European Journal of Engineering and Applied Sciences

ISSN: 2651-3412 (Print) & 2667-8454 (Online)
Journal homepage: http://dergipark.gov.tr/EJEAS
Published by Çorlu Faculty of Engineering, Tekirdağ Namık Kemal University

European J. Eng. App. Sci. 8(1), 31-38, 2025

Research Article

Image Enhancement and U-Net Based Brain Tumor Segmentation Using MRI

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Received: 21.05.2025 *Accepted: 18.07.2025* *DOI: 10.55581/ejeas.1703274*

Abstract: Brain tumor is a very fatal health problem and unfortunately it is getting more common in modern society. Developing medical methods and technologies make possible to detect the disease earlier, slow down its progress and treat it. Early detection is very crucial for the success of treatment processes. Usage of image processing and artificial intelligence methods can help medics for early detection of the disease. In this study, a deep learning based enhanced image segmentation approach has been proposed to detect brain tumors. Segmentation was performed on the brain magnetic resonance (MR) images which were taken from a public dataset. Classical U-Net structure were employed at segmentation process because of its compatibility and success in medical image segmentation. Performance of the proposed model was increased with the help of image processing techniques used in pre- and post-processing stages. After using some image enhancement techniques as post-processing, a 0.89 of the dice coefficient, a 0.85 of the sensitivity and a 0.89 of the F-score were obtained.

Keywords: *MRI, Deep Learning, U-Net, Brain Tumor Segmentation.*

MRG Kullanılarak Görüntü İyileştirme ve U-Net Tabanlı Beyin Tümörü Bölütlemesi

Öz. Beyin tümörü oldukça ölümcül bir sağlık sorunudur ve ne yazık ki modern toplumda giderek yaygınlaşmaktadır. Gelişen tıbbi yöntem ve teknolojiler, hastalığın daha erken tespit edilmesini, ilerlemesinin yavaşlatılmasını ve tedavi edilmesini mümkün kılmaktadır. Tedavi süreçlerinin başarısı için erken teşhis çok önemlidir. Görüntü işleme ve yapay zeka yöntemlerinin kullanılması, sağlık görevlilerinin hastalığın erken tespitine yardımcı olabilir. Bu çalışmada, beyin tümörlerinin tespiti için derin öğrenme tabanlı geliştirilmiş bir görüntü bölütleme yaklaşımı önerilmiştir. Halka açık bir veri setinden alınan beyin manyetik rezonans (MR) görüntüleri üzerinde bölütleme yapılmıştır. Medikal görüntü bölütlemesine uygunluğu ve başarısı nedeniyle bölütleme işleminde klasik U-Net yapısı kullanılmıştır. Ön işleme ve son işleme aşamalarında kullanılan görüntü işleme teknikleri yardımıyla önerilen modelin performansı arttırılmıştır. Son işlem olarak bazı görüntü iyileştirme teknikleri uygulandıktan sonra, 0,89 zar katsayısı, 0,85 hassasiyet ve 0,89 F-puanı elde edilmiştir.

Anahtar kelimeler: *MRG, Derin Öğrenme, U-Net, Beyin Tümörü Bölütlemesi.*

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1. Giriş

Brain tumor is an unwanted growth of cells inside the brain. The growth of these cells can cause pressure in the skull and this can be fatal. Basically, there are two types of brain tumors: cancerous (Malignant) and non-cancerous (Benign) brain tumors. Non-cancerous tumor masses grow relatively slowly and are usually not harmful. On the other hand, malignant brain tumors grow rapidly and can spread to other parts of the body.

Magnetic resonance imaging (MRI) is considered as the most important evolution in the medical imaging field since the discovery of the x-ray [1], as MRI can provide elegant resolution that gives it the ability of characterizing an extensive range of parameters in living subjects [2]. Medical image processing provided massive support for the medical field, starting with X-ray, computed tomography (CT), MRI, and other medical imaging techniques, it has many applications like the simulation of surgeries, tumor detection, heart segmentation and analysis of cardiac images, etc. Medical image processing includes procedures like image registration, segmentation, and image-guided surgery.

Image segmentation is the most crucial medical image process, in which the region of interest (ROI) is extracted from the image. Image segmentation is essential for various applications such as picture comprehension, feature extraction, analysis, and interpretation. It has several applications in medical science, including tissue categorization, tumor localization, tumor volume calculation, blood cell delineation, surgical planning, atlas matching, and image registration.

