Pusan National University

Computer Science and Engineering

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Development of an AI Model for Glaucoma Detection through Segmentation

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목 차

1. 서론

1.1. 연구 배경

Glaucoma is a chronic ophthalmology disease caused by damage to the optic nerve. This can lead to permanent blindness. As one of the primary causes of blindness in developed countries, it can result in irreversible vision impairment if not diagnosed and treated early. Patients may not notice symptoms until months or years after nerve damage has occurred, making timely detection crucial. According to published data, the number of glaucoma patients is estimated to reach 110 million by 2040 [1], underscoring the importance of prevention and early treatment.

To ensure timely treatment, early screening for glaucoma is essential. The three main techniques used for detection are intraocular pressure (IOP) assessment, visual field testing, and optic nerve head (ONH) evaluation [2]. Of these, ONH assessment, which involves analyzing the Cup-to-Disc Ratio (CDR) from fundus images, is particularly valuable. The CDR, calculated as the ratio of the vertical cup diameter to the vertical disc diameter, provides a precise indicator of glaucomatous damage, as glaucoma patients typically exhibit a significantly larger CDR compared to healthy individuals, as shown in Figure 1.

IOP measurement, while commonly used, has limitations as some patients with glaucoma may have normal IOP levels. Hence, CDR is a more accurate marker for detecting glaucoma progression.

Manual segmentation of the optic disc (OD) and optic cup (OC) for CDR calculation is time-consuming and requires subjective judgment, making it challenging for less experienced physicians to achieve accurate results. Automation of this process can help improve the accuracy, speed, and consistency of glaucoma diagnosis, enhancing patient care and enabling early intervention.

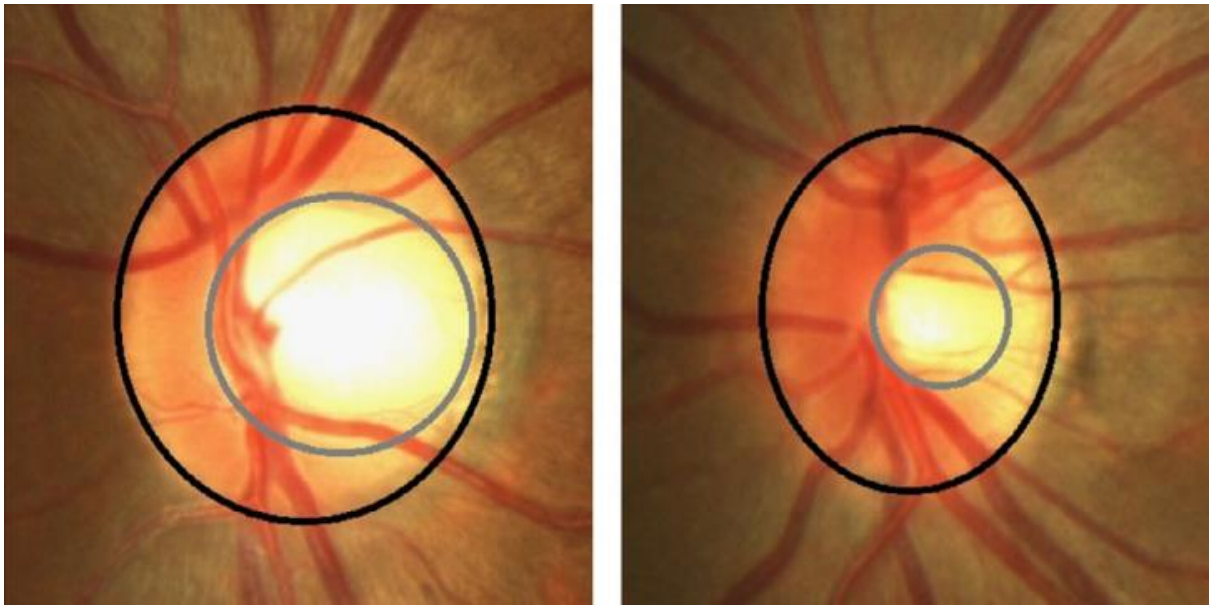


Figure 1. The black line indicates the optic disc area and the grey line indicates the optic cup area. [8]

1.2. 기존 문제점

Early diagnosis is crucial to prevent permanent optic nerve damage. Manual segmentation of the optic disc and cup is time-intensive, requiring skilled professionals and about eight minutes per eye. Automated segmentation can expedite mass screenings and offer vital support in regions with limited access to specialists. Moreover, the clinical significance of this project lies in its potential to transform glaucoma screening practices. Automated segmentation of the optic disc and cup enables rapid and accurate assessment of CDR, which is a critical parameter in glaucoma diagnosis. This approach can enhance early detection, allowing for timely interventions and potentially preventing vision loss in many patients [3].

