Optimizing Brain Tumor Segmentation Through CNN U-Net with CLAHE-HE Image Enhancement

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Abstract. Accurate segmentation of brain tumors in medical images is paramount for precise diagnosis and treatment planning. In this study, we introduce a robust approach for brain tumor segmentation employing Convolutional Neural Networks (CNNs) with Contrast-Limited Adaptive Histogram Equalization (CLAHE) and Histogram Equalization (HE) preprocessing techniques. We leverage the CNN U-Net architecture, enhanced with CLAHE-HE preprocessing, to achieve high precision in brain tumor segmentation. Our evaluation demonstrates the effectiveness of this approach, revealing substantial improvements in accuracy (reaching up to 0.9982), loss (reducing to 0.0054), Mean Squared Error (MSE, decreasing to 0.0015), Intersection over Union (IoU, increase up to 0.9953), and Dice Score (increase up to 0.9977) during training, validation, and testing phases. Notably, the capacity of our model to generalize effectively is evident through the close alignment of validation performance with training results. These findings underscore the potential of preprocessing techniques in enhancing medical image analysis, with the proposed approach showcasing the promise of revolutionizing brain tumor segmentation, thus contributing to more accurate and reliable diagnoses in clinical settings. Future works may explore innovative preprocessing methods and the application of the proposed approach to other medical image segmentation tasks, which will further advance its capabilities and possible applications areas.

Keywords: Brain Tumor Segmentation, CNN U-Net, CLAHE-HE Enhancement, Medical Image Analysis, Deep Learning in Biomedical Imaging.

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1 Introduction

Medical image analysis has witnessed remarkable progress due to the integration and the advancements of deep learning techniques [1], particularly Convolutional Neural Networks (CNNs) [2]. Brain tumor segmentation in medical images is essential for accurate diagnosis and treatment planning [3]. Accurate segmentation can facilitate identifying tumor boundaries and measuring tumor size and growth rate [4], [5]. Such insights are invaluable in clinical decision-making and monitoring patient responses to treatment [6].

Over the years, several methods have been proposed for brain tumor segmentation [3], [7]–[10]. Traditional methods often relied on handcrafted features and machine learning algorithms [11], but these approaches struggled with the complexity and heterogeneity of tumor appearances in medical images [12]. The emergence of deep learning, and specifically CNNs, has revolutionized this field [13], [14]. CNNs can learn intricate patterns and representations directly from the data, making them well-suited for tasks like tumor segmentation [4], [15]–[17].

The U-Net is a notable CNN architecture that has demonstrated promise in medical image segmentation tasks [18]. U-Net is an encoder-decoder network known for capturing fine details in the segmented regions while maintaining contextual information [19]. However, even with robust architectures like U-Net, challenges persist in brain tumor segmentation [20]. Variability in tumor appearance, edema, and the intricate textures of healthy brain tissue require further methodological improvements to increase accuracy [21], [22].

This research addresses these challenges by introducing a CNN-U-Net model enriched with CLAHE-HE preprocessing. This processing enhances image contrast, making subtle details more discernible, which is especially beneficial in medical imaging [23], [24]. This study comprehensively evaluates the proposed model' performance, focusing on essential metrics for modeling and segmentation.

Previous studies have shown the effectiveness of deep learning models in medical image segmentation, and the inclusion of preprocessing techniques like CLAHE-HE is supported by [25], [26]. Techniques such as CLAHE-HE have been utilized to enhance contrast and improve the overall quality of medical images [27], aiding in separating tumors from surrounding healthy tissue.

The structure of this article is as follows: Section 2 details the method, covering CNN U-Net and image enhancement techniques. Section 3 presents empirical results and their implications, including comparisons with traditional methods. Finally, in Section 4, we offer conclusions of our approach.

2 Research Method

In this section, we present our method for brain tumor segmentation, highlighting the fusion of Convolutional Neural Networks (CNN) with the U-Net architecture and the utilization of CLAHE and HE for image enhancement. A visual representation of our methodology is illustrated in Figure 1.

