Residual Convolutional Neural Network for Diabetic Retinopathy

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2 authors, including:

Mohamad Ivan Fanany
University of Indonesia

Residual Convolutional Neural Network for Diabetic Retinopathy

Syahidah izza Rufaida, Mohamad Ivan Fanany
Machine Learning and Computer Vision Laboratory
Faculty of Computer Science, Universitas Indonesia, Depok, Indonesia
Corresponding Authors: syahidah.izza51@ui.ac.id, ivan@cs.ui.ac.id

***Abstract*—This research proposes a method to detect diabetic retinopathy automatically based on fundus photography evaluation. This automatic method will speed up diabetic retinopathy detection process especially in Indonesia which lack of ophthalmologist. Besides, the difference of doctor ability and experience may produce an inconsistent result. Thus, with this method, we hope automatic detection of diabetic retinopathy will speed up with a consistent result so blindness effect from diabetic retinopathy can be prevented as early as possible. Convolutional Neural Network (CNN) is one of neural network variant which can detect the pattern on an image very well. Residual CNN is one of CNN variant which can prevent accuracy degradation for a deep neural network. Therefore this inspire us to apply Residual CNN on diabetic retinopathy. This Residual Network can detect diabetic retinopathy with kappa score 0.51049.**

Keywords—Neural Network, Differentiable Neural Computer, Sequence, Classification

I. Introduction

Diabetes mellitus is a metabolism abnormality which is insufficient production of insulin or lack of utilization of insulin, causing blood glucose levels to rise. This causes the blood vessels become damaged and in the long term lead to complications in the eye area called Diabetic Retinopathy, kidney (Diabetic Nephropathy) and nerves (Diabetic Neuropathy).

In the long term, Diabetic Retinopathy can lead to blindness if not treated properly. Diabetic Retinopathy is a major cause of blindness in United States. If diabetic retinopathy can be detected earlier, the effects of blindness can be avoided by providing and measuring proper treatment. Currently, Diabetic Retinopathy identified by evaluating images of the retina by experts for blood vessels abnormalities detection. Usually the eye expert will analyze the blood vessel to differentiate a healthy image with DR-eye, because excess glucose causes the pressure in the blood increased so that the blood vessels will be weak and damage. The weak blood pressure will be choked and swollen even broken which cause blood leakage which block the light enters to the retina. But this raises another problem that the variation of the ability of experts to analyze and also need this method need a complete technology and equipment to get good image of the retina.

Indonesia is the country that has the fourth most people with diabetic retinopathy disease according to the international health agency WHO (World Health Organization). Currently the process of detection of Diabetic Retinopathy is done manually by the eye experts by evaluating the image of the retina. Evaluations were performed to detect abnormal blood vessels. This causes the process of screening to detect diabetic retinopathy will become long [1]

In addition, different ability and experience of ophthalmologists may produce different analysis or disagreement between ophthalmologists [2]. In developing countries, the number of ophthalmologist is limited especially in an archipelago country like Indonesia where the ophthalmologist did not spread to every corner of the island. In addition to the technology and tools used are not as complete as in the developed countries and not distributed equally throughout the country.

This has motivated us to continue research on automatic detection of diabetic retinopathy to reduce dependence with experts. Furthermore, the experts can focus in providing complete medications and treatments of diabetes advanced stages that is also the number has reduced.

Machine Learning is widely used to solve many problems in biomedical informatics [3]. Some automated systems have been created such as the classification of cancer stages [4], Alzheimer's [6, 7], and bone segmentation [8, 9]. This proved successful in helping the work of experts so that experts can focus more on the phase of treatment.

Convolutional Neural Network is a machine learning algorithm that is known to recognize image data very well [10]. This is due to the structure of the network that forms a two-dimensional area such as the arrangement of pixel values in the image so that it can capture the connection between the pixels in the image. Deep Convolutional Neural Network has been widely used in solving quite complex classification tasks [11, 12, 13].

