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Deep learning-based brain tumor segmentation: A comparison of U-Net and SegNet algorithms

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ABSTRACT

Brain tumors are among the diseases that pose a serious health concern worldwide and can lead to fatal outcomes if left untreated. The segmentation of brain tumors is a critical step for the accurate diagnosis of the disease and effective management of the treatment process. This study was conducted to examine the success rates of deep learning-based U-Net and SegNet algorithms in brain tumor segmentation. MRI brain images and black and white masks belonging to these images were used in the study. Image processing techniques, including histogram equalization, edge detection, noise reduction, contrast enhancement, and Gaussian blurring, were applied. These techniques have highlighted tumor boundaries, defined edges more precisely, smoothed images, and emphasized the difference between tumors and healthy tissues; thus, they have contributed to improving the quality of MR images and achieving more accurate results in the segmentation process. As a result of the segmentation operations performed with U-Net and SegNet algorithms, the U-Net algorithm achieved an accuracy rate of 96%, while the SegNet algorithm's accuracy rate was measured at 94%. The study determined that the U-Net algorithm provided a higher success rate and was more effective in brain tumor segmentation. In particular, the contribution of image processing steps to segmentation success was observed.

Derin öğrenme tabanlı beyin tümörü segmentasyonu: U-Net ve SegNet algoritmalarının karşılaştırılması

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ÖZET

Beyin tümörleri, dünya genelinde ciddi bir sağlık sorunu oluşturan ve tedavi edilmediği takdirde ölümcül sonuçlara yol açabilen hastalıklar arasında yer almaktadır. Beyin tümörlerinin segmentasyonu hastalığın doğru teşhisi ve tedavi sürecinin başarılı bir şekilde yönetilmesi için kritik bir adımdır. Bu çalışma görüntü işleme yöntemleri ve derin öğrenme tabanlı U-Net, SegNet algoritmalarının beyin tümörü segmentasyonundaki başarı oranlarını incelemek amacıyla gerçekleştirilmiştir. Çalışmada MR beyin görüntüleri ve bu görüntülere ait siyah-beyaz maskeler kullanılmıştır. Görüntü işleme teknikleri olarak histogram eşitleme, kenar bulma, gürültü azaltma, kontrast iyileştirme ve Gaussian bulanıklaştırma yöntemleri uygulanmıştır. Bu teknikler tümör sınırlarını belirginleştirip, kenarları daha hassas bir şekilde tanımlayarak görüntüleri pürüzsüzleştirmiş ve tümör ile sağlıklı dokular arasındaki farkı vurgulamıştır; böylece MR görüntülerinin kalitesini artırarak segmentasyon işleminde daha doğru sonuçlar elde edilmesine katkı sağlamıştır. U-Net ve SegNet algoritmaları ile yapılan segmentasyon işlemleri sonucunda U-Net algoritması %96 doğruluk oranına ulaşırken SegNet algoritmasının doğruluk oranı %94 olarak ölçülmüştür. Çalışmada U-Net algoritmasının daha yüksek bir başarı oranı sunduğu ve beyin tümörü segmentasyonunda daha etkin olduğu tespit edilmiştir. Özellikle, görüntü işleme adımlarının segmentasyon başarısına katkısı gözlemlenmiştir.

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1. INTRODUCTION

Brain tumors are a life-threatening health issue with high mortality rates worldwide. Early diagnosis of brain tumors plays a significant role in planning the treatment process and prolonging patients' lives [1]. However, accurately diagnosing brain tumors and determining their size is a complex process. Traditional medical imaging methods offer limited accuracy in this process, whereas with the increasing use of artificial intelligence and deep learning techniques in the medical field, more accurate and faster diagnostic methods have been developed. In particular, deep learning-based segmentation algorithms like U-Net and SegNet are frequently preferred in medical image processing and show promise in the process of determining tumor boundaries in brain MRI images.

The aim of this study is to compare the success rates of the U-Net and SegNet algorithms in brain tumor segmentation and to demonstrate the potential for their use in clinical applications. In this study, 3064 MRI images and their corresponding black-and-white masks were used, with various image processing techniques applied before the segmentation process. Histogram equalization enhances the contrast in the image, allowing for a clearer definition of tumor boundaries, while edge detection algorithms enable more precise identification of the tumor and surrounding tissue boundaries. The noise reduction method eliminates artifacts in the image, improving the accuracy of the segmentation process. Additional techniques such as contrast enhancement and Gaussian blurring improve image quality, positively impacting the performance of the algorithms. [2]. After the application of these methods, segmentation was performed using the U-Net and SegNet algorithms, and the performance of these two algorithms was evaluated using metrics such as accuracy, precision, and F1 score.