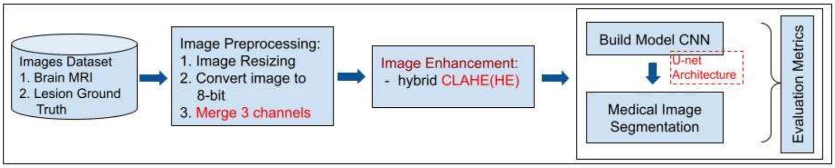
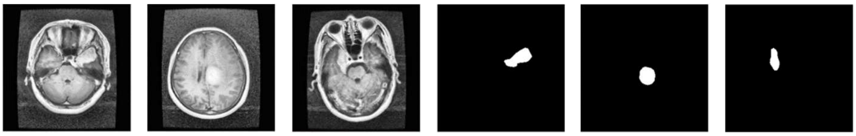


Fig. 1. Flowchart illustrating the step-by-step process of Brain Tumor Segmentation using the proposed methods, which combine Convolutional Neural Networks (CNN) with the U-Net architecture, along with the application of Hybrid CLAHE and HE for image enhancement.

2.1 Brain Tumor Dataset

This research used a dataset collected from Kaggle (www.kaggle.com) [28], comprised of 3064 Brain MRI Images (Figure 2. (a), (b) and (c)) and 3064 Ground Truth Tumor images (Figure 2. (d), (e), and (f)). Each image is standardized at 512x512 pixels with a 24-bit depth and a resolution of 96 dpi. We chose Kaggle for its quality and reliability, meticulously ensuring dataset representativeness, lack of biases, and high data quality [29], [30]. Ethical compliance, including data protection and patient privacy, underscores the dataset' suitability for rigorous and ethical segmentation research.



(a) (b) (c) (d) (e) (f)

Fig. 2. Samples of (a, b, c) brain MRI images and (d, e, f) corresponding ground truth

2.2 Image Preprocessing

In the initial phase of our medical image segmentation process, we focus on image preprocessing, comprising standardization and enhancement. Firstly, we resize the images from their original 512x512 pixel size to a consistent 256x256 pixel format [31], streamlining subsequent CNN processing and ensuring uniform image dimensions [32]. We then standardize these images from their initial 24-bit depth to an 8-bit grayscale format [25], [26], promoting uniformity and enabling seamless processing during the segmentation stages.

In our image enhancement process, we employ a hybrid of CLAHE and HE [33], [34]. HE improves image contrast based on intensity levels (Eq. 1), involving pixel probability (Eq. 2) and cumulative distribution functions (Eq. 3 and Eq. 4). Complementing this, CLAHE further enhances contrast without introducing artifacts or noise, thanks to a clip limit for histogram modification (Eq. 5). These rigorous preprocessing and enhancement steps ensure that our medical images are optimally prepared for the segmentation process, enhancing uniformity and data quality.

$$h(i) = n_i, \text{for i =0,1,2,...,(L-1)} \quad (1)$$

$$p_x(i) = p(x = i) = \frac{n_i}{n} \quad (2)$$

$$cdf_x(i) = \sum_{j=0}^{i} p(x = j) \quad (3)$$

$$h(v) = round\,\frac{cdf(v) - cdf_{min}}{n - cdf_{min}} \quad (4)$$

$$\beta = \frac{M}{n}\left(1 + \frac{a}{100}(s_{max} - 1)\right) \quad (5)$$

2.3 Brain Tumor Segmentation using CNN-U-Net

In this section, we delve into our method of brain tumor segmentation, employing the Convolutional Neural Network (CNN) [26] with the U-Net architecture (Figure 3), designed to automate segmentation from medical images.

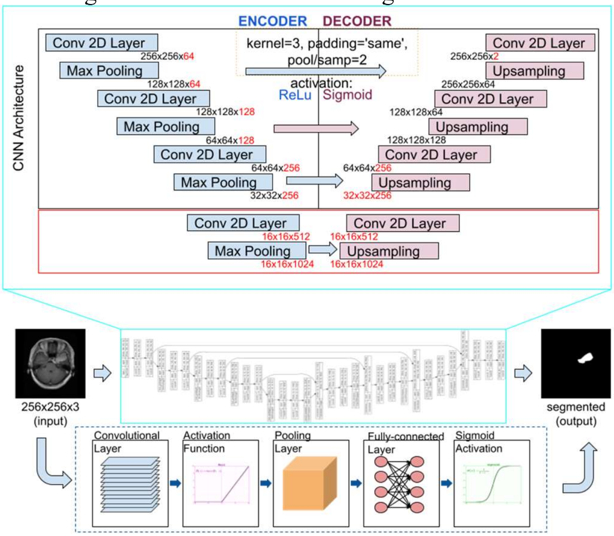


Fig. 3. Architecture of the proposed CNN-U-Net model for brain tumor segmentation.