Brain tumor segmentation is the process of separating tumor tissues (active tumor, edema, and necrosis) from normal brain tissues. The precise and repeatable measurement and morphology of tumors are critical for brain tumor diagnosis, treatment planning, and monitoring response to oncologic therapy.

MR image segmentation methods can be divided into three different categories, as Gordillo and others mentioned in [3]. The first category is manual segmentation, in which radiologists or other clinicians use their anatomical knowledge to segment the area of interest. Manual segmentation is considered as the most time-consuming method, as the clinician has to go slide by slide through dataset to find the most representative one and draw the wanted area. Another disadvantage of manual segmentation is that the selected region differs when the person doing the segmentation is changed, and that depends on the experience of each clinician. Nevertheless, it is counted as the most accurate method. It is required for the validation ground truth of the other two methods. The second category is semi-automatic methods, which combine computers and human expertise. In these methods, the involvement of a human operator is required to initialize the process by giving arguments and parameters or to give feedback during the process or sometimes to evaluate the results. The third category is fully automatic methods, which use human knowledge in algorithms to provide the fastest and most accurate ways to segment MR images. In these methods, the whole process is figured out by computers starting from the pre-processing, defining the critical parameters, up to testing results, and finding the accuracy.

As the implementation of deep learning algorithms started to be involved in almost all the fields, we can see the increasing usage of it in medical image processing as well. While surveying the last researches in the topic, it has been recognized that the deep learning based segmentation model has proved robust performance when compared to classical segmentation methods and even classic machine learning methods. However, it still vastly depends on other steps in the model like pre-processing and post-processing [4].

In this work a deep learning based model is proposed to segment MR images. The model includes pre-processing the images by reducing the non-brain tissues in it. After that, the pre-processed images will be fed into a U-Net network to segment the tumor region, then the segmented image will be post-processed by using robust image processing techniques to increase the accuracy of the resultant images.

Table 1 Symbols and Abbreviations

MRI	Magnetic Resonance Imagining
MR	Magnetic Resonance
CT	Computed Tomography
ROI	Region of Interest
ML	Machine Learning
DL	Deep Learning
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
CNN	Convolutional Neural Network
TCIA	The Cancer Imaging Archive
TCGA	The Cancer Genome Atlas
IOU	Intersection Over Union
JI	Jaccard Index

1.1. Related Works

De Radd et al. [5] trained 72 different models to analyze the impact of various preprocessing methods in MR images segmentation. They used 24 different preprocessing methods in three different datasets. They conclude that preprocessing plays an essential role in increasing the accuracy of the segmented image, and finding the preprocessing method with the highest impact is related to the specific application in which the preprocessing method is used.

Kondrateva et al. [6] performed a massive analysis of the conventionally preprocessing methods used in brain MR images, and the importance of using them. They assigned that there are mainly four categories of preprocessing methods used in preprocessing of brain MR images. These methods are the rigid registration, different voxels resampling methods, methods that affect the voxel's intensity distribution, and the skull stripping. They used U-Net network in their work. Their results show that generally the usage of preprocessing is very crucial to achieve accurate results. Also, they reported that the skull stripping method recorded the highest Dice coefficient compared to the other methods for segmenting the whole tumor. Although the skull stripping has proved the best results as a preprocessing method [6] for MR images segmentation, it is considered as the most time consuming one.

Furtado [7] worked on proving the importance of post-processing in segmenting the MRI of the abdominal organs using deep learning algorithms. The author used some traditional post-processing techniques, namely; atlas fencing, noise removal, envelope continuity, and smoothing the edges. The results in [7] proved that using post-processing can improve the DL segmentation Jaccard index by a total of %12-%25 over the segmentation of different organs (left kidney, right kidney, spleen, and liver).

Most of the improvements achieved in the performance of deep network models were focused on architectural details. In [8] a deep learning-powered approach of two cascade stages for brain tumor segmentation in different MRI modalities is presented. The first stage performs the region of interest while a multi-classification process is implemented in the second stage. The two stages are using multi-modal fully convolutional neural networks inspired by Unet. The model showed high accuracy and fast processing performance while performed over the BraTS (2018) dataset.