State of the art from Deep CNN was born from Imagenet Large Scale Visual Recognition Challenge (ILSVR). This competition is conducted annually since 2010 and the largest competition of computer vision. ILSVR is a competition to classify 1.2 million images into 1000 classes. One of the existing state of the art from CNN is residual neural networks proposed by kaiming he in 2015. The Residual-Net CNN variant is designed to eliminate accuracy degradation due to CNN networks that have a deep structure, by adding a shortcut between their networks [14].

There are several research was conducted related to diabetic retinopathy detection. However previous research still used small dataset such as DRIVE (Digital Retinal Images for Vessel Extraction) dataset which only consist of 40 retinal images or STARE (Structure analysis of the retina) only consist of 65 retinal images [15, 16, 17]. Some research using its primary dataset from local hospital [18, 19] but yet the dataset size still less than 200 images. This provides an opportunity for author to explore EyePACS dataset which has much more images (80.000 images) for diabetic retinopathy detection. There is a research also used EyePACS dataset on 2016 which used 5000 images for validation, while 75000 images used for training [20].

In this work, the author uses the Residual-net network on CNN to detect diabetic retinopathy automatically. This research is expected to accelerate the process of retinal image evaluation to detect diabetic retinopathy disease, as well as variation of analysis results can also be avoided due to the standard method in classifying diabetic retinopathy stage.

II. Materials and Methods

A. *Dataset*

Dataset used by this research was collected by Eye Picture Archive Communication System or known as EyePACS. EyePACS was designed to use telemedicine to help diabetic retinopathy screening process in community clinics across the state. Pilot program was first launched in 2005 by opening 13 sites in California's Central Valley to send Diabetic Retinopathy screening result image to clinicians at UC Berkeley for analysis. Currently EyePACS is already used in more than 360 locations in more than 19 countries around the world.

Dataset provided by EyePACS as fundus photography image which has been labeled into 4 classes: 0 (No DR), 1 (Mild), 2 (Moderate), 3 (Severe) and 4(Proliferative DR). This category based on Early Treatment Diabetic Retinopathy research (ETDRS). Shown in Figure 1 the example of fundus photography image for each class. The number of dataset published by EyePACS is 88.702 images, and for each image has a different size. Before using the image, we need to crop and resize each image to 128x128 pixel. The size of the entire dataset reach 50GB.

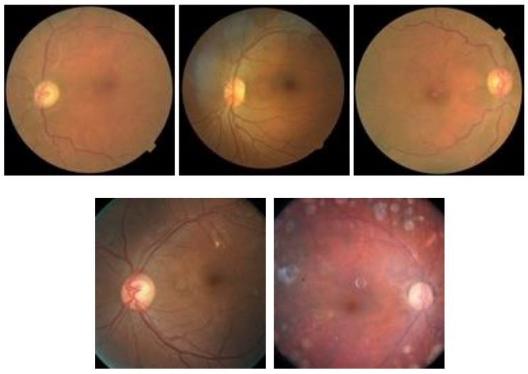

Figure. 1. Example Images for each Class. From left : 0 (No DR), 2 (Mild DR), 3 (Severe DR), 4 (Proliferative DR).

TABLE 1
Dataset Distribution

DR class	Total
0 - Health	65343
1 - Mild	6205
2 - Moderate	13153
3 - Severe	2087
4 - Proliferative DR	1914

Distribution of EyePACS retinal dataset is described in Table 1. It can be seen that the number of samples in each class is very unbalanced. The sample from negative class (health) reach 75% of the total dataset while the number of sample from positif class below 10% for each class.

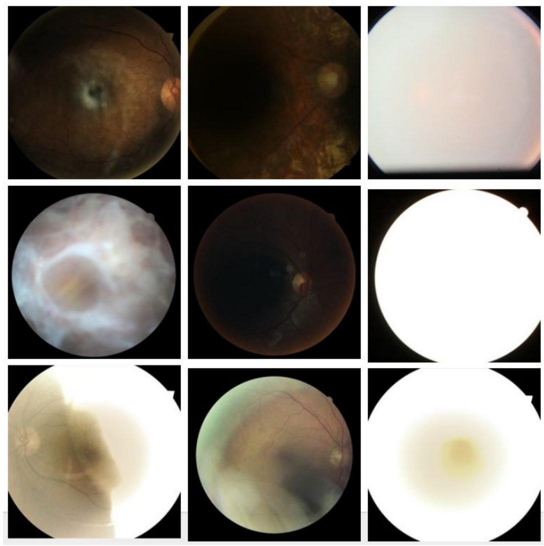

Figure 2. An Example of a Retina Image that has Lighting Noise

The dataset contains very much noise in its lighting. In some images even looks burning until the nerves and blood vessels are no longer visible. Some examples of images that have noise can be seen in Figure 2.