The process initiates with the CNN's convolutional layer, meticulously extracting image features and enhancing complexity analysis through non-linear activation functions, most notably ReLU [25]. Subsequently, a pooling layer effectively reduces spatial dimensions, optimizing the model's resilience to input image variations. One or more fully connected layers responsible for segmentation and classification scrutinize these processed outputs.

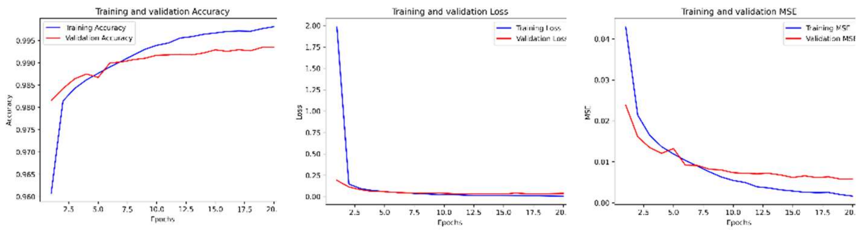
Our model is trained and tested using the 80%:20% data split, ensuring robust performance and validation. The evaluation metrics encompass a range of parameters [35], including accuracy, loss, Mean Squared Error (MSE), and the assessment of segmentation through the Intersection over Union (IoU) and Dice methods. This comprehensive approach guarantees precise brain tumor delineation and provides a thorough performance assessment of our proposed model.

3 Results and Discussion

This research further developes previous medical image segmentation research [25], [26] to detect the brain tumor. We evaluate the performance of the CNN-U-Net model with CLAHE-HE enhancement in brain tumor segmentation. We discuss the accuracy, loss, and MSE measurements based on the proposed model. In addition, we evaluate the results of segmentation based on the IoU and Dice measurement performance.

3.1 Performance Evaluation on Training and Validation Datasets

Based on the experiment, we evaluate the performance of our CNN-U-Net model with CLAHE-HE enhancement on training and validation datasets. This evaluation is focused on essential metrics likeloss, accuracy, and MSE with 20 epochs (10 batch-size).The results are shown in Figure 4.



(a) (b) (c)

Fig. 4. Performance of (a) accuracy, (b) loss, and MSE of CNN-U-Net based on training and validation after CLAHE-HE processing.

In the training phase, we observe significant trends. Initially, there is a consistent increase in training accuracy, with values rising from 0.9778 to 0.9980. This underscores the model's proficiency in discriminating between tumor and non-tumor regions in brain images. Subsequently, a substantial reduction in training loss becomes evident, decreasing from 1.0047 to 0.0062 during the initial epochs. This substantial decline in loss reflects the model's capacity to capture intricate patterns crucial for precise brain tumor segmentation. Finally, the MSE consistently diminishes, ultimately reaching an impressive 0.0017 by the end of the training period, indicating that the model's predicted segmentation aligns closely with the ground truth data.

Examining training and validation curves reveals the model' exceptional ability to generalize effectively, as evidenced by the close alignment of validation performance with training performance. Notably, the early stopping mechanism activates at epoch 18, indicating that further training would likely result in only marginal improvements, reinforcing the model's convergence towards optimal segmentation performance. This trajectory is characterized by a concurrent decrease in loss, increased accuracy, and a minimized MSE. These outcomes emphasize the model's proficiency in accurately delineating brain tumor boundaries within medical images, a critical aspect for diagnostic applications. Furthermore, they underscore the promise of integrating the CNNU-Net architecture with CLAHE-HE enhancement for brain tumor segmentation, highlighting its potential for transformative impact in medical image analysis.

