GAN-based Image-to-Image Translation of Fundus Photography: Topcon to Eidon

1st Jaehan Joo
Electronics Engineering
Pusan National Univ.
Busan, Republic of Korea
jhjoo2018@pusan.ac.kr

2nd Jeongbin Seo
Electronics Engineering
Pusan National Univ.
Busan, Republic of Korea
sjb9612@pusan.ac.kr

3rd Geonho Choi
Electronics Engineering
Pusan National Univ.
Busan, Republic of Korea
cgh2022@pusan.ac.kr

4th Suk Chan Kim*
Electronics Engineering
Pusan National Univ.
Busan, Republic of Korea
sckim@pusan.ac.kr

***Abstract*—This paper proposes a technique to translate Topcon to Eidon fundus photography using a multimodal image-to-image translation technique based on the BicycleGAN model. The proposed approach aims to address the limitations of Topcon-type fundus photography and leverage the advantages of Eidon-type fundus photography, which captures high-resolution images of the retina using a confocal scanning technique. To this end, we constructed a dataset comprising 475 pairs of Topcon and Eidon fundus images from the same subjects, and we used it to train the proposed model. We evaluated the generated Eidon-type fundus images qualitatively and quantitatively using various image quality metrics, including SSIM, MSE, PSNR and FID. Our results demonstrate that the proposed technique can effectively translate Topcon-type fundus photography to high-quality Eidon-type fundus photography. This technique could potentially enhance the diagnosis and treatment of retinal diseases by providing high-resolution images that capture fine details of the retina.**

***Index Terms*—Image-to-Image translation, Generative Adversarial Model, Fundus Photography, Eidon, Topcon**

I. Introduction

Deep learning-based artificial intelligence models have shown remarkable performance in medical diagnosis and image analysis [1], [2]. The field of ophthalmology, which relies heavily on medical images, has also witnessed significant improved performance with the use of artificial intelligence models [3]–[6]. In particular, fundus photography, which is used in ophthalmology to examine the interior surface of the eye, has been extensively studied using deep learning-based methods [4], [7]–[10].

Fundus photography is a medical imaging technique that is used to examine the interior structure of the eye. Medical professionals can examine the vitreous humor, retina, choroid, optic disc, and other structures within the eye through fundus photography, and use this information to diagnose conditions such as glaucoma, cataracts, vitreous hemorrhage, diabetic retinopathy, and hypertensive retinopathy [11]. Fundus photography can be divided into two main types: wide-field and posterior pole imaging. Of these, posterior pole imaging is the most commonly used for diagnosing ophthalmic conditions, and is the focus of this study. In particular, Topcon and Eidon devices are widely used for posterior pole fundus photography. Eidon-type fundus photography is particularly advantageous, as it uses a True-color confocal scanning technique that captures high-resolution images of the retina with a white light-emitting diode of 440-650 nm wavelength, which can be obtained rapidly and automatically without a mydriatic agent. The sensor also detects all colors of 500-700 nm wavelength to reflect the actual color of the retina. These advantages provide higher diagnostic resolution compared to Topcon-type fundus photography.

Recently, the multimodal image-to-image translation technique using the BicycleGAN model [12] has been proposed, which has shown promising results in various applications, such as image colorization, style transfer, and super-resolution. In the field of ophthalmology, there have been studies using the generative model for image enhancement, segmentation, and synthesis [13]–[15]. However, to the best of our knowledge, there has been no study on the translation of Topcon-type fundus photography to Eidon-type fundus photography using the BicycleGAN model.

In this paper, we propose a novel application of the BicycleGAN model for fundus photography, specifically for the translation of Topcon to Eidon type. The proposed technique is motivated by the advantages of Eidon-type fundus photography, which uses a confocal scanning technique and captures high-resolution images of the retina. We trained the proposed model on a dataset of 475 pairs of Topcon and Eidon fundus images collected from the same subjects. The generated images were evaluated both qualitatively and quantitatively using various metrics, including SSIM, MSE, PSNR and FID. The results demonstrate the effectiveness of the proposed technique in generating high-quality Eidon-type fundus images from Topcon-type fundus images.

