A Combination of Image Enhancement and U-Net Architecture for Segmentation in Identifying Brain Tumors on CT-SCAN Images

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***Abstract*—A brain tumor is a condition where the abnormal growth of brain cells around the brain spreads to any part of the body uncontrollably. Brain tumors can be detected by recognizing tumor patterns in brain images by segmentation that separates brain tumor features in brain images. Sometimes the image data still has low quality, so image enhancement is needed to improve image quality. This paper proposed to improve the quality of a 2D brain tumor image and the performance of segmentation. Image enhancement consists of two stages, namely contrast enhancement and noise reduction. The contrast enhancement used is Contrast Limited Adaptive Histogram Equalization (CLAHE) and gamma correction, while the noise reduction used is a Gaussian filter. Parameters in measuring the results of the quality of the image are Mean Square Error (MSE) and Structural Similarity Index Measure (SSIM). U-Net architecture is applied in the brain tumor segmentation process. Parameters in evaluating the performance of the segmentation model are accuracy, sensitivity, specificity, and mean Intersection over Union (IoU). The results of brain tumor image improvement obtained are MSE of 0.018 and SSIM of 0.9748. The results of brain tumor segmentation obtained were 98% accuracy, 77.85% sensitivity, 99.12% specificity, and 82.31% mean IoU. Sensitivity below 80% is caused by too small a portion of the tumor. Even though the sensitivity was below 80%, the model was able to separate the tumor from the background.**

Keywords—Brain Tumor, Contrast Limited Adaptive Histogram Equalization, Gamma Correction, Gaussian Filter, U-Net.

I. INTRODUCTION

A brain tumor is an abnormal growth of brain cells in or around the brain that spreads to any part of the brain uncontrollably [1]. Based on data from the International Agency for Research on Cancer, more than 126,000 people in the world each year suffer from brain tumors and more than 97,000 people die due to brain tumors [2]. The brain tumor is one of the most dangerous diseases and is the second leading cause of death, so prevention and early detection are needed [3]. Brain tumors can be detected by recognizing tumor patterns in brain images. Sometimes brain tumor images taken using special cameras still contain many problems namely, the results obtained are blurry, and a lot of noise, contrast, and lighting are still lacking.

Image enhancement is one of the stages in image processing that is carried out to improve image quality [4]. Image enhancement is needed to improve image quality, such as in the segmentation process. One of the stages of image enhancement is contrast enhancement. Contrast enhancement is the process of increasing the intensity of the image so that the color intensity range is complete [5]. Contrast enhancement steps commonly used include Contrast Limited Adaptive Histogram Equalization (CLAHE) and gamma Correction [6]. CLAHE is a method developed for the problem of low contrast and color unevenness, especially in medical images. The advantage of CLAHE is that it produces output with little noise [7]. In addition to its advantages, CLAHE also has disadvantages, namely noise in the image will also be processed and contrast restrictions so that the brightness level of the image is still not bright and has not been able to extract important features in the image [8]. Gamma correction can be used to overcome the shortcomings of CLAHE. The advantage of gamma correction is that it is effective in improving image quality because it increases the intensity of brightness in an image [9]. In addition to increasing contrast, another step that can be used in image enhancement is noise reduction. The process of reducing the amount of noise in image data so that information from image data is not lost is called noise reduction [10]. One of the noise reduction that can be used is the Gaussian filter. The advantage of the GGaussian filter is that it can reduce noise and is effective in smoothing image data [11].

Image enhancement plays an important role in the segmentation process because it will provide good and accurate results [12]. Segmentation is a process to obtain information about the parameters in the image data that separates the object and the background [13]. In image segmentation, digital image processing is one of the important steps in the image pattern recognition stage. One method that is widely used for image data segmentation is Convolutional Neural Network (CNN). CNN is an algorithm that can group and detect objects in the image automatically and receive input data in the form of m×n [14]. One type of CNN architecture that is commonly used in the segmentation process is the U-Net architecture [15]. The advantage of U-Net is that it can accept two-dimensional and three-dimensional input images [16]. The U-Net architecture was applied to several studies,

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namely Kotaridis and Lazaridou [17] which obtained an accuracy of 94% and IoU of 88% on satellite images, but did not show sensitivity and specificity. Research by Yang and Qiu [18] got an accuracy value of 95.94% on medical images, but did not calculate sensitivity, specificity, and IoU.