Dong et al. [9] used conventional U-Net architecture to segment brain tumor in MR images. They used BRATS 2015 dataset to train and evaluate their model. After augmenting the images given in the dataset, they changed the cost function from the cross entropy to the Soft Dice metric. Their model had competitive results when compared to the winning models in the BRATS 2015 competition. In the method presented in [10], the authors employed a non-overlapping batch-wise U-Net. They achieved to obtain a Dice coefficient of 93% which exceeded the traditional U-Net by %3. The core idea of the study presented in [10] is to divide the original MR image into 4 pieces and feed it to the U-Net, then do the same with the ground truth images. The main benefit of dividing the original image into smaller pieces is to get more accurate results and reduce the possibility of the network missing some details during the segmentation process.

2. Methodology

To avoid the U-Net drawbacks and improve the performance of the segmentation process we propose to do some non-architectural tuning in this study. We first suggest to decrease the non-brain tissues in MR images. We preferred to use MATLAB Thresholder App to easily remove the parts of the skull shown with light colored pixels which can confuse the network while segmenting the image. In addition, we employed some robust image post-processing techniques to remove the FP (False Positive) pixels totally and reduce the FN (False Negative) pixels after segmenting the tumors. This approach increases the accuracy of the segmentation by default. The presented model can be seen in Figure 1.

2.1. Skull Stripping

Skull stripping has been recognized as an essential preprocessing procedure that enables most effective segmentation and helps to the accurate identification of brain illnesses. In [8], Fatima et al. presented a massive review on the existing state of-the-art of skull stripping. They divided the traditional skull stripping methods to 5 categories. The first category is the deformable surface–based skull stripping methods. They are based on an image gradient that determines the location of the brain surface and is described by active contours. The second category is the mathematical morphology–based skull stripping methods. These methods employ a sequence of thresholding, morphological erosion, and dilation processes. The algorithms, which are based on the mathematical morphological procedures and the edge detection, are capable of accurately extracting the brain from a normal brain MR image. The third category includes the intensity-based skull stripping methods. The approaches based on intensity distributions of brain MR images utilized for threshold classification have been used in intensity-based skull stripping. The fourth category contains template-based skull stripping methods. These methods rely on MRI templates or atlases to differentiate brain tissues from non-brain tissues by developing an initial approximation for the brain mask. Finally, the hybrid based skull stripping methods have been considered as the fifth category in which is the merging of many previously established skull stripping methods.

The approach used for skull stripping in this study can be considered as a method from the third category among categories mentioned above as it depends on thresholding colored MR images based on the difference of intensities between the skull and the brain tissues. In the pre-processing step the skull is removed from the MR images to help the network get the right features to segment the tumor area. Being colored of the MR images used in this study is very helpful in stripping the skull. By using the MATLAB thresholder application, one of the color spaces can be chosen, and then by using the different channels, histogram thresholds are found to segment the desired mask. In this case, the skull is masked firstly and then removed.

2.2. U-Net

U-net is an important framework of CNN and has advantages like a large number of feature channels in the first part of the architecture which allows the network to give better contextual information about the image to higher resolution layers.

The traditional U-net architecture is mainly composed of two parts; encoder and decoder. Encoder, also known as the contracting path, is the first part of U-net and includes convolution and max pooling which is the same as CNN. This part is present in nearly all CNN networks and its job is to create a compact representation of the input image. It extracts feature information from the input data for the use of the second part. The main idea of the encoder part is to dimensionally reduce the input image and create parts of that image to extract deeper image features. On the other hand the decoder is used for enlarging the image to its original size since it is our goal to get an output that is similar in size to the input. Each layer has the same architecture. Transposed convolutions are used to upsample the condensed representation of the image. Also, to provide more information while decoding, skip connections are used where the feature maps of the encoder are concatenated to the output of the transposed convolutions of the same level. Skip connections enables us to use feature context information collected in the encoder part to support our segmentation map [11]. The original U-net architecture is shown in Figure 2.