Although currently existing models for glaucoma segmentation of the optic cup (OC) and optic disc (OD) show promising results, they are not yet practical for clinical use due to an error rate of around 5–15%. We aim to enhance these models by integrating novel techniques to improve segmentation accuracy and reduce this error margin, making the models more reliable for real-world applications.

1.3. 연구 목표

The primary objective of this research is to develop an effective and reliable system for

detecting glaucoma through image segmentation techniques. This involves designing and implementing a machine learning-based segmentation model to accurately identify and segment key anatomical structures in retinal fundus images, particularly the optic disc and optic cup, which are essential for diagnosing glaucoma. The research aims to improve the precision of the segmentation model, enabling it to effectively distinguish between healthy and glaucomatous optic nerve structures, with a particular focus on early-stage glaucoma detection for timely intervention.

The model's performance will be assessed using standard evaluation metrics such as the Dice coefficient, Intersection over Union (IoU), and accuracy, ensuring it meets clinically relevant standards.

2. 연구 배경

In our project, we emphasize the ingenuity of our approach through the integration of several advanced techniques. Specifically, we employed CBAM (Convolutional Block Attention Module) to enhance the model's focus on critical regions, transformer blocks to capture long-range dependencies in the image, and DC-UNet to improve feature propagation and segmentation accuracy. These components differentiate our model from conventional U-Net architectures, offering a novel combination that has not been previously applied in glaucoma segmentation. This innovation underscores the uniqueness of our work and its potential to advance medical image analysis.

2.1. U-Net

U-Net[4] is a convolutional neural network architecture designed specifically for medical image segmentation tasks. It has become one of the most widely used models for biomedical image analysis due to its ability to produce highly accurate segmentation results even with limited training data. The U-Net architecture follows a symmetric encoder-decoder structure. The encoder, often referred to as the contracting path, is responsible for capturing context by gradually reducing the spatial dimensions of the input image while increasing the depth of the feature maps. This is achieved through successive layers of convolution, max pooling, and non-linear activation functions, which

allow the network to learn increasingly abstract representations of the input data.

On the other side, the decoder, known as the expansive path, reconstructs the segmentation map by up-sampling the feature maps and combining them with high-resolution features from the encoder through skip connections. These skip connections play a critical role in U-Net's success, as they ensure that spatial information lost during down-sampling in the encoder is preserved and passed to the decoder, leading to more precise segmentation boundaries. Figure 2 shows the visualization of U-Net structured model.