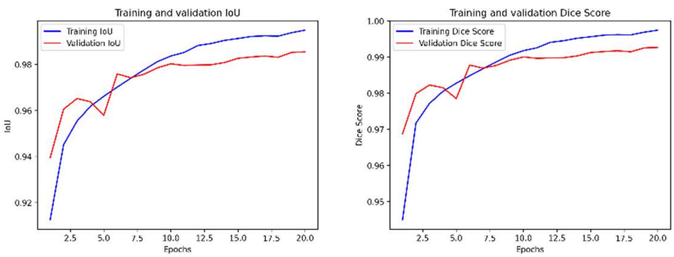
3.2 Performance Analysis Based on Brain Tumor Image Segmentation Results

In this section, we comprehensively analyze our model's performance for brain tumor segmentation using key evaluation metrics: Intersection over Union (IoU) and Dice Score.

IoU is a fundamental metric for assessing the degree of overlap between the predicted and ground truth tumor regions. This metric measures the intersection of the predicted and actual tumor masks divided by their union. We observed a consistent improvement in IoU as training progressed, as shown in Figure 5. (a). Over the 20 training epochs, the model's IoU steadily increased, signifying its capacity to capture tumor regions more accurately. The IoU for the validation set peaked at 0.9803, indicating a solid alignment between the model's predictions and actual tumor boundaries.

The Dice Score is another pivotal metric for quantifying the similarity between the predicted and ground truth tumor regions. It is calculated as twice the intersection of the predicted and actual masks divided by their sum. Similar to IoU, the Dice Score exhibited continuous improvement during training, as shown in Figure 5. (b). The Dice Score reached its highest value of 0.9900 during validation, indicating that the model precisely delineated tumor boundaries.

The observed trends in IoU and Dice Score metrics indicate the model' evolving accuracy in segmenting brain tumors. This consistent improvement underscores the model's utility as a robust tool in diagnosing and planning treatment for brain tumors. Healthcare professionals can rely on this model to make highly accurate clinical decisions, enhancing patient care and outcomes.



(a) (b)

Fig. 5. Performance of (a) IoU and (b) dice score of brain tumor segmentation results.

3.3 Predicted Segmentation Results on Brain MRI Images

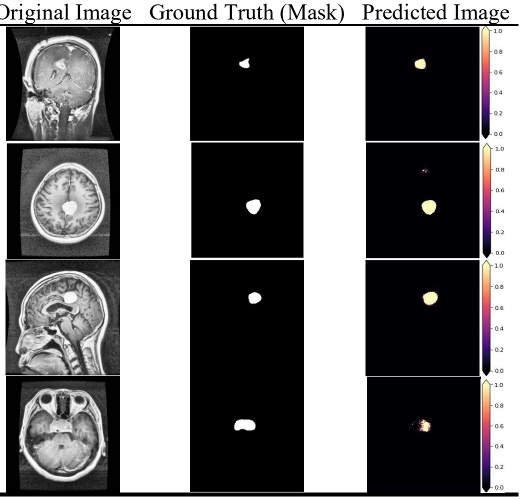
After evaluating our segmentation model's performance, we subjected it to new MRI brain images for a comprehensive assessment of its accuracy in generating masks. In Table 1, we present the results of this prediction, providing a side-by-side comparison of the original image, the ground truth mask image, and the predicted mask image.

The predicted mask image is a crucial component in brain tumor segmentation, as it indicates the regions identified by our model as potential tumor locations. Upon close inspection of Table 1, it becomes evident that the predicted mask closely approximates the shape and location of the ground truth mask image, signifying the model's proficiency in accurately delineating brain tumor boundaries.

The spatial alignment between the predicted mask and the ground truth mask is a crucial aspect. A strong alignment suggests that our model can precisely locate tumor regions. This is particularly important for clinical applications where the accurate identification of tumor boundaries is vital. The color and intensity values in the predicted mask are observed to be close to ≈ 1. This indicates that the model successfully identifies tumor regions, as they are assigned values approaching the maximum intensity, while the surrounding healthy tissues have values close to zero.

Table 1. Prediction of brain tumor segmentation with the range of values that approximate the mask's shape.