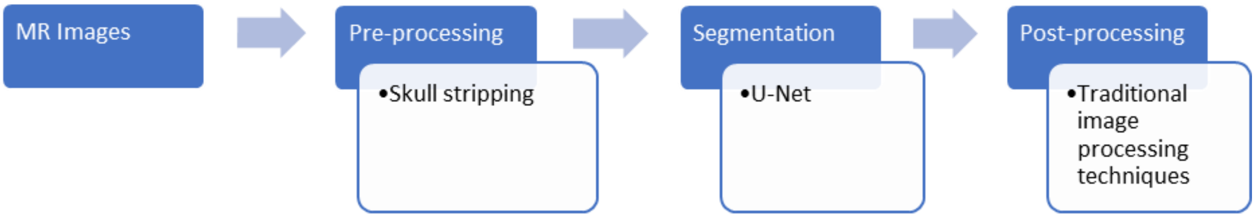


Figure 1. *Model flow diagram.*

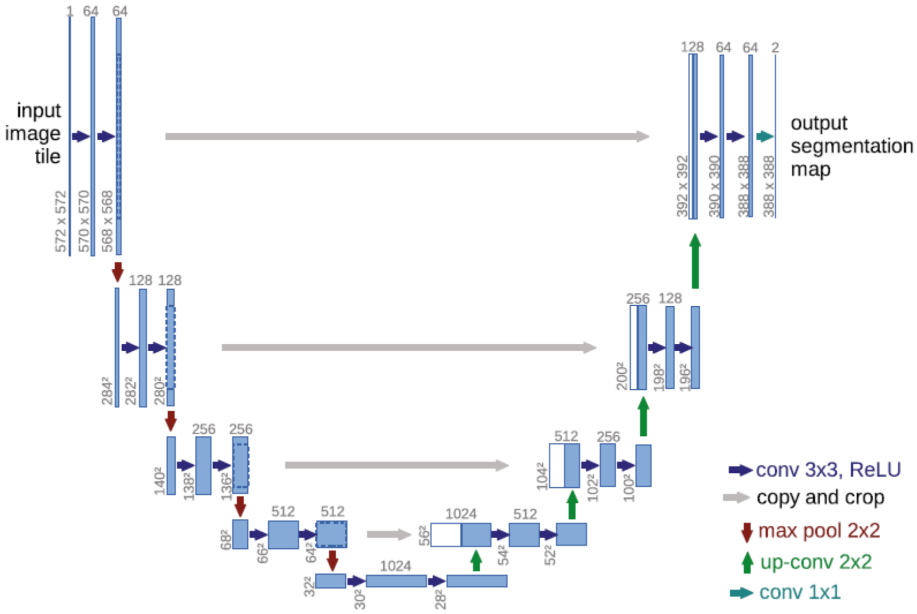


Figure 2. *The U-net architecture.*

2.3. Traditional Image Processing Techniques

The category of techniques known as "image processing" deals with the manipulation of digital images using computer algorithms. Image enhancement is one of the most important image processing applications, in which the acquired image is altered to suit the specifications of the task for which it will be employed.

The segmented images using the U-Net architecture proposed above need some image processing techniques to be performed to remove some parts which are segmented to be tumor while they are not (FP parts). In this step volumetric constraints have been applied as the segmented region with the bigger area is selected to be the tumor, and the other regions are neglected. After selecting the region with the biggest area, the Morphological operations-explained in the next section- are implemented over the segmented region. After that, it has been found that some segmented tumors have holes inside the ROI, and in order to remove them some other code lines were added. After segmenting the ROI correctly, gaps found on the segmented regions have been covered using image filling operation.

3. Experiments and Results

3.1. Dataset

The dataset used in this study contains MR images of the brain with its manual abnormality segmentation masks which can be used as ground truth. This dataset is open to use for scientific studies and is provided by The Cancer Imaging Archive (TCIA) [12]. All the MR images included in the dataset were provided by TCIA. The dataset corresponds to 110 patients in the lower-grade glioma collection of the Cancer Genome Atlas (TCGA). Moreover, the sequence about the fluid-attenuated inversion recovery (FLAIR) and genomic cluster data are available in the dataset. Information of patients and the clusters of tumor genom can be found together in a csv file. All MRI slices are in the form of 3 modalities and RGB colour format. The dataset includes 7858 images totally. As the dataset was too big and time consuming according to our computational facilities, in this study 1000 images were selected for the training process, and 150 images were used for the testing process. The chosen images included the images with the tumor shown. The images with no tumor shown in it were not used.

3.2. Preprocessing

As explained in the methodology part, a pre-processing step of stripping the skull was applied to the images before feeding it to the network. The result of the pre-processing step can be seen in Figure 3.