The results of the study reveal that the U-Net algorithm demonstrates higher performance with an accuracy rate of 96%, making it a more effective method for brain tumor segmentation. The study aims to guide future research and contribute to the development of automatic segmentation systems that can be used in the diagnosis of brain tumors.

1.1. Related Work and Motivation

Brain tumor segmentation and classification have become significant research topics in the field of medical imaging. In the literature, various deep learning methods and architectures have been developed and applied for the accurate and effective segmentation of brain tumors. Some studies in this area include:

Magadza et al. used deep learning architectures such as U-Net and multi-stage CNNs for brain tumor segmentation. The study highlights two-way data flow and multi-stage segmentation approaches for the automatic segmentation of tumor regions from MRI images. These methods combine local and global image information to enhance accuracy and have been successfully tested on large datasets. [3].

Biratu et al. examined regional growth, shallow machine learning, and deep learning methods for brain tumor segmentation and classification. The study evaluates automatic segmentation and classification techniques using MRI images, focusing on the strengths and weaknesses of different approaches. Additionally, it highlights commonly used metrics for measuring segmentation performance and models that have been successfully tested on the datasets used. [4].

Liu et al. examined the development of deep learning methods for brain tumor segmentation, focusing on various architectural designs, data imbalance, and multi-modality integration. The study evaluates the impact of different deep learning models on accuracy. Methods developed using multi-data flow and customized loss functions to improve segmentation accuracy are emphasized. [5].

Rehman et al. proposed a model called BU-Net, which enhances the U-Net architecture for brain tumor segmentation. BU-Net aims to acquire broader contextual information through the addition of “residual extended skip (RES)” and “wide context (WC)” modules to the U-Net structure. The model considers the scale variations of tumor regions with the RES module, which transfers low-level features to intermediate levels and expands the receptive field. BU-Net has demonstrated superior performance compared to existing methods, achieving high Dice scores for tumor core, whole tumor, and enhanced core subregions in the BraTS2017 and BraTS2018 datasets. [6].

Ottom et al. developed a deep learning-based model called Znet for brain tumor segmentation using 2D MRI images. Znet aims to achieve more accurate segmentation with a small amount of data by utilizing "skip-connection" and "encoder-decoder" architectures to expand the data. The model achieved a 96% training Dice score and a 92% test Dice score on low-grade glioma data. It also demonstrated high performance in other metrics, such as pixel accuracy and F1 score. Znet stands out as a generalized solution that can be applied to different pathologies and imaging modalities. [7].

Khan et al. proposed a method that combines K-means clustering and deep learning for brain tumor classification. In the study, the K-means algorithm was initially used for segmentation of brain tumors from MRI images, followed by classification of the tumors as benign or malignant using the VGG19 model. To improve classification performance, the size of the training data was increased through synthetic data augmentation. This method was tested on the BraTS 2015 dataset and demonstrated higher accuracy compared to existing techniques. [8].

These studies highlight the success of deep learning-based methods aimed at improving the accuracy of brain tumor segmentation. Brain tumor segmentation is often a complex process that requires the accurate detection and separation of tumor regions. Although various deep learning models and architectures have addressed this problem, the existing methods in the literature still have some limitations. For example, some models do not yield effective results on certain datasets or tumor types, while others face challenges such as data imbalance and high computational costs.

Additionally, most existing methods fail to make sufficient adaptations to improve the precision of tumor segmentation. Characteristics of tumors, such as their varying contrast, shape, and size in images, are significant factors affecting the performance of the algorithms used. Therefore, more advanced and customized models are required for the accurate classification and segmentation of tumors.

In this context, this study aims to compare the success rates of the U-Net and SegNet algorithms in brain tumor segmentation, focusing on their unique architectures and practical applications in medical imaging. U-Net, known for its encoder-decoder structure, is specifically designed to achieve high segmentation accuracy in biomedical images. In contrast, SegNet provides faster and more efficient results by processing lower-resolution data. By comparing the performance of these models, this study seeks to identify the more effective method for brain tumor segmentation and explore potential improvements for developing more advanced segmentation techniques, such as hybrid models or combined algorithmic approaches.

The findings of this research aim to address the existing challenges in brain tumor segmentation, providing valuable insights for clinical applications and research advancements. Improving accuracy and efficiency in segmentation is vital for early diagnosis and effective treatment, making the development of robust models a priority in this field.

2. MATERIAL and METHODS

In this study, the performances of deep learning-based U-Net and SegNet algorithms for automatic brain tumor segmentation were compared. Segmentation of brain tumors is crucial in the medical diagnostic process, as it allows for the precise determination of tumor boundaries and sizes. In this study, 3064 magnetic resonance (MR) brain images and corresponding black-and-white tumor masks were used. To precisely delineate tumor regions, image processing techniques were applied prior to the segmentation process to enhance the quality of the MR images and ensure more efficient performance of the segmentation algorithms. The steps of the study are detailed below:

2.1. Dataset

The dataset consists of a total of 3064 MR images, covering various types of brain tumors. These images exhibit diversity in terms of tumor position, size, and shape. Corresponding black-and-white masks are available for each MR image in the study. These masks were used to label the tumor regions. Before processing each image in the dataset, standard preprocessing steps were applied. These steps ensure data cleaning and prepare the data for subsequent processing.