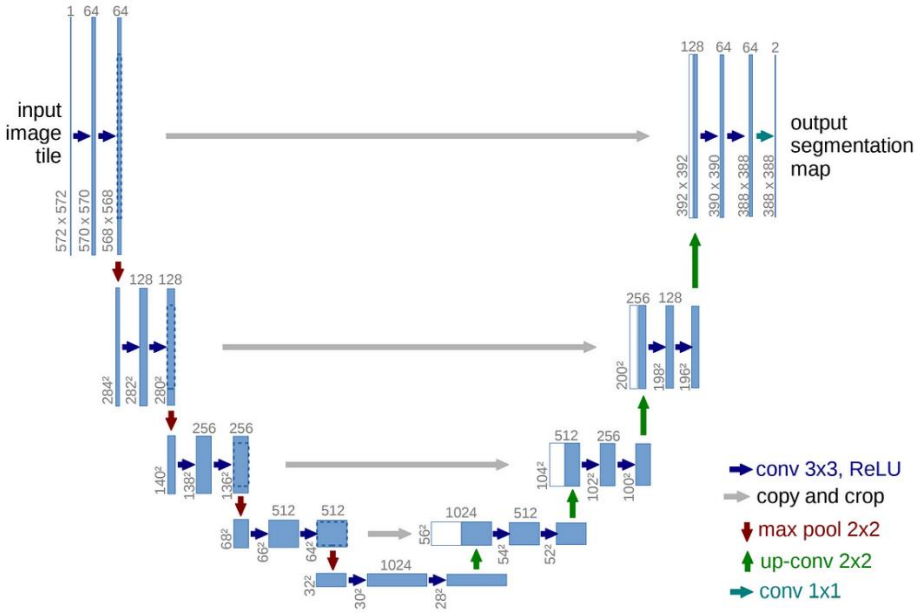


Figure 2. U-Net model illustration

2.2. CBAM

Convolutional Block Attention Module [5] is an efficient attention mechanism used in convolutional neural networks (CNNs) to enhance model performance by focusing on the most important features within the data. CBAM applies attention to both the channel and spatial dimensions of feature maps. It operates in two stages: first, the channel attention mechanism determines which feature map channels are most relevant to the task at hand, enhancing those that carry valuable information and suppressing less useful ones. Following this, the spatial attention mechanism identifies which specific regions within the feature maps are important, highlighting significant areas while downplaying irrelevant ones. By combining these two attention processes, CBAM allows the model to

focus more effectively on informative features, both in terms of channels and spatial regions. This results in improved performance for tasks such as image classification and object detection. Additionally, CBAM is designed to be lightweight and can be easily integrated into existing CNN architectures, providing a boost in accuracy without adding significant computational complexity. Figure 3 illustrates main two attention modules in CBAM.

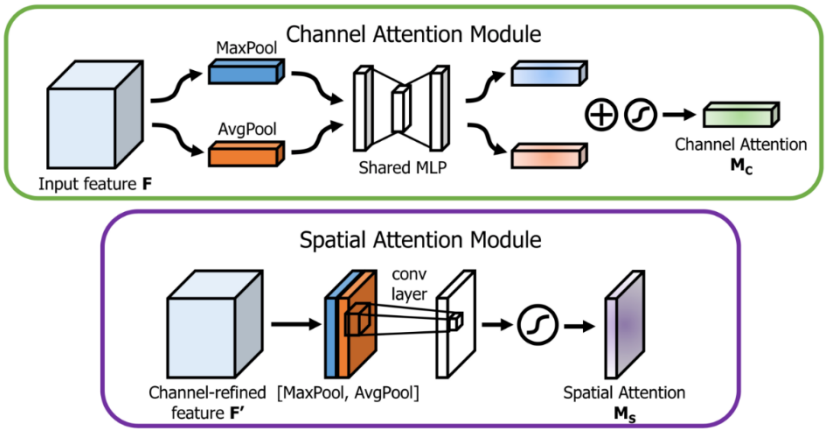


Figure 3. CBAM illustration of "CBAM: Convolutional Block Attention Module"

2.3. Transformer

Transformer is a deep learning architecture introduced in 2017 in the paper "Attention is All You Need," [6] which transformed natural language processing (NLP). Unlike traditional recurrent neural networks (RNNs), Transformers use a self-attention mechanism that processes all input tokens simultaneously, enabling greater parallelization. The architecture consists of an encoder and a decoder, each made up of multiple identical layers. The encoder generates continuous representations of input sequences using multi-head self-attention, capturing relationships between words regardless of their distance. The decoder produces output sequences while maintaining autoregressive properties through masked self-attention. Transformers excel at capturing long-range dependencies and have achieved state-of-the-art results in various NLP tasks, such as translation and summarization. They have also inspired numerous adaptations, leading to powerful models like BERT and GPT. This versatility has established the Transformer as a foundational component in modern AI research and applications. Figure 4 illustrates the model architecture of the transformer.