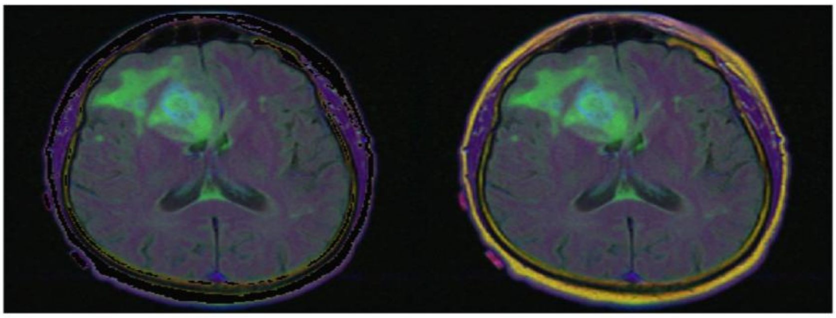
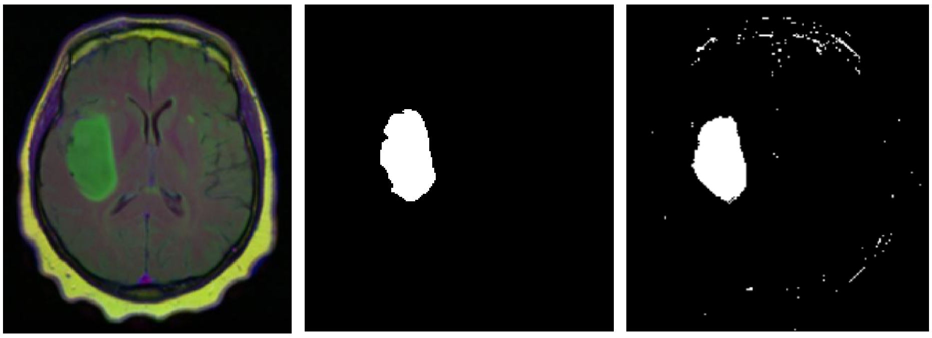


Figure 3. *Skull stripping.*



(a) **(b)** **(c)**

Figure 4. *(a) Original MRI, (b) Ground truth, (c) Segmented image.*

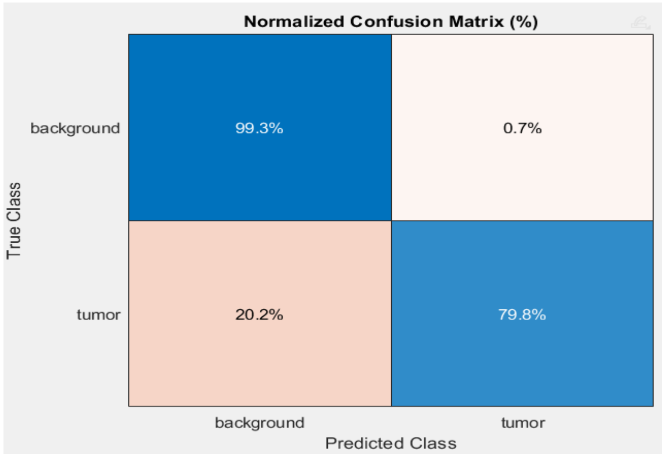


Figure 5. *Confusion matrix.*

3.3. Training the U-net

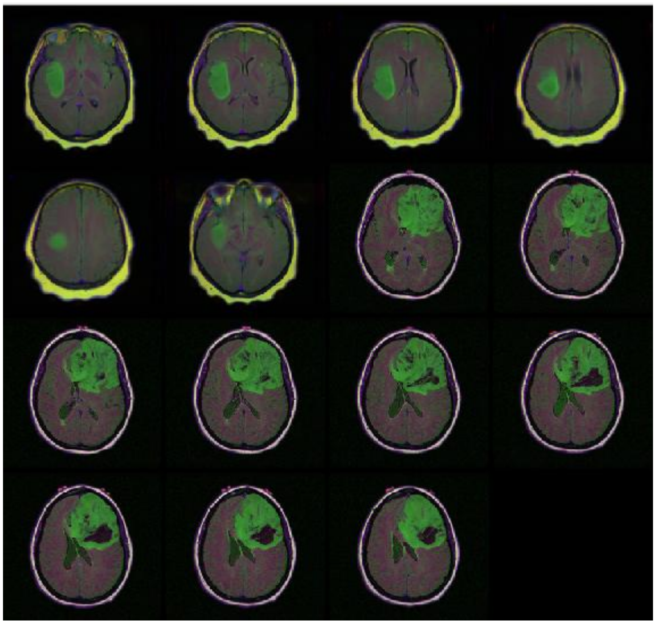
The U-Net used in the study have the original network architecture published by Ronneberger et al. in 2015 [11] which explained in the methodology section. The preferred U-Net structure was built using MATLAB codes. The training options were chosen as follows: the training function was "rmsprop", the mini batch size was 16, the learning rate was 0.001, and the max epochs were 12.