2.2. Image Processing Techniques

To improve the accuracy of segmentation, image processing steps were used to optimize the quality of the MR images. The applied image processing techniques are as follows:

2.2.1. Histogram Equalization

Histogram equalization has balanced the contrast levels in the image, making the tumor area more distinct from the surrounding tissue. This step aims to make the details in low-contrast regions more clearly visible [9]. The formulas below illustrate the histogram equalization formulas. Formula 1 represents histogram calculation, formula 2 represents cumulative distribution function, formula 3 represents equalized values, and formula 4 represents the creation of the new image. Figure 3 depicts the histogram equalized CT images and graphs [10].

$$p_r(r) = \frac{n_r}{mn} \tag{1}$$

$$s_k = \sum_{j=0}^{k} p_r(r_j) \tag{2}$$

$$s_k = round(L-1) \times s_k \tag{3}$$

$$I(x,y) = s_{I(x,y)} \tag{4}$$

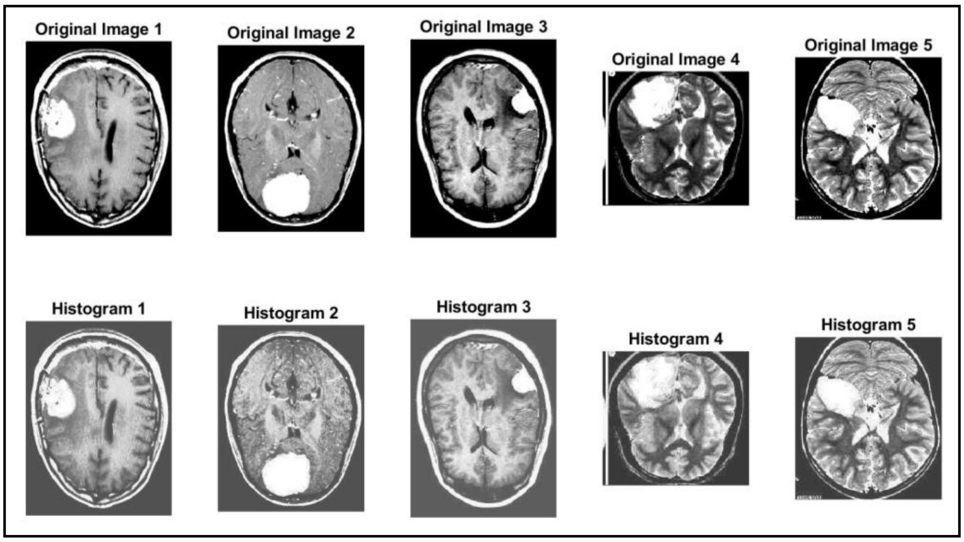

Figure 1. Histogram equalization

2.2.2. Noise Reduction

MR images often contain various artifacts and noise. Since these noises can negatively affect segmentation accuracy, a noise reduction filter was applied. In this study, the Gaussian filter was specifically preferred, allowing unnecessary noise to be filtered out and ensuring that the images became smoother.

