딥 러닝을 사용한 초광각 망막 이미지에서 당뇨망막증의 등급 평가

Van-Nguyen Pham[1], Kim-Ngoc T. Le[2], 추현승 [1,2]
[1] 성균관대학교 전자전기컴퓨터공학과
[2] 성균관대학교 AI 시스템공학과

nguyenpv195@g.skku.edu, ltkngoc0228@skku.edu, choo@skku.edu

Diabetic Retinopathy Grading in Ultra-widefield fundus image Using Deep Learning

Van-Nguyen Pham[1], Kim-Ngoc T. Le [2], Hyunseung Choo[1,2]
[1]Dept. of Electrical and Computer Engineering, Sungkyunkwan University
[2]Dept. of AI Systems Engineering, Sungkyunkwan University

요 약

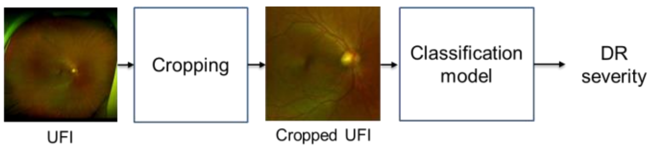
Diabetic retinopathy (DR) is a prevalent complication of diabetes that can lead to vision impairment if not diagnosed and treated promptly. This study presents a novel approach for the automated grading of diabetic retinopathy in ultra-widefield fundus images (UFI) using deep learning techniques. We propose a method that involves preprocessing UFIs by cropping the central region to focus on the most relevant information. Subsequently, we employ state-of-the-art deep learning models, including ResNet50, EfficientNetB3, and Xception, to perform DR grade classification. Our extensive experiments reveal that Xception outperforms the other models in terms of classification accuracy, sensitivity, and specificity. his research contributes to the development of automated tools that can assist healthcare professionals in early DR detection and management, thereby reducing the risk of vision loss among diabetic patients.

1. Introduction

Diabetic retinopathy (DR), a prevalent complication of diabetes, poses a significant threat to vision health worldwide. If left undiagnosed and untreated, DR can progress silently, leading to severe vision impairment and even blindness. In the face of this growing healthcare challenge, the development of efficient and accurate methods for early DR detection and grading is of paramount importance. This study addresses the imperative need for precise DR grading by presenting a novel approach tailored for the assessment of diabetic retinopathy in ultra-widefield fundus images (UFI). Fundus images provide valuable insights into the state of retinal health and are essential for the early detection of DR. However, the unique characteristics of ultra-widefield fundus images, which encompass a vast retinal area, present distinct challenges in image analysis.

To enhance the effectiveness of DR grading in UFIs, we propose a method that leverages deep learning techniques, as shown in Figure 1. Our approach begins with a crucial preprocessing step, where UFIs are carefully cropped to isolate the central region containing the most relevant information for DR assessment. This strategic cropping not only streamlines the computational process but also enables the model to focus on the critical features that indicate the presence and severity of DR. Next, the cropped UFI is passed through a classification model such as ResNet50, EfficientNetB3, and Xception. By utilizing the inherent capacity of these models to discern intricate patterns and extract informative features, we embark on the critical task of DR grade classification. Extensive experimentation reveals that Xception emerges as the top-performing model, exhibiting remarkable accuracy, sensitivity, and specificity in DR classification. The superiority of Xception underscores its ability to robustly identify and categorize varying degrees of diabetic retinopathy within UFIs.

Figure. Overall process of DR grading



2. Experiment

Our dataset includes 1,444 UFI, each of them is labeled into three severities: no DR, non-proliferative DR, and proliferative DR. The number of images in each class is 600, 424, 420. For each class, 100 images are used for testing, the rest is used for training. To assess the models' efficacy, we employ a range of popular performance metrics, including classification accuracy, recall, precision, and f1-score. These metrics provide a comprehensive evaluation of the models' ability to classify UFIs into distinct DR severity.

We leverage the power of transfer learning by initializing the selected deep learning models with pre-trained weights on large-scale image datasets such as ImageNet. Fine-tuning is performed on our UFI dataset to adapt the models to the task of DR classification. Furthermore, to enhance model generalization and mitigate overfitting, we apply data augmentation techniques to the training set. These techniques include random rotation and horizontal flip.

First, we conduct experiments with multiple cropping ratios to identify the one with good performance. Resnet50 is used as the classification in these experiments. The results are shown in Table 1. The cropping ratio is varied from 20% to 100% size of the original UFI. The ratio of 70% leads to the best performance across all metrics.

Table 1. Performance with multiple cropping ratios

cropping ratio (%)	accuracy	precision	recall	f1
20	0.6600	0.6651	0.66	0.6522
30	0.7067	0.7072	0.7067	0.6976
40	0.7633	0.7653	0.7633	0.7642
50	0.7600	0.7587	0.7600	0.7572
60	0.7533	0.7652	0.7533	0.7562
70	0.7700	0.7726	0.7700	0.7705
80	0.7533	0.7543	0.7533	0.7537
90	0.7433	0.7418	0.7433	0.7348
100	0.7467	0.7481	0.7467	0.7456

Next, with the cropping ratio of 70%, we apply multiple classification models to select the one with the best performance. Three well-known models are involved: Resnet50, EfficientNetB3, and Xception. The results are shown in Table 2. Xception outperforms others across all evaluation metrics

Table 2. Performance comparison of multiple models

model	accuracy	precision	recall	f1
Resnet50	0.7700	0.7726	0.7700	0.7705
EfficientNetB3	0.7633	0.7696	0.7633	0.7622
Xception	0.7733	0.7726	0.7733	0.7724

3. Conclusion

In this study, we have presented a novel approach for the automated grading of DR in UFIs utilizing deep learning techniques. Our methodology has encompassed crucial steps, from data preprocessing and model selection to training and evaluation, yielding valuable insights into the state-of-the-art deep learning models' performance for DR classification. The central premise of our approach is the preprocessing of UFIs through strategic cropping, focusing on the most informative regions of the images. This step not only optimizes computational efficiency but also enhances the models' capacity to identify critical features indicative of DR. In our exploration of deep learning architectures, we have evaluated three formidable models—ResNet50, EfficientNetB3, and Xception. These models have demonstrated exceptional capabilities in discerning intricate patterns within UFIs, thus forming the backbone of our automated DR grading system. Our rigorous experiments and extensive evaluations have revealed Xception as the standout performer among the models considered.

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