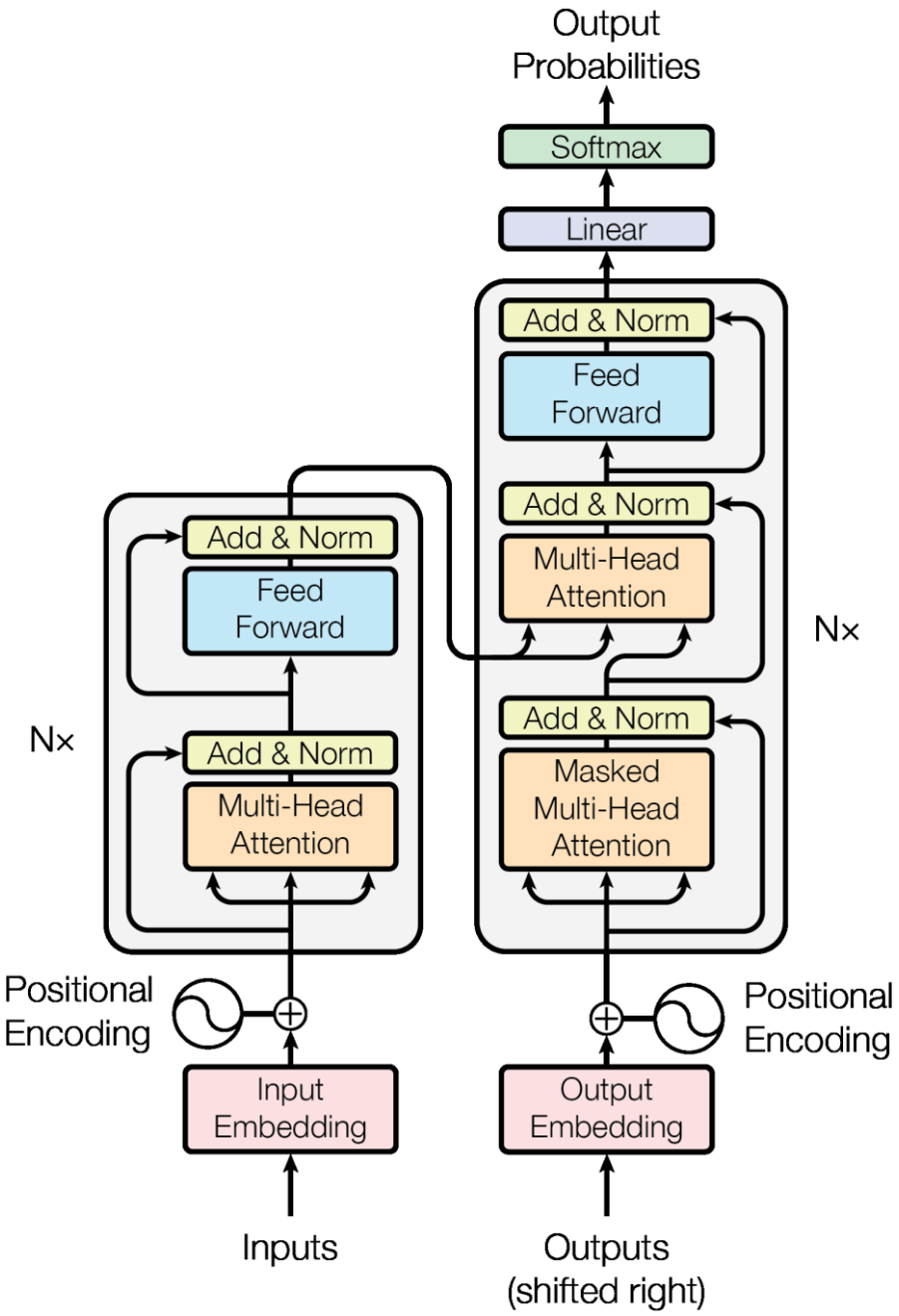


Figure 4. An illustration of Transformer from "Attention Is All You Need" [6]

2.4. DC U-Net

Dense Convolutional U-Net, is an advanced variant of the traditional U-Net architecture, specifically designed for medical image segmentation tasks. Dense Convolutional indicates the integration of dense connections into the U-Net framework. Dense connections, derived from DenseNet architecture [7], ensure that each layer is connected to every subsequent layer in a feed-forward manner, promoting feature reuse and

efficient learning of complex representations. This allows the network to capture both low-level and high-level features more effectively, which is crucial for detailed segmentation in medical images.

Like the standard U-Net, DC U-Net follows an encoder-decoder structure. The encoder compresses the input image into smaller, feature-rich representations, while the decoder reconstructs the segmentation map. To ensure spatial information is preserved during the reconstruction, skip connections are included between corresponding layers in the encoder and decoder. The inclusion of dense connections in this architecture facilitates better feature propagation, leading to improved accuracy, especially in cases where subtle details are critical.