B. Residual Convolutional Neural Network

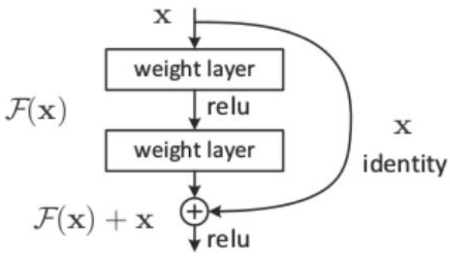

Figure 3. Residual Neural Network [14]

In 2015, Kaiming he found an anomaly that too deep network will experience accuracy degradation. this degradation accuray not caused by overfitting. Figure 3 is an illustrations from residual framework that use identity mapping as a shortcut. This shortcut does not require additional parameters or complex calculation [14]

III. Experiment

The computing environment used in experimenting is a desktop computer with the following specifications:

- Intel Core TMi7-5820K CPU 3.3 Ghz processor
- GeForce GTX TITAN X 12GB GPU
- 64 GB Memory
- 240 GB hard drive
- Operating System: Ubuntu 14.04 LTS 64 bit

In this research all experiments were conducted in one computational environment. Source code is implemented using Python version 3.0 programming language. We also used open source libraries such as Nolearn, Lasagne and Scikit Learn for building block.

This experiment, we used 35126 images as training dataset in total and 39424 as testing dataset. Dataset distribution for training and testing can be seen at figure 4.

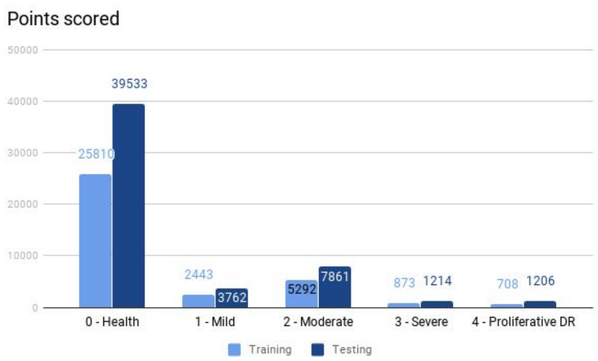

Figure 4. Dataset Distribution for Training and Testing

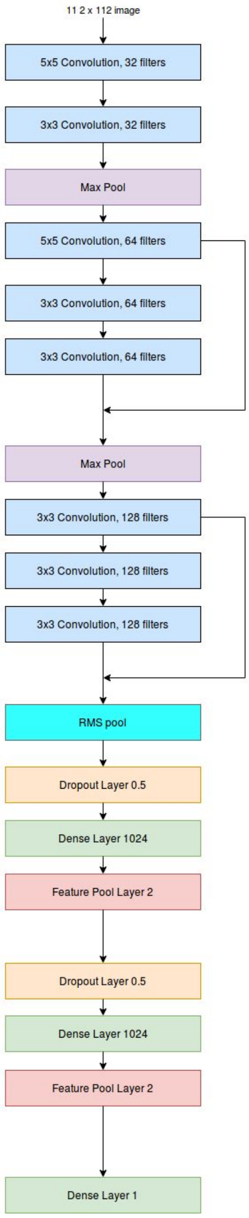

Figure 5. Proposed Residual Network

The CNN structure used in this research consists of 8 convolution layers with 32 filters with size 5x5 on the first convolution layer. Next on the second convolution layer there are 32 filters with size 3x3. On the next layer there is max pooling layer with size 2x2. Then 3 convolution layers that have 64 filters are stacked and there is a shortcut from the third layer of convolution to the fifth convolution layer or so-called residual network. Then the merge results on the previous layer will go into max pooling with the same configuration as before. Residual network is also done on 3 subsequent layer convolution which has as many as 128 filters. A shortcut is created from the sixth convolution layer to the eighth layer.