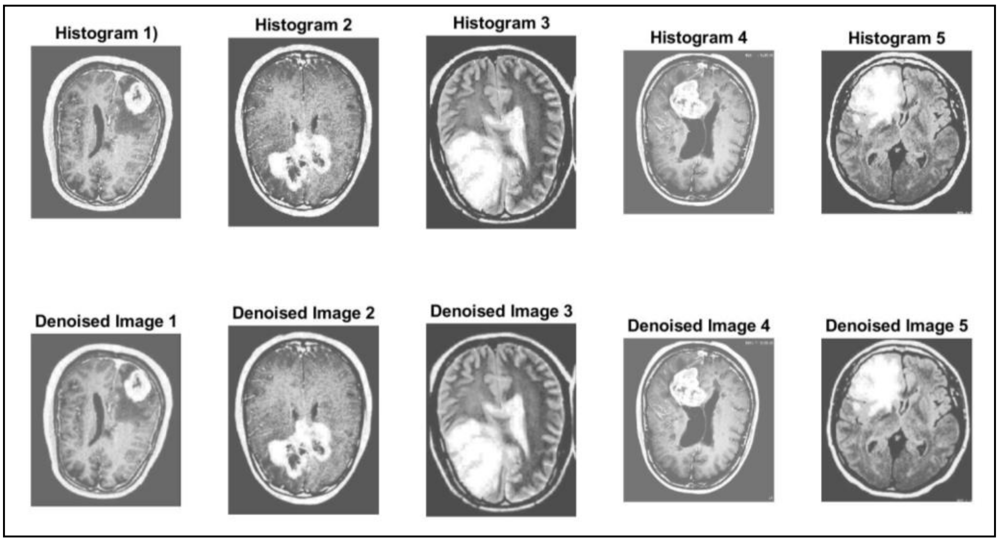

Figure 2. Noise reduction

2.2.3. Contrast Enhancement

Increasing the contrast in an image is important to facilitate the separation of the tumor from the surrounding tissues [11]. Therefore, the contrast of the image was enhanced to make the difference between the tumor region and healthy tissue more prominent. Here, *r* represents the original pixel value, and *s* represents the new pixel value.

$$s = \frac{(r - r_{min})}{(r_{max} - r_{min})} \times (s_{max} - s_{min}) + \quad s_{min} \tag{5}$$

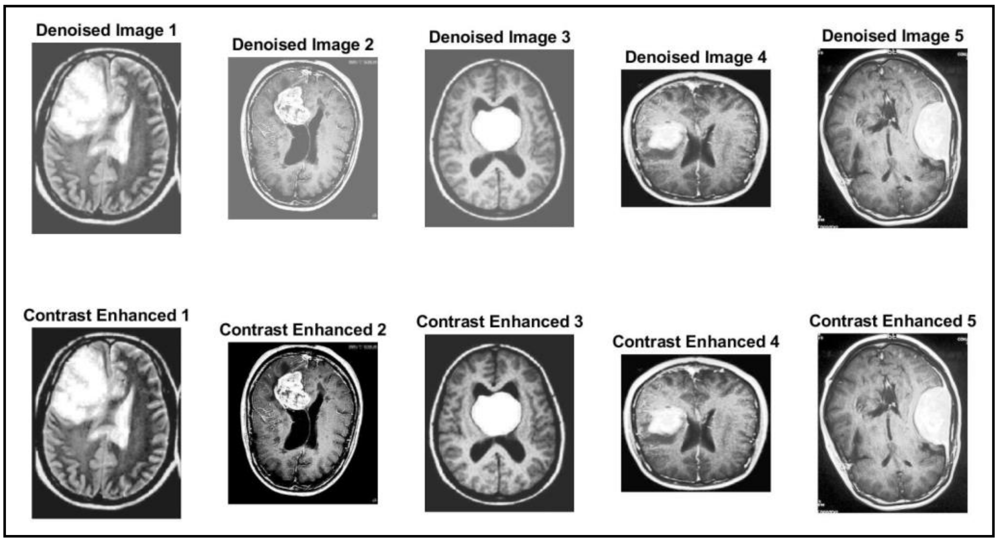

Figure 3. Contrast enhancement

2.2.4. Gaussian Blur

The Gaussian blur filter was used to smooth the boundaries identified by the edge detection algorithm. This process contributed to the segmentation by softening the sharp edges in the image. Here, G(x, y) represents the pixel weight.