II. Related Work

A. Generative Adversarial Networks

Generative Adversarial Networks (GANs) [16] is a type of deep neural network architecture that consists of a generator and a discriminator. The generator is responsible for generating new data samples that are similar to the training data, while the discriminator is responsible for distinguishing between the generated data and the real data. During the training process, the generator tries to generate data samples that can

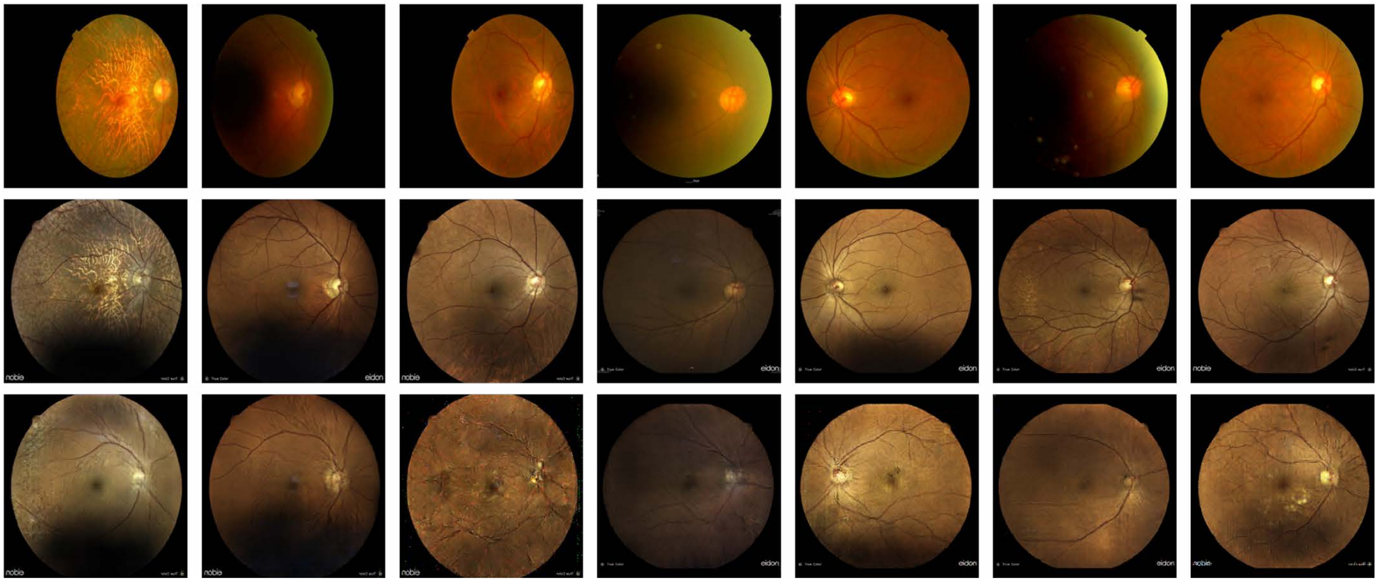

Fig. 1. Qualitative evaluation results using a 3×7 image grid. Each row shows a Topcon image (input), a Real Eidon image (Ground Truth), and a Generated Eidon image (Fake), respectively.

fool the discriminator, and the discriminator tries to correctly classify the real and generated samples. The training process continues until the generator generates data samples that are indistinguishable from the real data by the discriminator. GANs have been used in various applications, such as image generation, image-to-image translation, and style transfer. There have been many variations of GANs proposed in recent years to improve their stability and quality of the generated data, including Conditional GANs (cGANs) [17], Wasserstein GANs (WGANs) [18], and Progressive GANs (PGANs) [19].

B. *Multimodal Image-to-Image Translation: BicycleGAN*

In this paper, we employ BicycleGAN [12], a generative model that generates diverse and realistic images from a sketch, to perform image translation from Topcon to Eidon fundus photography. BicycleGAN resolves the mode collapse problem of many-to-one mapping in image-to-image translation by training the mapping network, enabling it to generate diverse styles of images. In this study, we utilize the Topcon fundus photography as the encoder input of BicycleGAN and train the model by comparing the Eidon fundus photography with the decoder output.