Original Image	Ground Truth (Mask)	Predicted Image



3.4 Comparison of CNN-U-Net Approach with and without CLAHE-HE Preprocessing

Based on the graphs performances of our proposed method, we provide a comprehensive analysis of the impact of preprocessing on our CNN-U-Net model's performance, based on the results presented in Table 2. The training phase, as revealed in Table 2, demonstrates the effectiveness of our CNN-U-Net model, with a high accuracy of 0.9979 and minimal loss of 0.0054. Notably, including CLAHE-HE preprocessing in the CNN-U-Net +CLAHE-HE variant results in an even higher accuracy of 0.9982 and a slightly reduced loss of 0.0054. This underlines the significance of preprocessing in augmenting the model's ability to learn from the training data. Additionally, the MSE decreases from 0.0016 to 0.0015, indicating a refinement in feature extraction.

A more pronounced impact of preprocessing emerges upon transitioning to the validation dataset. The CNN-U-Net model exhibits commendable accuracy at 0.9933 but struggles with a relatively higher loss of 0.0286. In contrast, the CNN-U-Net with CLAHE-HE variant demonstrates a marginal improvement in accuracy (0.9936) and a reduced loss (0.0391). This disparity underscores the role of preprocessing in maintaining model performance during validation. The reduced loss indicates a mitigation of overfitting, enhancing the model's ability to generalize to unseen data.

Table 2. Results of metrics performance evaluation.

Method	Accuracy	Loss	MSE	IoU	Dice Score
Training					
CNN-U-Net	0.9979	0.0054	0.0016	0.9943	0.9971
CNN-U-Net +CLAHE-HE	0.9982	0.0054	0.0015	0.9953	0.9977
Validation					
CNN-U-Net	0.9933	0.0286	0.006	0.9853	0.9926
CNN-U-Net +CLAHE-HE	0.9936	0.0391	0.0057	0.986	0.9929
Testing					
CNN-U-Net	0.9928	0.0428	0.0064	0.9852	0.9926
CNN-U-Net +CLAHE-HE	0.9934	0.0409	0.0059	0.9863	0.9931

During the testing phase, the robustness of our models is evident. CNN-U-Net maintains a high level of accuracy at 0.9928, confirming its proficiency with independent datasets. However, CNN-U-Net with CLAHE-HE outperforms it with an even higher accuracy of 0.9934 and a lower loss of 0.0409. This advantage of preprocessing translates into improved MSE values. Moreover, it substantially enhances segmentation quality, as demonstrated by consistently better Intersection over Union (IoU) and Dice Score values.

Our analysis affirms the significant and discernible impact of preprocessing, particularly CLAHE-HE, on the performance of the CNN-U-Net model. Preprocessing amplifies the model's ability to learn from the training data and plays a crucial role in sustaining its performance during validation and adapting to new, independent datasets. This underscores the pivotal role of preprocessing in medical image analysis, contributing significantly to overall model accuracy and robustness.

4 Conclusions

In this study, we proposed a comprehensive approach for brain tumor segmentation in medical images, leveraging the CNN-U-Net architecture enhanced with CLAHE-HE preprocessing. Our model exhibited impressive performance across the training, validation, and testing phases. During the training phase, it displayed a consistent increase in accuracy, signifying its proficiency in distinguishing between tumor and non-tumor regions while concurrently reducing training loss and achieving an impressive reduction in MSE. The validation phase mirrored these trends, indicating the model's capacity to generalize effectively.

The early stopping mechanism activated at epoch 18, suggesting that further training would yield only marginal improvements. These results underscore our model's capability to accurately delineate brain tumor boundaries within medical images, a crucial component for diagnostic applications. Furthermore, the study highlights the potential of integrating the CNN-U-Net architecture with CLAHE-HE enhancement for brain tumor segmentation, promising transformative implications for medical image analysis. Our findings emphasize the significant role of preprocessing techniques, particularly CLAHE-HE, in enhancing model accuracy and robustness, paving the way for more accurate and reliable diagnoses in practical medical applications. Future works could involve exploring novel preprocessing methods and the application of the proposed approach to other medical image segmentation tasks, which will further advance its capabilities and possible applications areas.

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