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2\sigma^2}} \tag{6}$$

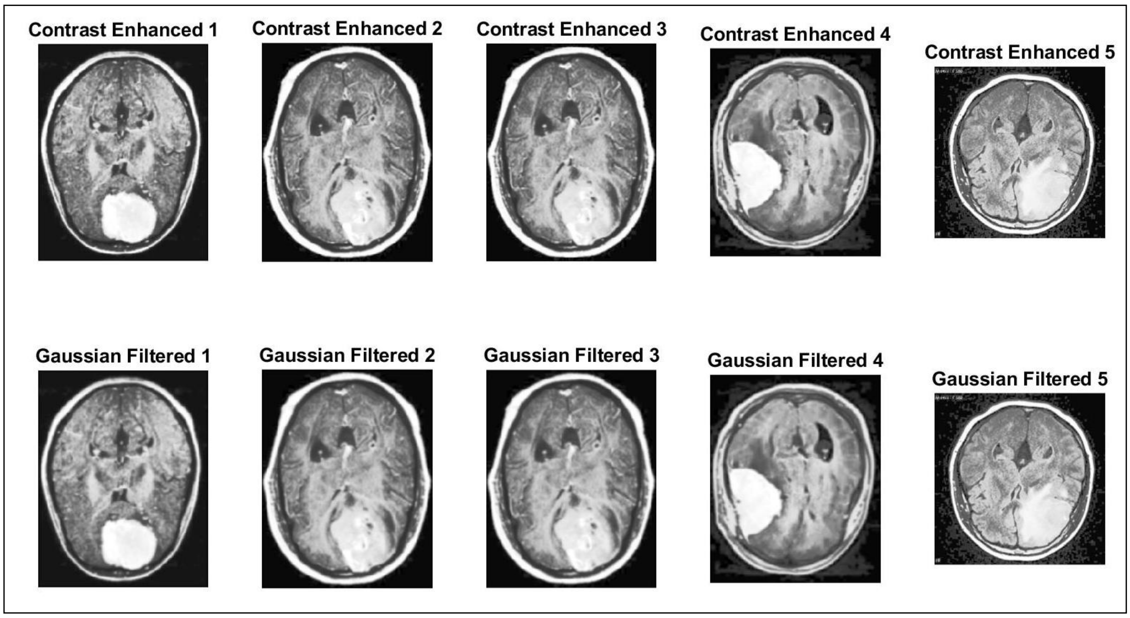

Figure 4. Gaussian filtered

2.3. Deep Learning Models

After the image processing steps, the segmentation of the MR images was performed using the U-Net and SegNet algorithms. U-Net and SegNet are deep learning-based architectures that are widely used in medical image segmentation, particularly for tasks such as this one..

2.3.1. U-Net

U-Net is a deep learning model, particularly used in medical image segmentation. It was developed by Ronneberger and his team in 2015. The model gets its name from its "U"-shaped symmetric structure and is a fully convolutional network (FCN). U-Net is widely used in fields such as medical imaging, biomedical analysis, and cell segmentation due to its ability to perform segmentation with high accuracy, even with low-resolution images. The U-Net model consists of two main parts: the encoder and the decoder. The encoder progressively reduces the input image into a smaller, more information-dense form, while the decoder uses this information to reconstruct the output image to its original resolution. Convolutional layers and transitions are used in both parts of the model. [12].

The encoder stage behaves like a classic CNN (Convolutional Neural Network), learning the features of the image in progressively smaller sizes and at higher levels of abstraction. Features are extracted through convolution and max-pooling operations. Each convolutional layer defines different aspects of the image. During this stage, while the image size is reduced, the number of features increases. When the encoder stage is complete, the model obtains a low-resolution image with rich feature information. The decoder stage aims to reconstruct the image reduced in the encoder back to its original resolution. In this stage, resizing operations called "up-sampling" are performed. This process allows the image to be enlarged back to its original size.

Additionally, the information from each layer of the encoder stage is combined with corresponding layers in the decoder stage through skip connections. This merging allows the recovery of details lost during the encoder stage and improves the segmentation accuracy of the model. One of the key features of U-Net is these connections, which establish direct links between layers at the same level in the encoder and decoder stages. These skips help recover fine details that could be lost during segmentation. Thanks to skip connections, the model achieves highly accurate segmentation results and works efficiently even with small-sized datasets.

The U-Net model has been successfully applied in areas such as brain tumor, lung lesions, retinal blood vessels, and cell segmentation. Especially in medical applications, accurately delineating the region where the tumor is located is of critical importance in disease diagnosis and treatment processes.