This study will perform a combination of image enhancement and segmentation on brain tumor images. The stages of image enhancement carried out are contrast enhancement and noise reduction. Contrast enhancement methods used are CLAHE and gamma correction. CLAHE is used to flatten the histogram and increase the contrast of brain tumor images significantly, while gamma correction is used to make the image brighter. To handle noise reduction, the study uses a Gaussian filter. The results of brain tumor image enhancement will be applied to the segmentation process using U-Net architecture to obtain features for detecting brain tumors. The parameters used to measure the performance of image enhancement are MSE and SSIM. The parameters used to measure the performance of U-Net architecture in brain tumor segmentation are accuracy, sensitivity, specificity, and mean IoU.

II. Related Work

Several studies used brain tumor datasets, namely Kim et al [19] which segmented U-Net with an accuracy of 50.5% but did not improve the image on the dataset. In addition, the study did not show the results of sensitivity, specificity, and IoU. Research by [20] carried out contrast enhancement on retinal image data using a Gaussian filter and CLAHE obtained 0.903 but did not show MSE results and did not segmentation. The study by [21] improved the image of retinal using CLAHE and did segmentation using U-Net obtained 95.51% accuracy, 80.64% sensitivity, and 97,67% specificity, but did not show the results of the IoU, MSE, and SSIM.

III. Methodology

A. Datasets

The dataset used is taken from Kaggle, namely the brain tumor dataset. The dataset consists of 1000 image data and 1000 ground truth data. The average size of images data and ground truths data are 512×512 pixels. The images contained in the dataset are converted into Red, Green, and Blue (RGB) images. Then, the green channel is taken on the images that have been converted to RGB.

B. Contrast Enhancement

From the original image, green channel is taken because the green channel provides maximum contrast between the image and the background. Based on [22], the equation for obtaining the green channel is in Equation (1).

$$g(x,y) = \frac{G(x,y)}{R(x,y)+G(x,y)+B(x,y)} \tag{1}$$

Where g(x,y) is the green channel in the image, R(x,y) is the image pixel with the red color intensity, G(x,y) is the image pixel with the green color intensity, and B(x,y) is pixels are blue pixels image intensity. Contrast enhancement is performed using CLAHE and gamma correction on green channel images. Based on [23], the process of calculating CLAHE can be calculated using Equation (2).

$$g = [g_{max} - g_{min}] \times P(f) + g_{min} \tag{2}$$

Where g is to calculate the pixel value, g_max and g_min are maximum and minimum pixel values. After that, apply gamma correction to the CLAHE image. The equation that can be used for gamma correction is based on [24] as in Equation (3).

$$g(x) = x_{max}\left(\frac{x}{x_{max}}\right)^{\gamma} \tag{3}$$

Where g(x) is the output of the corrected pixel x value, x_max is the maximum intensity.

C. Noise Reduction

After the contrast enhancement is complete, noise reduction is performed on the image that still has noise. Noise reduction was used, namely a Gaussian filter. Based on [25] Gaussian filter equation can be seen in Equation (4).