DC U-Net is particularly effective in medical imaging tasks such as organ or lesion segmentation, where accurate identification of regions is vital. Its dense connectivity and efficient feature reuse make it well-suited for handling limited datasets, a common challenge in the medical field. By combining the strengths of dense connections and U-Net's encoder-decoder design, DC U-Net provides enhanced performance for detailed segmentation tasks like glaucoma detection and tumor segmentation.

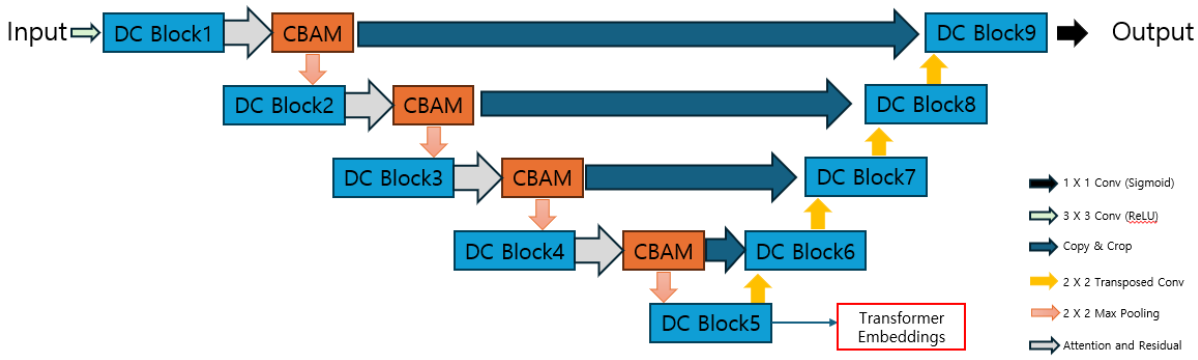


Figure 5. Diagram that illustrates an example of the application of CBAM and a hybrid of the DC-UNet with a Transformer-based mode

Here, in Figure 5 we attach the illustration of our model. When reading about the

research, we hope that this illustration will aid your understanding of our work.

3. 연구 내용

3.1. Data Acquisition

To effectively train and evaluate our glaucoma segmentation model, we utilized three publicly available ophthalmic datasets: REFUGE, ORIGA, and G1020. Each dataset provided retinal fundus images along with corresponding segmentation masks delineating regions of interest pertinent to glaucoma detection.

Dataset Details:

REFUGE: Contains a comprehensive set of retinal images specifically curated for glaucoma assessment.

ORIGA: Offers a diverse range of images with varying degrees of glaucomatous features.

G1020: Provides high-resolution images aiding in precise segmentation tasks.

The images and masks from these datasets were meticulously preprocessed to ensure consistency and optimal input for the neural network:

The model was trained by the combined data, not respectively due to lack of data.

3.2. Image Preprocessing

3.2.1. Color Conversion

All images were converted from BGR to RGB color space to align with standard processing practices.

3.2.2. Resizing

Each image was resized to a standardized dimension of 64×64 pixels to reduce computational complexity while retaining essential features.

3.2.3. Normalization

Pixel values were normalized to the range [0, 1] by dividing by 255.0, facilitating faster convergence during training.

3.3. Data Aggregation and Preparation

After preprocessing, images and masks from all three datasets were aggregated to form a comprehensive dataset.

3.3.1. Label Encoding

The segmentation masks, initially containing pixel-wise class labels, were flattened and encoded using a label encoder to transform categorical labels into numerical format

3.3.2. Reshaping

Encoded masks were reshaped back to their original spatial dimensions.

3.3.3. One-Hot Encoding

Masks were converted into a categorical format with three classes (background, optic disc, optic cup) using one-hot encoding, facilitating multi-class segmentation.

3.3.4. Data Splitting

The dataset was split into training and testing sets using an 80-20 split to evaluate the model's generalization capabilities.

3.4. Model Architecture

To capture both local and global features essential for accurate segmentation, we designed an advanced neural network architecture integrating several state-of-the-art components:

3.4.1. Base Architecture:

3.4.1.1. TransUNet V2

An enhanced version of the traditional U-Net, incorporating transformer blocks to model long-range dependencies within the image data.

3.4.1.2. Encoder-Decoder Structure

The network follows a symmetric encoder-decoder paradigm, enabling precise localization and contextual feature extraction.