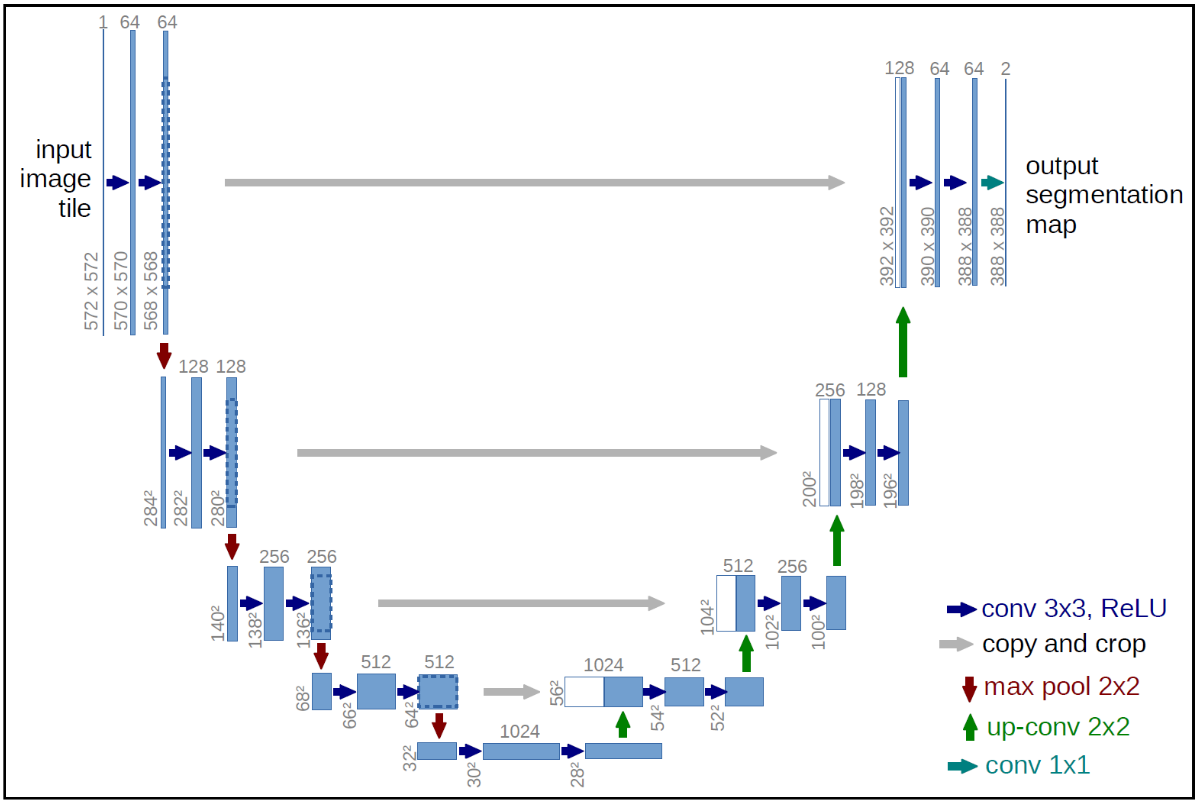

Figure 5. U-Net architecture [12]

2.3.2. SegNet

SegNet is a deep learning model used for image segmentation. It was developed by Badrinarayanan and his team in 2015. SegNet is specifically designed for semantic segmentation and assigns each pixel in the image to a specific class. This model is often preferred in segmentation applications that require large-scale and detailed analysis, such as cityscape images. SegNet is particularly used in applications like object detection, medical imaging, and environmental mapping.

SegNet is fundamentally built on an encoder-decoder architecture. While similar to U-Net, it has certain differences. Notably, the use of encoding-decoding phases and the "max pooling" index are distinctive features of SegNet. [13]. The encoder phase uses convolution and max-pooling operations to extract features from the input image. In SegNet's encoder phase, the image size is reduced while the number of features is increased during each pooling operation. For each max-pooling layer, the pixel that gives the maximum value is recorded, and this information is stored using a method called "index pooling." These stored max-pooling indices are then kept for use in the decoder phase. This approach reduces detail loss and enables more accurate segmentation. The decoder phase uses the features obtained in the encoder phase to resize the image and bring it back to its original resolution. Unlike U-Net, in SegNet the "upsampling" operation in the decoder phase is performed using max-pooling indices.

These indices contain information obtained from the max-pooling operations in the encoder phase. Thus, during the upsampling process, the stored max-pooling indices are used to increase accuracy and minimize detail loss. The decoder phase finally ends with a "softmax" layer, which assigns each pixel to a specific class. This way, the model's output image has each pixel assigned to a class. One of SegNet's most notable features is its use of max-pooling indices during the upsampling process. The direct use of pooling indices from the encoder phase in the decoder phase reduces computational cost and provides more efficient segmentation. The use of these indices reduces unnecessary connection layers, accelerating the model's learning process.

SegNet, its customizable structure and detail-sensitive architecture, is preferred for tasks that require high accuracy. It particularly provides successful results in segmentation, such as distinguishing objects like roads, vehicles, and buildings in urban road images.

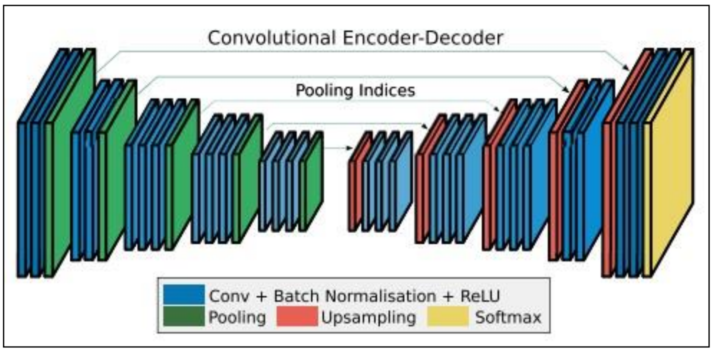

Figure 6. SegNet architecture [13]

2.3.3. Training Process and Hyper Parameters

The dataset is split into 80% training and 20% testing data to be used during the training and testing phases of the segmentation algorithms. This ratio provides an adequate amount of data to evaluate the model's overall performance. During the training process, the model learns the necessary parameters to differentiate between tumor and healthy tissue regions in the dataset. After the training phase, the model's accuracy is calculated on the test data to assess its performance..

During model training, two epochs were used to achieve high accuracy in a short period. The number of epochs was optimized to prevent overfitting. During this process, hyperparameters such as learning rate and optimizer were adjusted to improve the model's performance. Adam optimizer was preferred for both U-Net and SegNet models, as it provides a fast and efficient learning process and increases the model's accuracy. The learning rate is a parameter that affects the segmentation accuracy by allowing the model to learn faster or slower.

