안저 영상에서 당뇨병 망막병증 등급을 위한 data augmentation

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Data Augmentation for Diabetic Retinopathy Grading in Fundus Images

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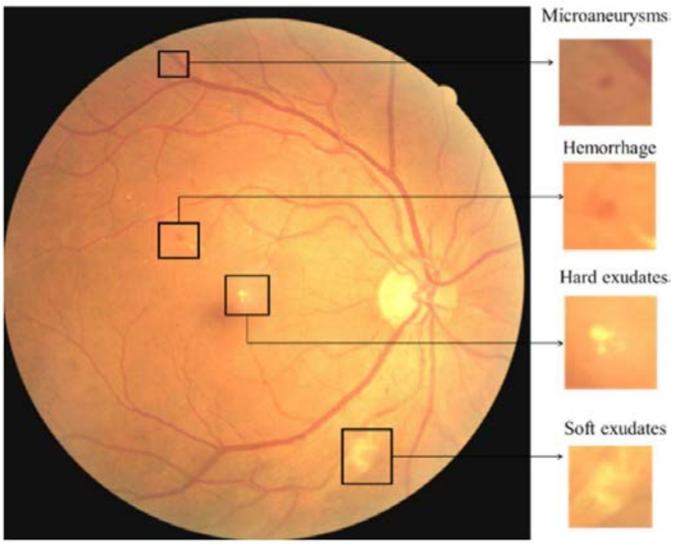
요 약

Diabetic retinopathy (DR) is one of the leading diseases causing vision loss. Early detection of this disease has a crucial role in protecting patients' eyes. Recent works have achieved impressive result when performing DR detection on fundus images using deep learning. In the deep learning-based approach, data augmentation has significant impact on the result. Recently, many data augmentation policies have been proposed and achieved state-of-the-art performance on different tasks. In this work, we compare effects of three data augmentation policies on DR grading in fundus images.

1. Introduction

Diabetic retinopathy (DR) is one of the four major blinding diseases. It is a retinal complication caused by diabetes. Because of leak blood and overflow of glucose in the retinal blood vessels, abnormal lesions including microaneurysms, soft exudates, hard exudates and hemorrhages appear in the retina, which can damage the patient's vision. These lesions are illustrated in Figure 1. The manual diagnosis of DR by ophthalmologists is time-consuming, requires considerable effort, and is prone to disease misdiagnosis. Therefore, using a computer-aided diagnosis system can avoid misdiagnosis and reduce overall cost, time and effort. During the last decade, deep learning (DL) approach has emerged and been adopted in many fields, including medical image analysis. There has been a considerable number of efforts to automate DR image classification using DL to help ophthalmologists detect the disease in its early stages.

Data augmentation is a widely used method for generating additional data to improve deep learning systems Data augmentation is a technique that can be used to artificially expand the size of a training set by creating modified data from the existing one. Data augmentation is an effective technique to increase both the amount and diversity of data by randomly "augmenting" it. In the image domain, common augmentations include translating the image by a few pixels, or flipping the image horizontally. Intuitively, data augmentation is used to teach a model about invariances in the data domain: classifying an object is often insensitive to horizontal flips or translation. Automatic augmentation meth-



(Figure 1) Different types of DR lesions.

ods are a set of methods that design augmentation policies automatically. They have been shown to improve model performance significantly across tasks. Automatic augmentation methods have flourished especially for image classification in recent years with many different approaches that learn policies over augmentation combinations. The promise of this field is to learn custom augmentation policies that are strong for a particular model and dataset. In this paper, we investigate effects of three state-of-the-art automatic augmentation policies for diabetic retinopathy grading in fundus images. Three policies include AutoAugment [1], RandAugment [2], and TrivialAugment [3].