$$G(x,y) = \frac{1}{2\pi\sigma^2}\exp(-(x^2+y^2)/2\sigma^2) \tag{4}$$

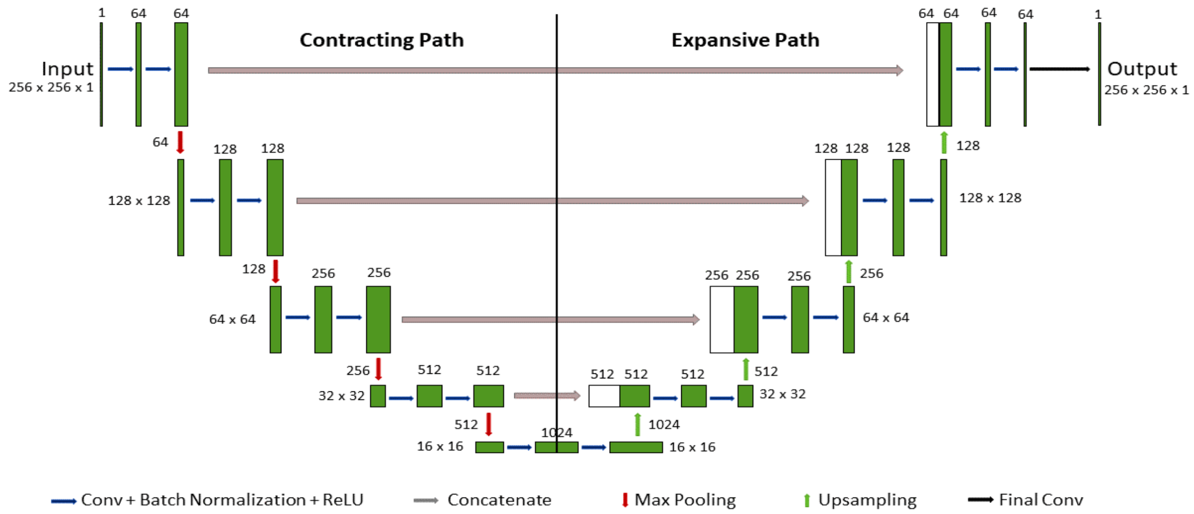


Fig. 1. U-Net Architecture

Where σ is the standard deviation of the distribution. Equation (4) is assumed to have an average of 0 with the distribution center on the line x = 0. The larger the value of σ, the wider the gaussian distribution curve and the lower the peak.

D. U-Net Architecture

The image that has been processed on image enhancement will be segmented using U-Net architecture. The segmentation process proposes to separate features into several regions, namely brain tumors and background. Before segmentation, the data is split using a percentage split. From 1000 image data and 1000 brain tumor ground truth data, data were divided into 80% training data and 20% test data so that the training data used was 800 data and the test data used was 200 data. In this study, the U-Net architecture can be seen in Fig 1.

Fig. 1 shows that U-Net architecture is divided into two, contracting and expansive. Contracting is part of the encoder function in the U-Net architecture that applies convolution blocks combined with max pooling to convert the input image into a representation of the desired feature. Expansive is part of the decoder function that is used to map the features obtained to pixel-dense objects that have upsampling, concatenation, and convolution operations. In the contracting section, there are 4 blocks where each block has 2 convolutional layers, 2 batch normalization layers, and 1 pooling layer. The size of the stride for the convolution layer is 2. The pooling layer used is 2×2 max-pooling. The number of filters from each block in the convolution layer is 64, 128, 256, 512, and 1024. In the expansive section, every 4 blocks consist of transposed convolution, merging feature maps based on contracting paths, and 2 convolution layers with 3×3 kernels. Each layer other than the output layer uses the activation function of the Rectified Linear Unit (ReLU). The sigmoid activation function is used in the final layer which is usually to calculate the probability of classifying two classes. The equation of the sigmoid activation function is written in Equation (5).

$$\sigma(z) = \frac{1}{1+e^{-z}} \quad (5)$$

In the output layer, for gradient optimization, Adaptive Moment Optimization (Adam) is used, which is an optimizer with low memory [26]. To calculate the loss from the training process, the binary cross entropy function is used because the brain tumor data used has two classes.

E. Evaluation

The performance evaluation parameters used in image enhancement are MSE and SSIM. The confusion matrix is used to evaluate the performance of the segmentation model. Performance evaluation parameters used in segmentation are accuracy, sensitivity, specificity, and mean IoU. The application of a combination of image enhancement and U-Net allows the model to make predictions more accurately because the image quality has been improved so that the accuracy, sensitivity, specificity, and IoU values produced are better.

