Application of Generative Adversarial Network for Data Augmentation and Multiplication to Automated Cell Segmentation of the Corneal Endothelium

Karolina Nurzynska
Silesian University of Technology
Gliwice, Poland *karolina.nurzynska@polsl.pl*

Krystian Jandy
Gdansk University of Technology
Gdansk, Poland *s184589@student.pg.edu.pl*

Paweł Weichbroth
Gdansk University of Technology
Gdansk, Poland *pawel.weichbroth@pg.edu.pl*

Abstract

Considering the automatic segmentation of the endothelial layer, the available data of the corneal endothelium is still limited to a few datasets, typically containing an average of only about 30 images. To fill this gap, this paper introduces the use of Generative Adversarial Networks (GANs) to augment and multiply data. By using the "Alizarine" dataset, we train a model to generate a new synthetic dataset with over 513k images. A portion of this artificial dataset is then used to train a semantic segmentation model for endothelial layer segmentation and its performance is evaluated showing that in average the mean intersection over union for all datasets is equal to 81%. In our opinion, the images of the endothelial layer, together with the corresponding masks generated by the GAN, effectively represent the desired data. The obtained results seem optimistic after visual inspection, since the segmentation is very precise.

Keywords: Generative Adversarial Network (GAN), Semantic Segmentation, Endothelial Layer,

1. Introduction

The increasing access to computational resources and advancements in calculation algorithms have made deep learning approaches more powerful. These approaches have proven their usefulness and versatility in a wide range of tasks from various domains, such as the popular GPT chat or dedicated solutions for medical and automotive applications. Although these approaches are well-equipped to handle many tasks, there is still room for improvement, especially in cases where the data is scarce and thus not necessary to train a complex model.

For instance, in the task of automatic segmentation of the corneal endothelial images, the datasets contain tens of images only. Yet, the problem of supporting the physicians with the possibility of automatic analysis of corneal endothelium is vital because this layer is critical for maintaining corneal transparency by regulating hydration and facilitating nutrient exchange. Therefore, Kucharski and Fabijańska address the corneal endothelial image segmentation issue by combining a convolutional neural network (CNN) with a watershed transform technique [5]. They also explore the possibility of synthesis of cell edges using generative adversarial neural (GAN) network [4]. In another study, a U-net-based convolutional neural network is used for cell segmentation [1]. While Nurzynska explored the impact of convolutional neural networks (CNNs) to delineate endothelial cells automatically [6].

This paper proposes the use of GANs for augmentation of the scarce medical data describing

the corneal endothelial layer. Then, it uses artificially generated datasets to train a model for automatic delineation of the corneal endothelial images.

2. Methodology

The experiments presented in this work consisted of two steps. Firstly, we trained the GAN model to prepare an artificial dataset composed of samples of the endothelial layer and matching masks delineating the cell's boundaries. We used the "Alizarine" [10] dataset for its preparation.

Only masked parts of the corneal endothelial images were selected for training in the training. Those 30 images were then divided into overlapping fragments of a fixed size 128×128 pixels with 30-pixel overlap. Each image fragment underwent augmentation through various transformations, including adjustments to brightness, contrast, and color saturation (with parameter ranges from 0.8 to 1.5), rotations at $0°$, $90°$, $180°$, and $270°$ angles, horizontal and vertical mirroring, the addition of salt-and-pepper noise, and Gaussian blurring at degrees 0, 1, and 2. All those combinations of transformations resulted in $513,184$ images and corresponding masks.

The Generative Adversarial Networks training process was conducted using an adapted implementation based on TensorFlow's tutorial on Deep Convolutional GANs (DCGAN) [8]. For the detailed architecture of the generator and discriminator, please refer to the web page (`https://www.tensorflow.org/tutorials/generative/dcgan`). Due to the large dataset size and memory constraints, the dataset was split into batches of 2000 image-mask pairs, totalling 4000 items per batch. The training proceeded over 100 epochs. We used the Binary Cross entropy loss function with the Adaptive Moment Estimation (Adam) optimizer set to a learning rate of 10^{-4} to train both networks. The GAN model was trained on a computer running Windows 11 equipped with 32 GB of RAM, an AMD Ryzen 7 5800X 8-Core processor with a frequency of 3.80 GHz, and an NVIDIA GeForce RTX 3070 graphics card with 8 GB of memory. The training process lasted approximately 30 hours and involved training the GAN model on 103 batches, corresponding to 206,000 samples.