After feature extraction by the convolution layer, there is a dropout layer to avoid overfitting [21]. Next is the layer of neural network for classification that is fully connected layer size 1024 and feature pool. Proposed Residual CNN structure can be seen on figure 5.

For initialization prior to entering the training phase, this research uses Orthogonal methods that can overcome the learning dynamics of deep learning compared to Gaussian [22].

This research uses L2 regularization because L2 has more efficient computation than L1 [23]. For each layer convolution in this research it uses leaky rectifier units as its nonlinearity to accelerate convergence [24].

1. Result

A. Momentum Optimization Function

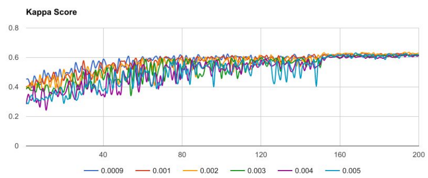

Figure 6. Kappa Score for Momentum

Figure 7. Validation Loss for Momentum

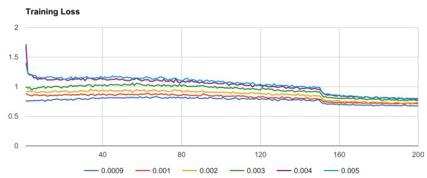

Figure 8. Training Loss for Momentum

For Momentum optimization function, there is no significant difference for some learning rate if the epoch is above 160. Based on figure 8, the smaller the learning rate the smaller the training loss.

B. Nesterov Momentum Optimization Function

For Nesterov Momentum optimization function, there is no significant difference for some learning rate if the epoch is above 160. Based on figure 11, the smaller the learning rate the smaller the training loss.

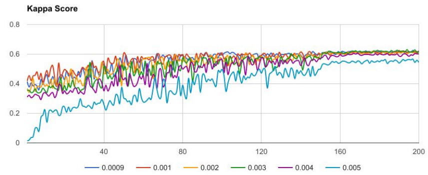

Figure 9. Kappa Score for Nesterov Momentum

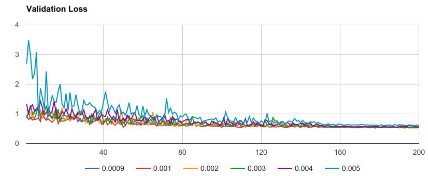

Figure 10. Validation Loss for Nesterov Momentum

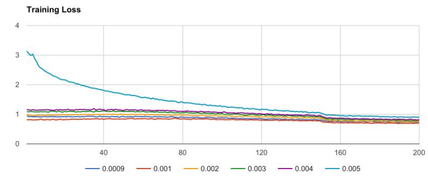

Figure 11. Training Loss for Nesterov Momentum

C. Adagrad Optimization Function

For Adagrad optimization function, there is no significant difference for some learning rate if the epoch is above 100.