In this study, the steps that will be carried out in image enhancement and segmentation of brain tumor images are shown in Fig. 2. Based on Fig. 2, in this study, a combination of image enhancement and brain tumor segmentation will be carried out. The stages of image enhancement used are contrast enhancement and noise reduction. The contrast enhancement of brain tumor images was performed using CLAHE and gamma correction. The noise reduction used is a Gaussian filter. After the brain tumor image is repaired, the segmentation process is carried out using the U-Net architecture. The results of the image enhancement will be based on the parameter values of MSE and SSIM, while the results of brain tumor segmentation will be based on the parameter values of accuracy, sensitivity, specificity, and mean IoU.

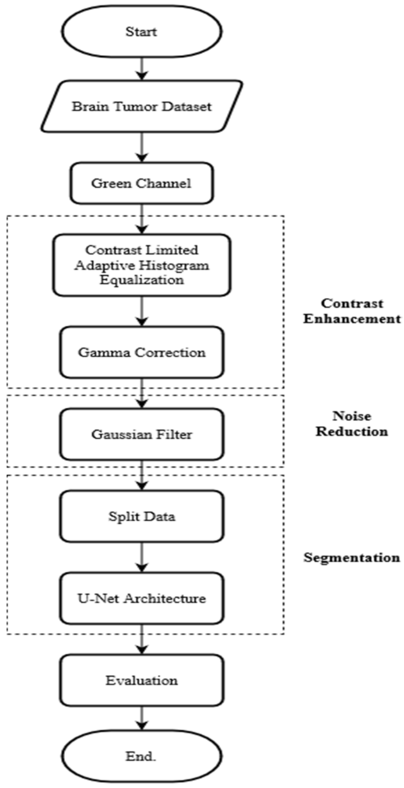
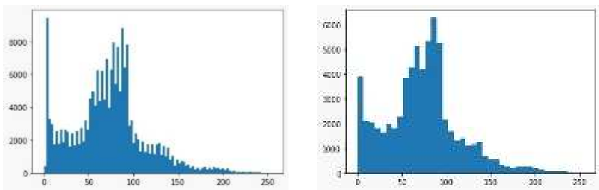


Fig. 2. Diagram of the Image Enhancement and Brain Tumor Segmentation Process

IV. Results And Discussion

A. Image Enhancement

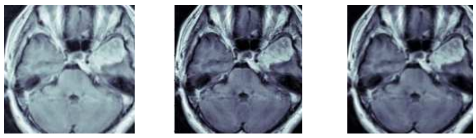
In this study, images were obtained from the brain tumor dataset in the form of original images and ground truth. The original image data in the brain tumor dataset is converted into the green channel first. The histogram results of the comparison between the original image and the green channel can be seen in Figure 3.



(a) (b)

Fig. 3. Comparison Histogram (a) Original Image and (b) Green Channel Image

From Fig. 3, it can be seen that by using the green channel, the brain tumor image becomes clearer and the tumor part in the brain image is more visible than in the original image. Furthermore, CLAHE is applied to the green channel image data so that the contrast in the green channel image increases. The application of CLAHE aims to make brain tumors in brain images appear thicker and have a significant color contrast than before. After that, the gamma correction method is applied so that the image data becomes brighter. In obtaining the best gamma value, a comparison of randomly selected gamma values of 0.5, 1, and 1.2 is used. The result of applying gamma correction can be seen in Figure 4.



(a) (b) (c)

Fig. 4. Gamma Correction of Brain Tumor Image (a) $\gamma = 0.5$ (b) $\gamma = 1.0$ (c) $\gamma = 1.2$

Based on Figure 4, it can be seen that at a gamma value of 0.5, the image data becomes brighter. At a gamma value of 1, the resulting brain tumor image does not show a significant difference so it looks similar to the brain tumor image in the application of CLAHE. At a gamma value of 1.2, the brain tumor image looks darker than the other gamma values. Noise reduction is applied after the contrast enhancement stage. Noise reduction is used, namely the Gaussian filter. After applying a Gaussian filter, the distribution of pixels becomes more even. The average MSE and SSIM values in 200 image data that have been improved contrast are 0.018 and 0.9748 respectively. Based on the parameters used, if the MSE value is close to zero, then the image quality is good. If the SSIM value is close to 1, it can be said that the image has good quality.

