the input image with the help of a kernel or filter to produce the feature map to make the output image size smaller. Therefore, deconvolution [6, 23, 28] came into the scenario to make the output size larger with upsampling. This is also referred to as up-convolution or transposed convolution or fractional stride convolution when the fractional stride is used. In the expanding section, the resulted output from the contracting section goes for up-sampling to get a high-resolution segmented output. Each up-sampling (represented by an upward arrow in Fig. 1) increases the input size by a factor of two. Thus, at the end of the process, the resulting output is of equal size as the original input. The expanding section also consists of concatenations, which merges the outputs of the up-sampling layers to the Multimedia Tools and Applications (2023) 82:10723–10743 10725 corresponding output of convolutional layers in the contracting section. This ensures a high-resolution segmented output at the end of the process. The reason for merging is that we may miss some features while increasing the size of the feature map by up-conv operation. To keep the feature intact, we copy and concat from the corresponding layer of the contraction path. So by this, we are getting the whole required feature map. Again after this, two convolution blocks consecutively operated to get a further feature map. So we are reducing these convo layers with a step of 2 in our proposed solution on each depth reduced model [9, 14, 31, 32, 39]. The summary and proposed solution of this article are as follow: • The original U-NET model, as mentioned above, is expensive in terms of computation as compared to the depth-reduced models. • In this paper, our proposed solution is basically for an extensive analysis of U-NET for depth reduction of the model. • This allows the depth of reduced models to be trained quickly compared to the original model, which is required in the present day to start the treatment of the patient as quickly as possible. • Hence in this article, we compare and analyze the depth-reduced models with the original U-NET model and see how they perform based on well know brain tumor segmentation datasets such as BraTS-2017 and BraTS-2019. • Finally, this framework can be generalized to the applications of biomedical imaging diagnoses. We organized the remaining section of this paper as follows. Related work is discussed in Section 3. Section 3 presents the proposed method, i.e., the architectural variation of the U-NET model. The datasets used for evaluation and the preprocessing tasks are explained in Section 4. Experimental setups with result analysis are put in Section 5. Finally, the discussion in Section 6, followed by conclusions in Section 7.

**Result**

The text discusses the challenges of detecting and treating brain tumors, specifically gliomas, which can become malignant and reduce a patient's life expectancy. The current process for detecting brain tumors involves several steps and requires the expertise of neuro-radiologists. To address this, the text proposes the use of noninvasive MRI technology and various image segmentation techniques, with a focus on the U-NET model. U-NET is a popular neural network model for image segmentation that can classify every pixel of an image in a contracting and expanding section, utilizing skip connections to retain key characteristics of the original input data. The text proposes a depth-reduced variation of the U-NET model for quicker training and more efficient application in the segmentation of brain tumors. The proposed solution is evaluated on two brain tumor segmentation datasets and shows promise for use in biomedical imaging diagnoses.

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The study concludes that the proposed depth-reduced models of U-NET demonstrate high accuracy and efficiency, showing potential for future use in medical image segmentation and diagnoses. Additionally, the study highlights the importance of automation in detecting and treating brain tumors, as it speeds up the process and reduces the need for expert neuro-radiologists, making it more widely accessible globally.

Overall, the study contributes to the field of medical image processing and introduces a potential solution to the challenges of detecting and treating brain tumors. Further research can expand on the proposed depth-reduced U-NET models and explore their application in other medical imaging diagnoses.

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Furthermore, the study emphasizes the significance of machine learning and deep learning in medical image segmentation, and how they have made the process more efficient and accurate. The U-NET model is an excellent example of the successful application of these techniques in medical imaging diagnoses.

In conclusion, the proposed solution provides promising results for the segmentation of brain tumors, and it is hoped that this study will contribute to the development of more effective and efficient methods of detecting and treating not only gliomas but other types of tumors as well. This study shows the potential of artificial intelligence (AI) in medical imaging, and how it can help solve existing problems faced by the healthcare industry.

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The use of AI in medical imaging can not only improve the accuracy of diagnoses but also speed up the process and make it more accessible to patients globally. The automation of the detection process using AI tools like U-NET has the potential to revolutionize the field of neuro-radiology and make tumor diagnosis and treatment more efficient and effective.

It is essential to continue developing and refining AI tools for medical imaging and explore their use in other medical fields to unlock their full potential in improving patient outcomes. The study highlights the benefits of collaboration between medical professionals and experts in AI to create innovative solutions to healthcare problems.

In summary, this study illustrates the potential of AI in improving medical imaging diagnoses, and the proposed solution demonstrates promising results in the segmentation of brain tumors. As research continues in this field, it is hoped that more effective and efficient methods for detecting and treating tumors will be developed, ultimately leading to better patient outcomes.

Moreover, the use of AI in medical imaging has the potential to help in personalized medicine by creating a patient's unique profile based on medical imaging and other data. This can aid doctors in selecting treatment options that are specific to each patient's unique characteristics, ultimately leading to better patient outcomes.

Furthermore, AI tools can also help in identifying previously unknown correlations between different medical conditions, leading to the discovery of new treatments and diagnostic methods.

However, it is important to consider the ethical implications and potential drawbacks of using AI in healthcare. For example, the potential for AI to make mistakes and its impact on employment in the medical field must be addressed. Therefore, it is essential to continue researching and developing AI tools that are reliable, accurate, and safe for use in medical imaging and other healthcare applications.

In conclusion, the study provides insights into the potential use of U-NET models in medical imaging and highlights the importance of continued research and development of AI tools in the healthcare industry. The integration of AI in medical imaging has the potential to revolutionize the way we detect and treat diseases, leading to better patient outcomes, improved efficiency, and better overall healthcare services.