3.4. Testing

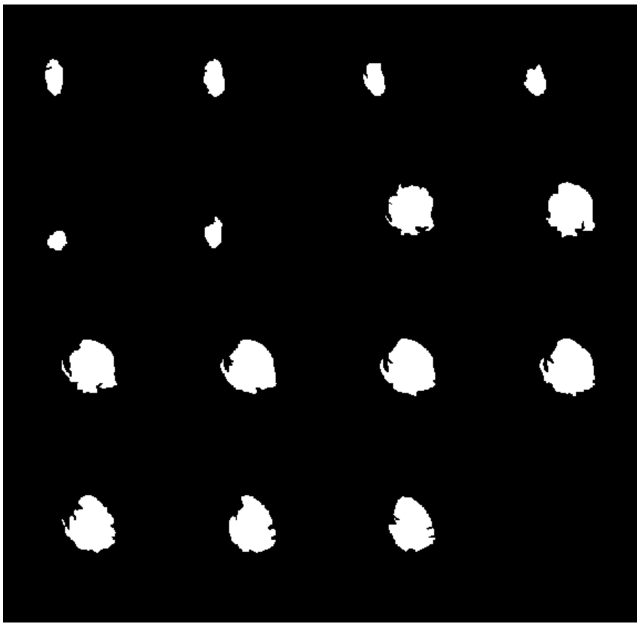
The trained U-Net architecture was then used to predict segmentation of the testing images. As seen in Figure 4, segmented image includes some pixels which are not in tumor area. Comparison of the segmented image and the ground truth show that the segmented image contains some FP and FN pixels. Decreasing the number of these pixels can be done by using some image processing techniques as the post-processing step. In Figure 5, the confusion matrix formed for the segmentation of the testing images can be seen. It is obvious that the segmentation performed by the U-Net needs more post-processing techniques to enhance the accuracy of the model.

3.5. Post-processing

For removing the small parts which are segmented as tumor while they are not, a volumetric constraints were applied to the testing dataset. In Figure 6, the whole testing dataset is shown beside its ground truth labels.

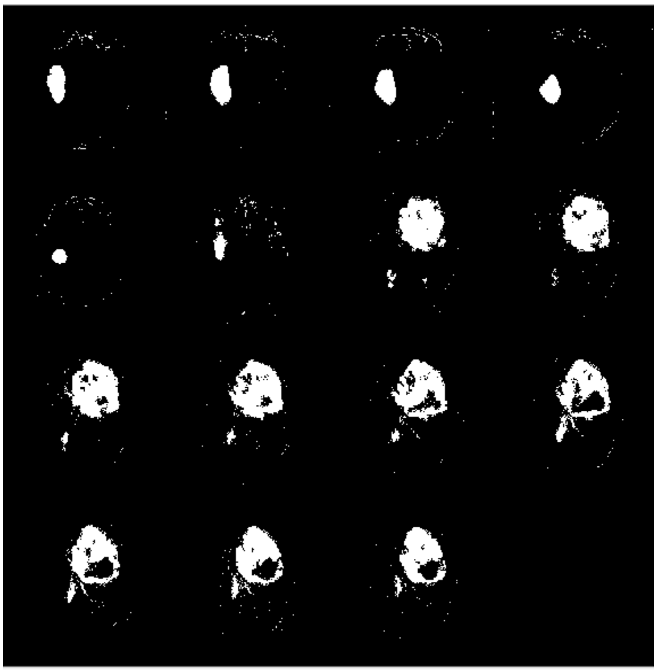


(a)