2.3.4. Performance Evaluation Metrics

In scientific research, metrics used to evaluate the effectiveness of proposed systems are of great importance, especially in classification problems, and these metrics can be easily calculated from the confusion matrix. In the confusion matrix, the cases where the algorithm made correct predictions are represented by true positive (TP) and true negative (TN) cells, while incorrect predictions are represented by false negative (FN) and false positive (FP) cells. In reality, cases that are positive but predicted as negative by the model are classified as false negative (FN), while cases predicted as positive but actually negative are recorded as false positive (FP). This structure allows for the analysis of the model's performance and errors, so areas for improvement can be identified. [14].

Table 1. The confusion matrix

	Target Class	
	0	**1**
Output Class	True Negative (TN)	False Negative (FN)
	False Positive (FP)	True Positive (TP)

Classification accuracy is a commonly used metric to evaluate the effectiveness of classification algorithms and is calculated as the ratio of correct predictions to the total number of predictions. Although accuracy is a simple evaluation criterion, other metrics such as specificity, sensitivity, precision and F-score are also used to evaluate algorithm performance in more detail. These additional metrics allow for a more comprehensive analysis of the model's success in different aspects. Specificity expresses the proportion of negative examples that are correctly predicted by the classifier, while sensitivity measures the proportion of positive examples that are correctly predicted. Precision indicates the proportion of correctly classified true positive examples within the total positive examples. The F-score is defined as the harmonic mean of precision and recall values. These metrics are calculated using specific formulas and play an important role in performance evaluations. This allows for a more comprehensive understanding of the reliability and accuracy of classification systems. Below are the formulas for performance metrics such as accuracy, specificity, sensitivity, precision, and F-score. [15].

$$accuracy = \frac{tp + tn}{tp + tn + fp + fn} \tag{6}$$

$$specifivity = \frac{tn}{tn + fp} \tag{7}$$

$$sensitivity = \frac{tp}{tp + fn} \tag{8}$$

$$precision = \frac{tp}{tp + fp} \tag{9}$$

$$f - score = \frac{(precision) \times (\text{sensitivity})}{(precision) + (sensitivity)} \tag{10}$$

These metrics evaluate the accuracy of the segmentation process in detail, determining which model achieves higher success. As a result of the experiments, it was found that the U-Net model has a higher accuracy rate compared to SegNet and, therefore, is a more suitable option for brain tumor segmentation.

2.3.5. Visualization and Results Analysis

After the segmentation process, the results of both models were visualized. Visual analysis is crucial for evaluating the segmentation quality and the accuracy of the masks. As a result, it was observed that the U-Net model detected tumor regions more clearly and created more accurate masks. This study demonstrates that the U-Net algorithm is more effective in automatic brain tumor segmentation and could be a suitable candidate for clinical applications. Success rates are shown in Table 2. Prediction results are visualized in Figure 7.

Table 2. Success rates

	Accuracy	**Specificity**	**Sensitivity**	**Precision**	**F-Score**	**Avg.**
U-Net	0.9644	0.9562	0.9716	0.9663	0.9617	0.9664
SegNet	0.9456	0.9506	0.9608	0.9507	0.9403	0.9496