B. Brain Tumor Segmentation

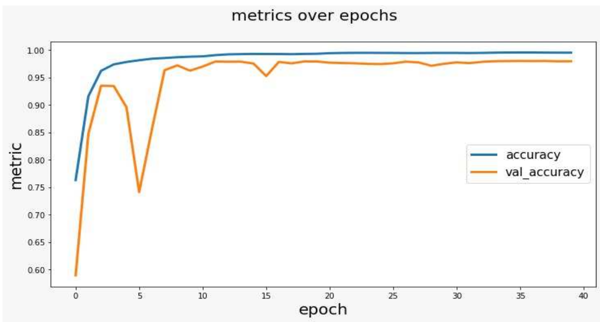


Fig. 5. Accuracy Graph of Training and Validation Data U-Net Segmentation

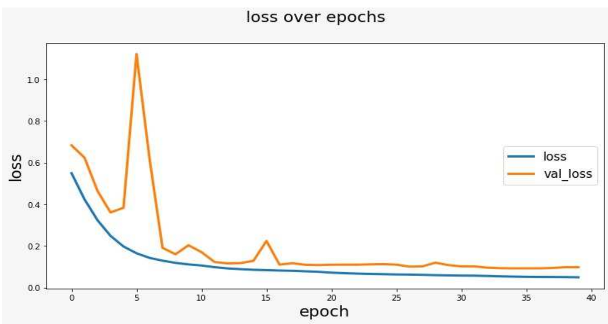
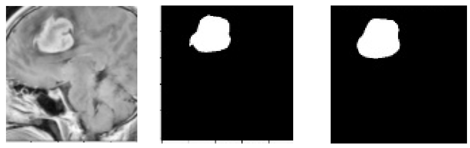


Fig. 6. Loss Graph of Training and Validation Data U-Net Segmentation

In the data training process using the U-Net architecture, optimization and loss estimation are performed first. The optimizer used is Adam and the loss function used is binary cross-entropy. From the training data process, the accuracy and loss values are obtained in the validation data. Accuracy and loss graphs obtained in the training data process can be seen in Figure 5 and Figure 6.

Based on Figure 5, it can be seen that the accuracy value obtained from the training process is increasing and in Figure 6 the loss value generated at each epoch is decreasing. This shows that the resulting model is good fitting. The blue line shows the accuracy and loss values in training, while the yellow line shows the accuracy and loss values in validation. A significant increase in the accuracy value occurred from epoch 6 to epoch 7. A stable accuracy value in the range of 98% occurred in epoch 30. A significant decrease in loss value occurred from epoch 6 to epoch 7. The loss value was stable at epoch 34. Because of the accuracy value and stable loss, the training process is stopped at the 40th epoch. To evaluate the performance of the U-Net architecture, the result of the segmentation process will be compared with the ground truth for an image. The comparison between ground truth and the result of segmentation of the U-Net architecture of brain tumor images can be seen in Figure 7.



(a) (b) (c)

Fig. 7. Comparison of Result From Segmentation U-Net (a) Original Image (b) Ground Truth (c) Result

Based on Figure 7, it can be seen that segmentation result with ground truth image of brain tumors is on average similar. Performance evaluation was carried out on the results of brain tumor image segmentation using a confusion matrix. Parameters used to determine the segmentation performance of U-Net architecture, namely accuracy, sensitivity, specificity, and mean IoU. The results of the accuracy, sensitivity, specificity, and mean IoU obtained from the segmentation of the U-Net architecture are 98%, 77.85%, 99.12%, and 82.31%, respectively. Although the sensitivity value obtained is still below 80%, the mean IoU value obtained is above 80% so the model made is capable of the intersection area between the brain tumor and the background. Sensitivity is below 80% because the background area in the brain tumor image is more dominant than the brain tumor part. In addition to accuracy and loss graphs, there is also a Receiver Operating Characteristic (ROC) graph which can be seen in Figure 7.