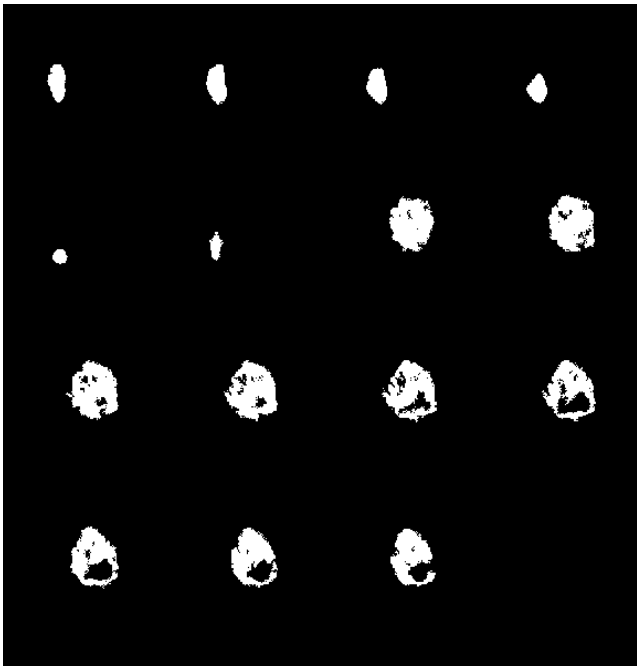


(b)

Figure 6. *(a) Testing MR images and (b) the ground truths.*



(a)



(b)

Figure 7. *Segmented images (a) before and (b) after applying the volumetric constraints.*

Effects of the volumetric constraints on the segmented images can be seen in Figure 7. After applying the volumetric constraints, holes in the segmented images still exist. In order to remove the holes, morphological image filling operation was used with the help of Matlab. As the result, the obtained images which are shown in Figure 8 have quite better evaluations when compared to the previous ones.

4. Results and Discussions

There are many image segmentation metrics used in literature. These metrics are used to evaluate the performance and accuracy of the image segmentation algorithms quantitatively. Mainly, the metrics compare the segmented regions to a reference or ground truth segmentation. The most common segmentation metrics are IOU (Intersection over union), also known as Jaccard Index (JI), Dice coefficient, sensitivity, and F-score [13,14]. Those metrics purely based on four important concepts; namely true positive (TP) which refers to the truly segmented tumor pixels, false positive (FP) which contains the background pixels segmented as tumor, false negative (FN) which contains the tumor pixels segmented as background, and true negative (TN) which refers to the background pixels segmented as background.

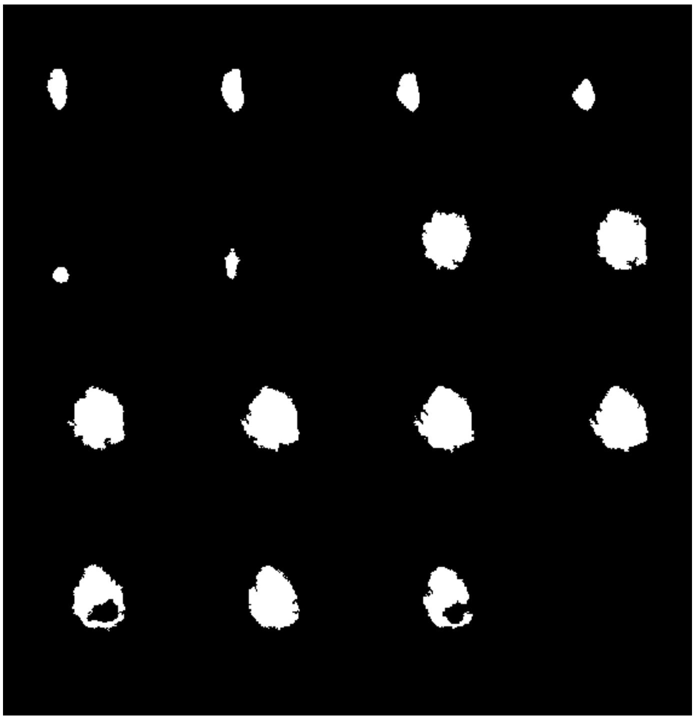
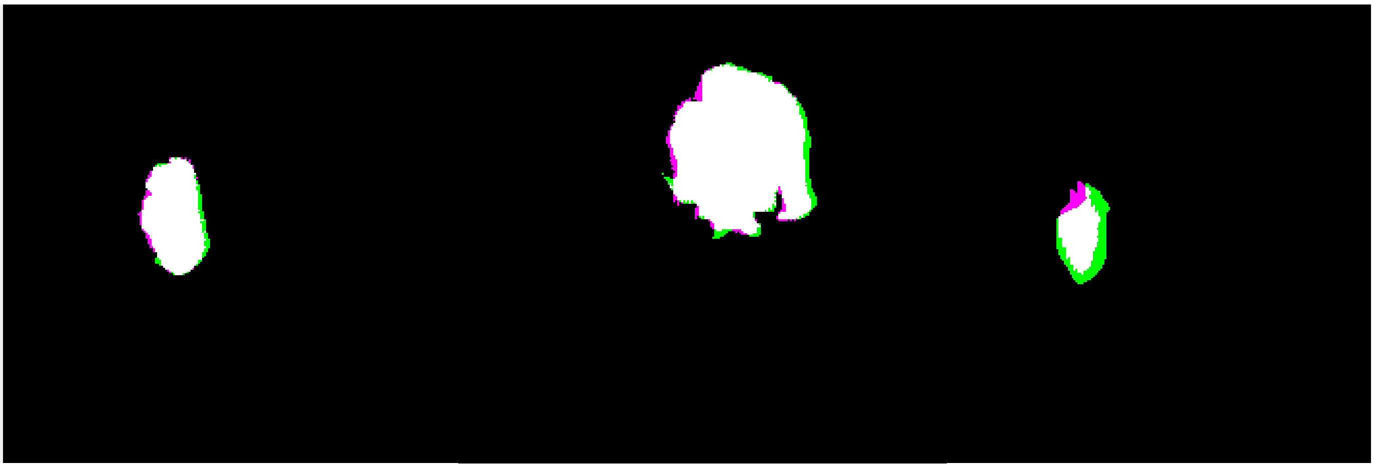