Secondly, the artificial dataset was applied to train a semantic segmentation model for automatic endothelial cell delineation. Since the artificial dataset comprises 10,000 samples, they have been divided into training, validation, and testing sets (8,000, 1,000, and 1,000 samples, respectively). To evaluate the applicability of the artificial endothelial layer dataset, a model for endothelial layer segmentation was trained following the idea presented in [6]. The network architecture was a small U-Net [9] with three pooling layers. It was trained for 100 epochs with Adam optimiser, and the learning rate was set to 3e-4. The batch size was set to 32 images of 128×128 pixel resolution to fit the resolution of the artificial dataset and refrain from adding any unnecessary transformation and aliasing. We applied the early stopping in the case of five epochs where the validation loss did not improve. This model was verified on all real data samples belonging to the Gavet collection [2], the "Rotterdam" dataset [11] supported with a semi-automatically prepared mask using KH algorithm [3], and the "Hard" dataset [7]. The experiments were performed on a computer with 64GB RAM and an NVIDIA GeForce RTX 3080 Ti running Windows.

3. Results

It was observed that the quality of generated images started to decline after the 94th batch, likely due to overfitting or discriminator dominance. Therefore, this state of the model was applied to create artificial data, which sample is presented in Fig. 1.

The images of the endothelial layer and their corresponding masks, created using the GAN model, effectively demonstrate the desired data. Nevertheless, to be applicable for further experiments, the images of endothelial cells were scaled to use a full grey-scale range. In contrast,

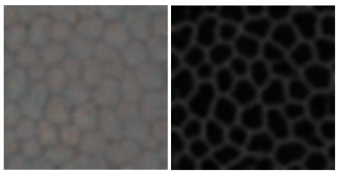


Fig. 1. Generated by GAN images of endothelial layer on the left and mask on the right.

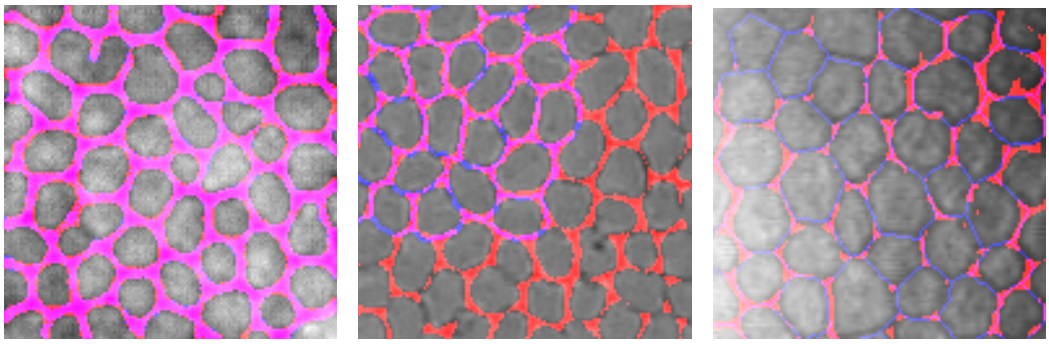
the masks were scaled and then thresholded at 127 to binarize them.

In the final experiment, the mean Intersection over Union metric (mIoU) is present for semantic segmentation quality in Table 1. However, its results seem optimistic after visual inspection presented in Figure 2. In this figure, we can observe that the segmentation for the artificial dataset is exact. Yet, in the case of samples from another dataset, it lacks one-pixel precision as the delineation is few-pixel wide. There are several reasons for the problems with correct endothelial cell delineation.

Firstly, the artificial dataset prepared thick masks presenting the cell's borders. From previous research, we know that using one-pixel-wide cell delineation while training improved the outcome [6]. Secondly, in the presented experiments, we concentrated on showing that exchanging the original but small dataset with a plethora of artificially generated data is good. As a consequence, we used the data as it is. However, one should support the uneven lighting conditions characteristic of the real datasets to achieve better results that are not present in the artificially generated data.