3.4.2. Encoder Enhancements:

The Encoder Enhancements are the main part of the project as this is our ingenuity of this project. Using both DC Blocks and CBAM for glaucoma has not been done before.

3.4.2.1. DC Blocks (Dilated Convolutional Blocks)

Implemented to expand the receptive field without increasing the computational load, allowing the network to capture multi-scale contextual information.

Multi-Scale Convolutions and Feature Aggregation were also used to extract features at different scales and to enrich the feature representation.

3.4.2.2. CBAM

Integrated to enhance feature maps by focusing on informative regions.

Channel Attention and Spatial Attention has been mentioned in 2.3.

3.4.3. Transformer Integration

3.4.3.1. Patch Embedding

The feature maps from the encoder were divided into patches and embedded into a lower-dimensional space suitable for transformer processing.

3.4.3.2. Transformer Blocks

Multi-Head Attention: Modeled dependencies across different regions of the image, allowing the network to understand global context.

Feed-Forward Networks: Applied position-wise transformations to enhance the representation capabilities.

Layer Normalization and Residual Connections: Ensured stable training and preserved gradient flow throughout the network.

3.4.4. Decoder Enhancements

The decoder is a very casual ResNet Decoder. If you are familiar with ResNet, then you can skip reading this part.

3.4.4.1. Skip Connections

Employed to concatenate encoder features with decoder layers, preserving spatial information lost during down-sampling.

3.4.4.2. Up-sampling

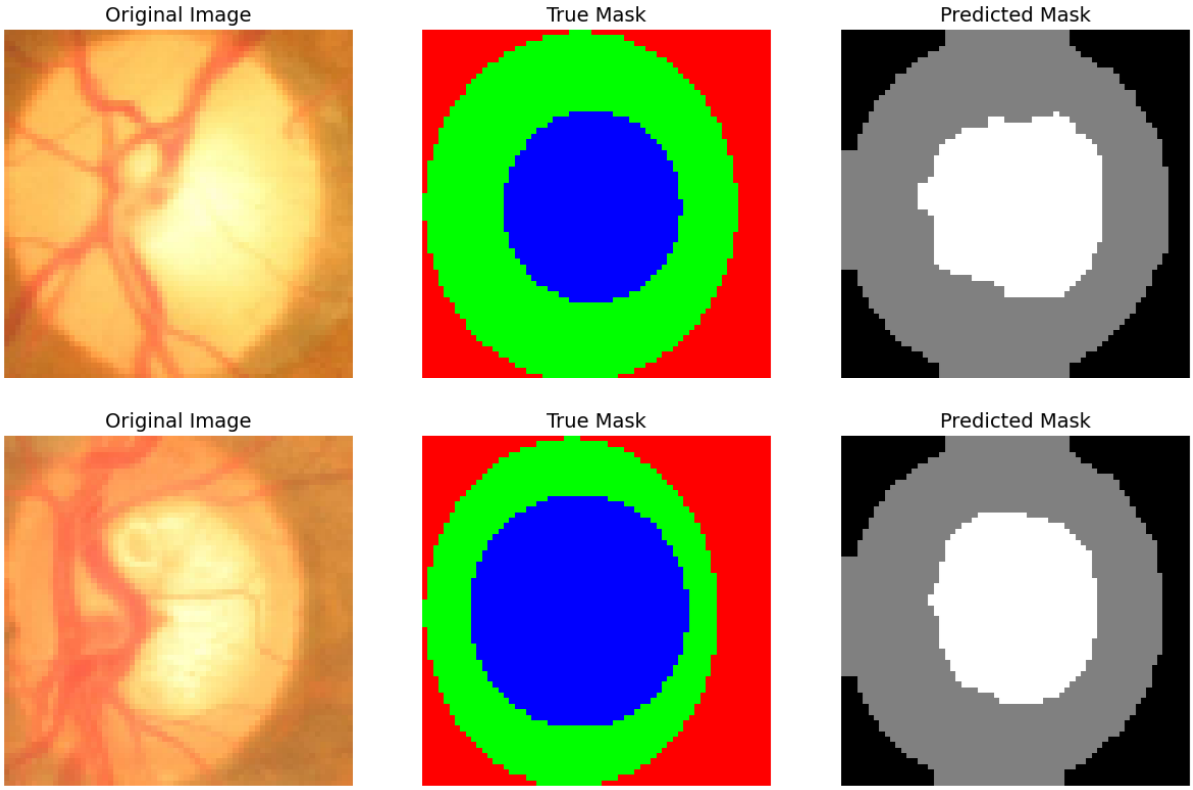
Used transposed convolutions to increase the spatial dimensions progressively, reconstructing the segmentation mask.