III. Experiments

A. *Datasets*

We randomly split the dataset of 475 Topcon and Eidon image pairs into two sets: a training set of 400 pairs and a validation set of 75 pairs. The training set was used to train our BicycleGAN model, and the validation set was used to evaluate the performance of the model during training. All images were resized to a resolution of 1024 by 1024 pixels and were processed to have a square shape of the retinal area using cropping and zero padding techniques. The dataset was collected in collaboration with the Yangsan Pusan National University Hospital, as there was no available open dataset that included pairs of Topcon and Eidon fundus images.

B. *Methods*

For the proposed image translation task from Topcon to Eidon fundus photography, we used the BicycleGAN model implemented in PyTorch framework. The training was performed on a single RTX-2080Ti GPU and the model was trained for 20,000 epochs with a batch size of 2. We used the real Topcon fundus images as the generator input and the ground truth images were the corresponding real Eidon fundus images. We did not use the conditional option in the model. The learning rate was set to 0.0002 with learning rate decay applied every 100 iterations. We used an image size of 256 by 256 for the training process.

C. *Qualitative Evaluation*

To visually evaluate the generated images, we used a 3×7 image grid in Figure 1. Each row of the grid shows a Topcon image (input), a Real Eidon image (ground truth), and a Generated Eidon image (fake), respectively. Figure 1 presents the visual comparison results between the Real Eidon images and the Generated Eidon images. As shown in the figure, the generated images closely resemble the real images in terms of color, texture, and other visual features. However, some small details, such as the blood vessels and optic disc, are not as clear as in the real images. Overall, the qualitative evaluation results demonstrate the effectiveness of the proposed technique in generating high-quality Eidon-type fundus images from Topcon-type fundus images.

D. *Quantitative Evaluation*

To quantitatively evaluate the performance of the proposed technique, we used several image quality metrics, including SSIM, MSE, PSNR and FID.

TABLE I
QUANTITATIVE EVALUATION RESULTS

Metric	Real Eidon vs Fake Eidon	Topcon vs Real Eidon	Topcon vs Fake Eidon
SSIM	0.4896	0.3343	0.3357
MSE	70.63	81.84	82.04
PSNR	20.96	13.26	13.97
FID	37.86	-	-

The results indicate that the proposed technique generates images that have high visual quality and are structurally similar to the real Eidon images. However, the quantitative evaluation results also suggest that further improvements are needed, particularly in terms of image details such as blood vessels and optic disc. Overall, the proposed technique has great potential for use in medical image processing and diagnosis, but further research is needed to improve its accuracy and applicability in real-world clinical settings.

IV. CONCLUSIONS

In this paper, we performed image-to-image translation between different types of fundus images (Topcon and Eidon). We collected a total of 475 pairs of data in two different forms, which were manually collected by clinicians since there is no publicly available fundus dataset that includes Topcon and Eidon pairs. To achieve this task, we used the BicycleGAN model, which is a generative adversarial network-based model. We used Topcon images as input and Eidon images as labels. The generated Eidon-type fundus images showed similar patterns to the real images, including blood vessels, fundus shape, and pathological features. This study confirms the potential of GAN models in medical image processing and diagnosis. However, additional research is necessary to improve the resolution of important information, such as the optic disc shape. Furthermore, the similarity between the generated images and real Eidon images has yet to be evaluated by a reliable metric. In future research, technical verification and clinical evaluation are required to determine the applicability of the proposed technique in real-world clinical settings.

ACKNOWLEDGMENT

This work is financially supported by Korea Ministry of Land, Infrastructure and Transportation(MOLIT) as "Innovative Talent Education Program for Smart City."

This work was supported by the Technology Innovation Program (or Industrial Strategic Technology Development Program) (00144500, Development of 3D ultrasonic sensor technology for vehicles based on meta structure) funded By the Ministry of Trade, Industry Energy(MOTIE, korea))

REFERENCES

[1] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. Van Der Laak, B. Van Ginneken, and C. I. Sánchez, "A survey on deep learning in medical image analysis," *Medical image analysis*, vol. 42, pp. 60–88, 2017.

[2] D. Shen, G. Wu, and H.-I. Suk, "Deep learning in medical image analysis," *Annual review of biomedical engineering*, vol. 19, pp. 221–248, 2017.

[3] R. Kapoor, S. P. Walters, and L. A. Al-Aswad, "The current state of artificial intelligence in ophthalmology," *Survey of ophthalmology*, vol. 64, no. 2, pp. 233–240, 2019.

