The Inception model using ImageNet data is used when using the FID score. However, since ImageNet data and ultra-wide-field fundus images are different, the FID of Real-Real data is compared based on the measured value. Looking at the FID value, it can be determined that the case with a small value is similar to the real data. Both the Normal and Disease data had the smallest values when the BEGAN model was used. When the Normal data was used, the diversity ratio value was 0.7, and in the case of Disease data, it was the lowest when it was 0.3. When the FID scores were compared, it was found that the BEGAN model had the smallest score among the three models, making it a suitable model for image synthesis.

IV. CONCLUSIONS

We have studied to generate new data using ultra-wide-field fundus images. Since there were no related existing studies, three GAN models, DCGAN / WGAN-GP / BEGAN, were selected, and the results of each study were compared. In the qualitative evaluation, the BEGAN (0.7) model was most similar to the real, and in the quantitative evaluation, the BEGAN (0.3) and BEGAN (0.7) generated data similar to the actual data according to the type of data. When synthesizing data using ultra-wide-field fundus images, BEGAN was the most suitable model among the three models. This study was conducted based on 20,000 epochs, but a similar image was generated when it exceeded 60,000 epochs. In Fig. 9, blood vessels, optic disk, and macula were all observed, and an image similar to the real one was created.

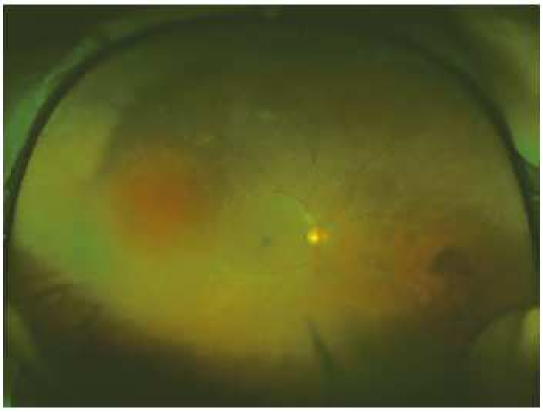

Fig. 9 Result synthesis image using BEGAN (60,000 epochs)

However, the same result was shown even if the input was changed due to mode collapse. There was no exact cause for the mode collapse, but according to the BEGAN v2[21] study, data quantity and data size can have an effect. Since the amount of data used in this study was small and the data size was larger than that of the existing GAN study, it could be inferred that mode collapse occurred. Therefore, it is necessary to study generative models suitable for medical data.

ACKNOWLEDGMENT

This work was supported by the 2022 education, research, and student guidance grant funded by Jeju National University. This article is excerpted from the presented at Master dissertation of the first author.

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