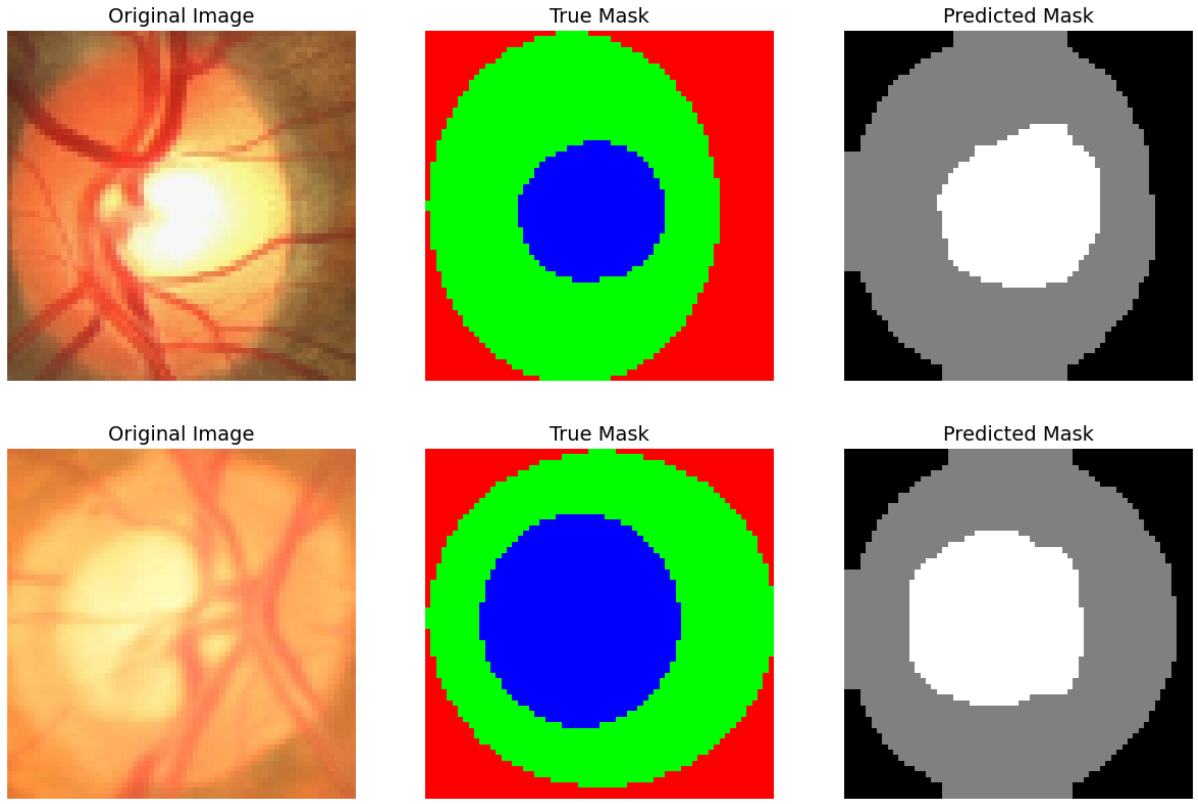
3.4.4.3. Output Layer

A final convolutional layer with a softmax activation function produced the pixel-wise class probabilities for segmentation.

3.5. Visualization

The following figures has been made by matplotlib.





4. 연구 결과 분석 및 평가

In this section, we provide an analysis of the results obtained from various experiments using our proposed model and compare its performance against existing models like U-Net. To evaluate the performance of the models, we used three key metrics: accuracy, Intersection over Union (IoU), and the Dice coefficient.