2. Automatic Data Augmentation Policies

AutoAugment [1] is an automated approach to find data augmentation policies from data. It formulates the problem of finding the best augmentation policy as a discrete search problem. It consists of two components: a search algorithm and a search space. At a high level, the search algorithm samples a data augmentation policy S, which has information about what image processing operation to use, the probability of using the operation in each batch, and the magnitude of the operation. The policy S is used to train a neural network with a fixed architecture, whose validation accuracy R is sent back to update the controller. Since R is not differentiable, the controller will be updated by policy gradient methods. The operations searched over are shearX/Y, translateX/Y, rotate, autoContrast, invert, equalize, solarize, posterize, contrast, color, brightness, sharpness, cutout and sample pairing.

RandAugment [2] is an automated data augmentation method. The search space for data augmentation has 2 interpretable hyperparameter N and M. N is the number of augmentation transformations to apply sequentially, and M is the magnitude for all the transformations. To reduce the parameter space but still maintain image diversity, learned policies and probabilities for applying each transformation are replaced with a parameter-free procedure of always selecting a transformation with uniform probability $\frac{1}{K}$. Here K is the number of transformation options. So given N transformations for a training image, RandAugment may thus express $(K \times N)$ potential policies. Transformations applied include identity transformation, autoContrast, equalize, rotation, solarixation, colorjittering, posterizing, changing contrast, changing brightness, changing sharpness, shear-x, shear-y, translate-x, translate-y.

TrivialAugment [3] (TA) is a simple method which takes an image x and a set of augmentations A as input. It then simply samples an augmentation from A uniformly at random and applies this augmentation to the given image x with a strength m, sampled uniformly at random from the set of possible strengths $\{0, \ldots, 30\}$, and returns the augmented image. This process is simple and parameter-free procedure. TA is not a special case of RandAugment, since RandAugment uses a fixed optimized strength for all images while TA samples this strength anew for each image. TA only applies a single augmentation to each image. This allows viewing the distribution of the TA augmented dataset as an average of the $|A|$ data distributions generated by each of the augmentations applied to the full dataset. The set of transformations used by TA is the same as that of RandAugment.

3. Experiments

We use APTOS-2019 dataset [4], in which, severity of DR is divided into five level: 0-No DR, 1-Mild, 2-Moderate, 3-Severe, and 4-Proliferative DR. Number of images for train and validation is given in table 1. Our experiments are conducted using Pytorch framework. Resnet50 [5] model is selected as the classifier. The model is trained for 100 epochs with a batch size of 8 by Adam optimizer with a learning rate of 1e-4. The learning rate is divided by a factor of 4 every 15 epochs.

<Table 1> Number of images used for train and validation

	0	1	2	3	4
Train	1355	280	749	143	220
Validation	450	90	250	50	75

We evaluate performance of the model in terms of four metrics: accuracy (%), precision (%), recall (%), and f1-score (%). The result is given in table 2. It is clear that RandAugment outperforms other methods for all metrics. In comparison with TrivialAugment, AutoAugment has better performance in terms of accuracy and precision but lower performance in terms of recall and f1-score.

<Table 2> Experient result

	Accuray	Precision	Recall	F1-score
AutoAugment [1]	83.83	72.38	65.48	67.97
RandAugment [2]	**84.48**	**73.27**	**65.68**	**68.40**
TrivialAugment [3]	83.50	70.17	66.83	68.22

4. Conclusion

In this work, we study effects of recent data augmentation policies on DR grading in fundus images. The experiment result shows that among three policies, RandAugment achieves the best performance.

Acknowledgement

This work was supported by the BK21 FOUR Project, the MSIT(Ministry of Science and ICT), Korea, under the ICT Creative Consilience program(IITP-2022-2020-0-01821) supervised by the IITP (Institute for Information & communications Technology Planning & Evaluation), the MSIT, under the Grand Information Technology Research Center support program (IITP-2022-2015-0-00742) supervised by the IITP, the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (NRF-2020R1A2C2008447), and IITP grant funded by the Korea government (MSIT) (No.2021-0-02068, Artificial Intelligence Innovation Hub).

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