[4] V. Gulshan, L. Peng, M. Coram, M. C. Stumpe, D. Wu, A. Narayanaswamy, S. Venugopalan, K. Widner, T. Madams, J. Cuadros, *et al.*, "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs," *Jama*, vol. 316, no. 22, pp. 2402–2410, 2016.

[5] M. D. Abràmoff, P. T. Lavin, M. Birch, N. Shah, and J. C. Folk, "Pivotal trial of an autonomous ai-based diagnostic system for detection of diabetic retinopathy in primary care offices," *NPJ digital medicine*, vol. 1, no. 1, p. 39, 2018.

[6] D. S. W. Ting, L. R. Pasquale, L. Peng, J. P. Campbell, A. Y. Lee, R. Raman, G. S. W. Tan, L. Schmetterer, P. A. Keane, and T. Y. Wong, "Artificial intelligence and deep learning in ophthalmology," *British Journal of Ophthalmology*, vol. 103, no. 2, pp. 167–175, 2019.

[7] P. Costa, A. Galdran, M. I. Meyer, M. Niemeijer, M. Abràmoff, A. M. Mendonça, and A. Campilho, "End-to-end adversarial retinal image synthesis," *IEEE transactions on medical imaging*, vol. 37, no. 3, pp. 781–791, 2017.

[8] A. V. Varadarajan, R. Poplin, K. Blumer, C. Angermueller, J. Ledsam, R. Chopra, P. A. Keane, G. S. Corrado, L. Peng, and D. R. Webster, "Deep learning for predicting refractive error from retinal fundus images," *Investigative ophthalmology & visual science*, vol. 59, no. 7, pp. 2861–2868, 2018.

[9] M. M. Islam, H.-C. Yang, T. N. Poly, W.-S. Jian, and Y.-C. J. Li, "Deep learning algorithms for detection of diabetic retinopathy in retinal fundus photographs: A systematic review and meta-analysis," *Computer Methods and Programs in Biomedicine*, vol. 191, p. 105320, 2020.

[10] P. M. Burlina, N. Joshi, M. Pekala, K. D. Pacheco, D. E. Freund, and N. M. Bressler, "Automated grading of age-related macular degeneration from color fundus images using deep convolutional neural networks," *JAMA ophthalmology*, vol. 135, no. 11, pp. 1170–1176, 2017.

[11] M. Yanoff and J. S. Duker, *Ophthalmology*. Elsevier Health Sciences, 2008.

[12] J.-Y. Zhu, R. Zhang, D. Pathak, T. Darrell, A. A. Efros, O. Wang, and E. Shechtman, "Toward multimodal image-to-image translation," *Advances in neural information processing systems*, vol. 30, 2017.

[13] A. You, J. K. Kim, I. H. Ryu, and T. K. Yoo, "Application of generative adversarial networks (gan) for ophthalmology image domains: a survey," *Eye and Vision*, vol. 9, no. 1, pp. 1–19, 2022.

[14] H. Cheong, S. K. Devalla, T. H. Pham, L. Zhang, T. A. Tun, X. Wang, S. Perera, L. Schmetterer, T. Aung, C. Boote, *et al.*, "Deshadowgan: a deep learning approach to remove shadows from optical coherence tomography images," *Translational Vision Science & Technology*, vol. 9, no. 2, pp. 23–23, 2020.

[15] T. K. Yoo, J. Y. Choi, and H. K. Kim, "A generative adversarial network approach to predicting postoperative appearance after orbital decompression surgery for thyroid eye disease," *Computers in biology and medicine*, vol. 118, p. 103628, 2020.

[16] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial networks," *Communications of the ACM*, vol. 63, no. 11, pp. 139–144, 2020.

[17] M. Mirza and S. Osindero, "Conditional generative adversarial nets," *arXiv preprint arXiv:1411.1784*, 2014.

[18] M. Arjovsky, S. Chintala, and L. Bottou, "Wasserstein generative adversarial networks," in *International conference on machine learning*, pp. 214–223, PMLR, 2017.

[19] T. Karras, T. Aila, S. Laine, and J. Lehtinen, "Progressive growing of gans for improved quality, stability, and variation," *arXiv preprint arXiv:1710.10196*, 2017.