Accuracy measures the overall correctness of the model, reflecting the percentage of correctly classified pixels in the image. However, since it may not fully capture the model's performance in the context of image segmentation, we also consider IoU and the Dice coefficient, which provide more specialized insights into segmentation quality.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

IoU quantifies the overlap between the predicted segmentation and the ground truth, measuring the ratio of the intersection of the two sets to their union. A higher IoU

indicates a more accurate segmentation by the model, with values ranging from 0 (no overlap) to 1 (perfect overlap).

$$IoU = \frac{|A \cap B|}{|A \cup B|}$$

The Dice coefficient, on the other hand, is similar to IoU but gives slightly more weight to correctly classified pixels, making it sensitive to small segmentation errors. It is defined as twice the area of overlap divided by the total number of pixels in both the predicted and ground truth masks. Like IoU, Dice values range from 0 to 1, with higher values indicating better segmentation performance.

$$Dice = \frac{2|A \cap B|}{|A| + B \vee}$$

By using these metrics, we can comprehensively assess the segmentation capability of our proposed model compared to U-Net, highlighting improvements or shortcomings in accuracy and overlap with ground truth segmentations.

We experimented with several models, including U-Net, U-Net with CBAM, ResUNet, DC-UNet with CBAM, SegNet with CBAM, and TransDC-UNet with CBAM. The following table summarizes the performance of these models across different evaluation metrics, including Pixel Accuracy, Intersection over Union (IoU), and Dice Coefficient:

4.1. Comparison of experimental results

Model	Pixel-Accuracy	IoU	Dice Coefficient
U-Net	0.9001	-	-
U-Net with CBAM	0.9064	0.8289	0.8812
ResUNet (Used ResNet34)	0.9001	0.7928	0.8722
DC-UNet with CBAM	0.8756	0.7788	0.8467
SegNet with CBAM	0.9043	-	-
TransDC-UNet with CBAM	0.8498	0.7403	0.7765

From the table, we observe that U-Net with CBAM achieved the best results in terms of both IoU (0.8289) and Dice Coefficient (0.8812), indicating improved segmentation

quality when attention mechanisms are employed. However, while some models demonstrated promising results, the performance of our proposed TransDC-UNet with CBAM did not surpass the baseline U-Net. In fact, the accuracy metrics show a slight decrease compared to U-Net and U-Net with CBAM.

The Pixel Accuracy values across all models remain relatively consistent, with minor variations. However, the Intersection over Union (IoU) and Dice Coefficient provide a more nuanced view, reflecting the differences in the model's ability to segment key anatomical structures, such as the optic disc and optic cup, with precision.

Although the performance of our model was lower than expected in terms of accuracy, we emphasize that the goal of this project was not merely to surpass U-Net in accuracy but to introduce ingenuity through the integration of state-of-the-art techniques such as CBAM, transformer blocks, and DC-UNet. The novelty of our approach lies in combining these elements, which, despite not yielding higher accuracy in this iteration, opens up new avenues for future refinement and optimization.

Future work will focus on improving the generalization capabilities of our model, exploring different combinations of hyperparameters, and further enhancing the model's structure to better capture the complexities of medical images.

5. 결론 및 향후 연구 방향

In this research, we aimed to enhance the segmentation model for glaucoma detection by integrating innovative techniques, including CBAM, transformer blocks, and DC-UNet. Although our model did not demonstrate an improvement in accuracy compared to the baseline U-Net model, the core achievement lies in the ingenuity of our approach. We introduced enhancements to the traditional U-Net model that incorporated modern techniques, which hold potential for further exploration.

As a summary of our model, the integration of CBAM allowed the model to focus on the most informative regions of the image, enhancing the attention mechanism both spatially and channel-wise. Similarly, the inclusion of transformer blocks facilitated the capture of long-range dependencies within the data, which is crucial in medical image analysis. Additionally, the DC-UNet structure provided the benefits of dense connections, enabling feature reuse and more effective learning, especially with limited datasets.

However, we provide the following suggestions for future work:

1. To obtain more data. 2,000 images were not enough, but this can be improved with a larger dataset that future medical research could bring about.
2. To consider more ways for preprocessing. Considering that nowadays there is not enough data to train in the medical field, data augmentation is not optional. However, alternative preprocessing methods could be utilized in the future as research in this field grows and improves.

Despite the lack of accuracy improvement, this study has demonstrated the potential of combining these advanced techniques in a novel way. The contribution of this work lies in the innovative architecture designed to push the boundaries of traditional models for medical image segmentation. Future work can build on this foundation to optimize the model further and explore its applications in different medical domains.

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