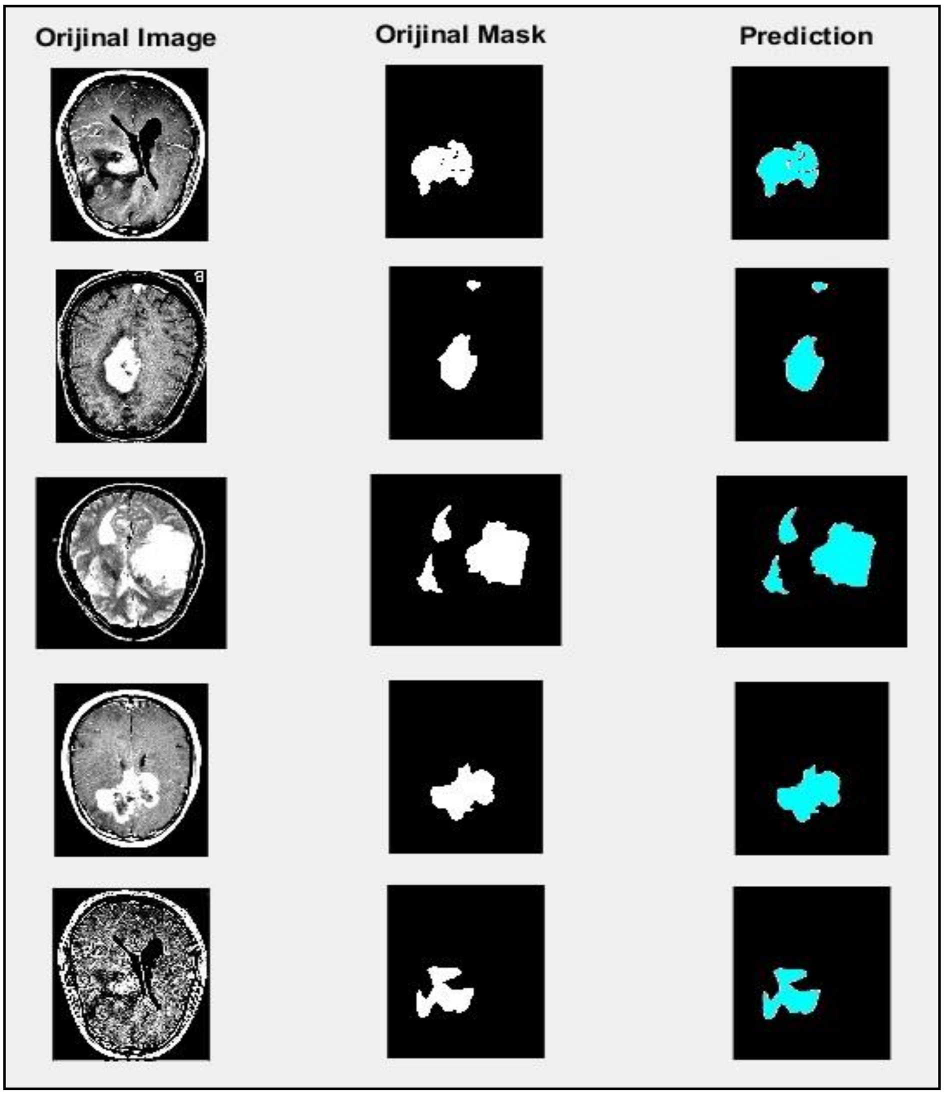

Figure 7. Results

3. CONCLUSION and EVALUATION

In this study, the performances of the U-Net and SegNet algorithms for automatic brain tumor segmentation were compared, and the segmentation successes of both models were evaluated in detail. The applied deep learning methods were combined with pre-processing techniques performed on MRI images, aiming to enhance segmentation accuracy. The obtained results reveal the effectiveness of the algorithms and the quality of the segmentation process. The U-Net model achieved a high segmentation success rate of 96%, indicating its effectiveness in delineating the boundaries between tumor and healthy tissue. The SegNet model achieved an accuracy of 94%. The segmentation successes of both models are quite satisfactory when compared to the results obtained in similar studies in the literature.

Visual analyses were performed by examining the segmentation results of both models. It was observed that the U-Net model delineated tumor areas more clearly and the details of the masks were more pronounced. SegNet, on the other hand, provided results with limited accuracy in some cases. In the images, the segmentation results obtained with U-Net showed more distinct tumor boundaries and a greater overlap between the mask and the original image.

It was determined that the learning process of both models was effective with 1000 epochs during the training process. While the model was trained with 80% of the data, 20% of the test data was used to evaluate the overall performance of the model. U-Net and SegNet were optimized with the specified hyperparameters, and both models achieved sufficient learning capacity. At the end of the training process, both models resulted in high segmentation accuracy.

The findings of this study demonstrate the effectiveness of deep learning-based approaches in brain tumor segmentation and provide important results for clinical applications. The high accuracy rate of the U-Net model offers a promising foundation for the development of automatic segmentation systems in the field of medical imaging. Specifically, the U-Net model's ability to precisely delineate tumor regions has the potential to be an important support tool for surgeons and radiologists. This helps in the decision-making processes for determining the size and location of tumors.

The results of this study provide new directions for future research. The application of different deep learning architectures, in addition to U-Net and SegNet, can contribute to improving segmentation quality. Moreover, increasing the diversity of the dataset and testing on more images will enhance the generalizability. Future work aims to further improve segmentation performance through the integration of different model combinations and techniques such as transfer learning.

In conclusion, the findings obtained in this study highlight the effectiveness of deep learning methods in brain tumor segmentation, and the high accuracy achieved by the U-Net model shows that it can be an important resource in medical applications. U-Net’s high segmentation performance is among the leading methods for medical imaging applications, emphasizing the need for continued research in this field..

CONFLICT OF INTEREST

There is no conflict of interest between any institutions, organizations, individuals, and authors in this study.

ETHIC

If your article is outside the scope of ethics, "There are no ethical issues regarding the publication of this article." The data used in our study is publicly available and is not subject to data privacy. (Cheng, Jun (2017). brain tumor dataset. figshare. Dataset. https://doi.org/10.6084/m9.figshare.1512427.v5)

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