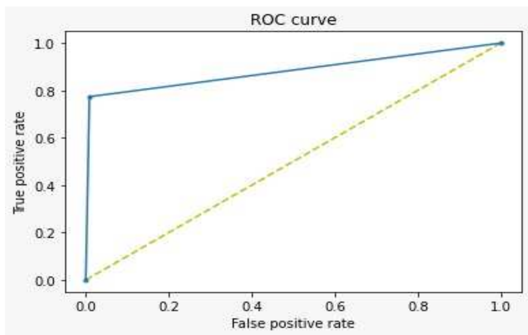


Fig. 8. ROC Graph of U-Net Segmentation

A good ROC chart has a True Positive Rate (TPR) and a False Positive Rate (FPR) of 1 or 100%. As seen in Figure 7, the TPR and FPR values obtained are 0.8826 or 88.26% so the resulting ROC graph is quite good. The results of image enhancement and segmentation obtained are compared with previous studies. A comparison of the results of image enhancement in this study and previous studies can be seen in Table 1.

TABLE I. COMPARISON OF MSE AND SSIM VALUES BRAIN TUMOR DATASET WITH PREVIOUS RESEARCH

Methods	MSE	SSIM
Erwin & Ningsih, 2020 [27] (CLAHE)	9.15	0.88
Dixit et al, 2021 [28] (Gamma Correction)	0.0034	0.83
Kumar dan Sodhi, 2020 [29] (Gaussian Filter)	0.38	0.92
Proposed Method	**0.018**	**0.9748**

Based on Table 1, it can be seen that Erwin's study [27] has MSE value that is not close to 0. Dixit et al's study [28} has MSE value that is closest to 0 compared to other studies but has the smallest SSIM value among studies other. Kumar and Sodhi's study [29] has an MSE value that is close to 0 and an SSIM that is close to 1 which is quite good. In addition to the results of image enhancement, the segmentation results of this study are also compared with previous research. The comparison can be seen in Table 2.

TABLE II. COMPARISON OF ACCURACY, SENSITIVITY, SPECIFICITY, AND IOU VALUES BRAIN TUMOR DATASET WITH PREVIOUS RESEARCH

Methods	Acc (%)	Sen (%)	Spe (%)	IoU (%)
Kim et al, 2020 [19] (U-Net)	50.5	-	-	-
Raja et al, 2018 [30] (Tsallis Entropy + Region Growing)	97.53	98.27	97.72	-
Amin et al, 2019 [31] (Weiner Filter + PF Clustering)	88	97	92	-
Proposed Method	**98**	**77.85**	**99.12**	**82.31**

Based on Table 2, Kim et al [26] have the lowest accuracy value among other studies and does not show the results of sensitivity, specificity, and IoU. Raja et al [30] have the highest sensitivity but still have accuracy and specificity under the proposed study. Amin et al [31] have a higher sensitivity value than the sensitivity in the proposed study but have lower accuracy and specificity values than the proposed study. In the proposed study, it can be seen that the accuracy and specificity are above 90%, and the IoU is above 80%. This shows that the image and segmentation enhancements that have been done are quite good. Although the sensitivity obtained is still below 80%, the model made is capable of determining the intersection area between brain tumors and the background from brain tumor image data.

V. CONCLUSION

Based on our proposed method, we have seen how image enhancement can improve the quality of images and U-Net architecture can perform accurate segmentation. The Image enhancement carried out in two stages, namely contrast enhancement and noise reduction, gave an MSE value of 0.018 and an SSIM value of 0.9748. The MSE value obtained is close to 0, while the SSIM value obtained is close to 1. This indicates that the repaired brain tumor image has good quality. Brain tumor segmentation using U-Net architecture was performed on the repaired brain tumor image. The segmentation results obtained are 98% accuracy, 99.12% specificity, 77.85% sensitivity, and 82.31% mean IoU. The accuracy obtained above 90% indicates that the model can produce ground truth predictions that are similar to the original ground truth. A mean IoU above 80% indicates that the model can determine the intersection area between the tumor and the background. Specificity and sensitivity are inversely proportional, meaning that the higher the specificity, the lower the sensitivity and vice versa. Sensitivity below 80% is due to the background being more dominant than the tumor. Even though the sensitivity was below 80%, the model was able to separate the tumor from the background.

ACKNOWLEDGMENT

The authors thank to Computation Laboratory, Mathematics and Natural Science Faculty, Universitas Sriwijaya for the support of this study.

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