Table 1. Semantic segmentation quality

Testing dataset	mIoU
Artificial	0.8099 ± 0.1011
Alizarine	0.7719 ± 0.0516
Gavet	0.7990 ± 0.0454
Hard	0.8092 ± 0.0325
Rotterdam	0.9280 ± 0.0121



(a) Artificial dataset (b) Alizarine dataset (c) Gavet dataset

Fig. 2. Visualization of the semantic segmentation quality. The manual delineation is presented in blue. The red colour presents the automatic segmentation delineation. The pink corresponds to areas where the automatic annotation overlayed the manual one. However, in the case of Alizarine dataset, we present the network performance also on the part of the image which is not supported with manual annotation - thus only red color is depicted in bottom-right border.

4. Conclusions

The research at hand tackles the issue of deep learning model training in situations where only small datasets are available. Utilizing a GAN model addressed the challenge, and from 30 original images and masks accessible in the "Alizarine" dataset, a new dataset of 10,000 sample pairs of the corneal endothelial layer and its mask was generated. The model was then tested on synthetic and real datasets, showing an average mean intersection over union of over 81%

Acknowledgment

This paper used Generative AI to verify spelling, grammar, and punctuation. Some sentences used the automatic paraphrasing option.

References

1. Fabijańska, A.: Segmentation of corneal endothelium images using a u-net-based convolutional neural network. Artificial intelligence in medicine **88**, 1–13 (2018)
2. Gavet, Y., Pinoli, J.C.: Visual perception based automatic recognition of cell mosaics in human corneal endothelium microscopy images. Image Analysis & Stereology **27**, 53–61 (2008), https://hal-emse.ccsd.cnrs.fr/emse-00509294
3. Habrat, K., Habrat, M., J.Gronkowska-Serafin, Piorkowski, A.: Cell detection in corneal endothelial images using directional filters. In: AISC Springer. vol. 389, pp. 113–123 (2016)
4. Kucharski, A., Fabijańska, A.: Corneal endothelial image segmentation training data generation using gans. do experts need to annotate? Biomedical Signal Processing and Control **85**, 104985 (2023)
5. Kucharski, A., Fabijańska, A.: Modified cnn-watershed for corneal endothelium segmentation: Image-to-image versus sliding-window comparison. In: Polish Conference on Biocybernetics and Biomedical Engineering. pp. 3–15. Springer (2023)
6. Nurzynska, K.: Problems with deep learning application to medical data: Automatic segmentation of corneal endothelium layer. Procedia Computer Science **225**, 134–143 (2023)
7. Piórkowski, A., Nurzynska, K., Gronkowska-Serafin, J., Selig, B., Bołdak, C., Reska, D.: Influence of applied corneal endothelium image segmentation techniques on the clinical parameters. Computerized Medical Imaging and Graphics **55**, 13–27 (2017). https://doi.org/10.1016/j.compmedimag.2016.07.010
8. Radford, A., Metz, L., Chintala, S.: Unsupervised representation learning with deep convolutional generative adversarial networks (2016)
9. Ronneberger, O., Fischer, P., Brox, T.: U-net: Convolutional networks for biomedical image segmentation. In: Navab, N., Hornegger, J., Wells, W.M., Frangi, A.F. (eds.) Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. pp. 234–241. Springer International Publishing, Cham (2015)
10. Ruggeri, A., Scarpa, F., Luca, M.D., Meltendorf, C., Schroeter, J.: A system for the automatic estimation of morphometric parameters of corneal endothelium in alizarine red stained images. Br. J. Ophthalmol. **94**, 643–647 (2010)
11. Selig, B., Vermeer, K., Rieger, B., Hillenaar, T., Luengo Hendriks, C.: Fully automatic evaluation of the corneal endothelium from in vivo confocal microscopy. BMC Medical Imaging **15**(13), 1–15 (2015). https://doi.org/10.1186/s12880-015-0054-3