Figure 8. *Segmented and enhanced images.*



(a) **(b)** **(c)**

Figure 9. *Samples results of the segmented images*

In Figure 9, we can see samples of the segmented images montaged with the ground truth labels, the green pixels show the FP pixels and the purpule pixels shows the the FN pixels. The IOU of the three samples shown in Figure 9 (a), (b), and (c) are 0.898, 0.910, and 0.547 respectively.

Before applying the post-processing techniques, the average IOU for the testing images was found as 0.75, and the average Dice coefficient was 0.82 in this study. After the post-processing, the average IOU of the final segmented MR images increased to 0.81; the average Dice coefficient showed a good improvement and increased to 0.89. The average sensitivity of the enhanced images was found as 0.85, and the average F-score was 0.89. Positive effect of the post-processing techniques can be seen in Table 2.

Deep learning-based works in the field of biomedical image processing have always focused on improving the structure of the deep learning model itself, with pre- and post-processing steps treated as secondary steps in the model. In this work, we focused on the pre-processing and post-processing steps to improve the segmentation accucacy and show the robustness of those steps. The aim of this work is to build a model that segments the brain tumor in MR images accurately. The first step in the model is pre-processing in which the skull has been stripped from the colored MRIs. The next step is the usage of a U-net architecture to segment the tumor. Finally, some traditional image processing techniques are used to improve the results given by the U-net. The adoption of pre- and post-processing procedures increased the average IOU from 0.75 to 0.81 and increased the average Dice coefficient from 0.82 to 0.89. The progressive effects of pre- and post-processing techniques are very clear because of the IOU and Dice coefficient results. It is still possible to improve the segmentation accuracies using different image processing procedures and deep learning architectures.

Table 2 Segmentation Results Before and After Image Enhancement

Segmentation Method	Average Dice Score	Average IOU
U-Net	0.82	0.75
U-Net + volumetric enhancement + image filling	0.89	0.81

5. Conclusion

In this paper, we proposed a brain tumor segmentation model that uses a skull stripper in the pre-processing step and some volumetric constraints are applied as a post-processing technique after segmenting the tumor with a U-Net network. The proposed method demonstrated the effectiveness of pre- and post-processing procedures. Robust pre- and post-processing approaches will aid in obtaining more accurate results when applying the commonly used deep learning networks that are already in use in the research field. Moreover, success and effectiveness of the U-Net architecture in biomedical image segmentation were seen in the results as described in the literature. As the future studies, enhanced and hybrid U-Net architectures can be used to obtain higher segmentation accuracies. Moreover, different datasets and segmentation problems can be used to test the success of the proposed methodology.

Author Contribution

Data curation – Shahd H.H. Abdalgadir (SA), Mahmut Ozturk (MO); Formal analysis - (SA, MO); investigation - (SA, MO); Experimental Performance - (SA, MO); Data Collection - (SA, MO); Processing - (SA, MO); Literature review - (SA, MO); Writing - (SA, MO); Review and editing - (SA, MO)

Declaration of Competing Interest

The authors declared no conflicts of interest with respect to the research, authorship, and/or publication of this article.

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