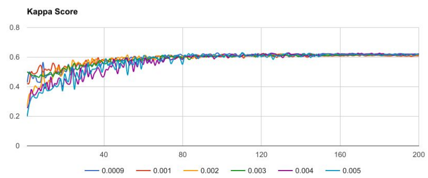

Figure 12. Kappa Score for Adagrad

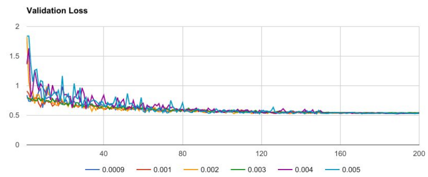

Figure 13. Validation Loss for Adagrad

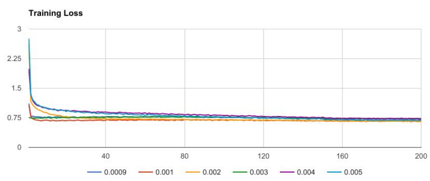

Figure 14. Training Loss for Adagrad

D. Comparison Between 3 Optimization Function : Momentum, Nesterov Momentum and Adagrad

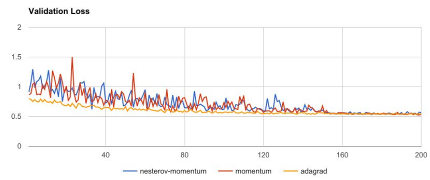

Figure 15. Kappa Score

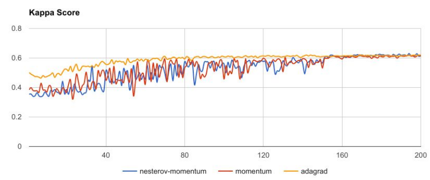

Figure 16. Validation Loss

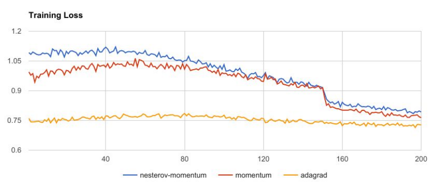

Figure 17 Training Loss

Adagrad optimization function has a smaller loss than the momentum activation function and the momentum nesterov. In addition, the adagrad optimization function is also faster to converge than momentum and nesterov momentum. Therefore it can be concluded that the adagrad optimization function gives the best result compared to momentum and nesterov momentum.

TABLE I. Dataset Distributions

Network	Kappa Score
Residual CNN	0,51049
CNN [20]	0,4398

The result of diabetic retinopathy classification can be seen on Table 2. Residual CNN increase the kappa score from CNN[20]. The increase obtained is reaching 0.07069. There is a difference in the number of datasets used for validation in this research with prior research. Previous studies [20] used 5000 images for validation while in this research we used 39424 images from the original image data.

2. Conclusion

A. Conclusion

In this research Residual Convolutional Neural Network method has been successfully applied to classify diabetic retinopathy disease. The preprocessing performed is one part of the methodology to detect diabetic retinopathy quite well by having a high kappa score.

The overall methodology in this research starting from the preprocessing stage, augmentation and the proposed network structure gave better results to increase the kappa score by 0.07069 to 0.51049 compared with the methodology performed by Harry Pratt [20].

The methodology used in this research also reduces the computation by resizing the image into 112x112 which is 4x smaller than 512x512[20]. With the reduced computation, the training time also increased 30 times faster from 350 hours to 8-10 hours compared from previous research by Harry Pratt[20].

B. Discussion

The EyePACS dataset has a much greater challenge than previously published such as diaretDB0, DRIVE and STARE. This is because the noise in the dataset varies from lighting noise, different image resolutions and different retinal shape (due to the round retinal structure being cut off by the shape of the box image). In addition, another problem arising from the EyePACS dataset is the number of samples in each class that are very unbalanced.

Deep learning requires a lot of training data to train its complex and deep networks. One of the deep learning obstacle to entering the health world is because of the limited amount of sample data. This is shown in previous retinal image dataset which less than 100 images. With this EyePACS dataset, the number of samples reach 80,000 images provides opportunities for deep learning to contribute to the problem of diabetic retinopathy detection.

Preprocessing is an important step if datasets have very much noise. Pre-preprocessing stages also need to be reviewed from the type of noise in the dataset. In this research, rotation and translation is a very necessary preprocessing in terms of the differences in blood vessels of each retina.

Augmentation needs to be done if the dataset has an unbalanced number of samples in each class. The augmentation technique is expected to represent the variation of data in a class, in order to avoid underfit during the testing process. In this research augmentation needs to be done so that the network can learn the character of each class with a balanced.

C. Future Work

The CNN Residual Method has successfully detected diabetic retinopathy although it is still in fairly low kappa values. There are several things that can be developed or improved to improve the value of this unsatisfactory kappa.

The CNN Residual Method has successfully detected diabetic retinopathy although it still receives low kappa values. There are several things that can be improved to get a higher kappa value

Preprocessing techniques can be improved for example by adding a channel of blood vessel segmentation to the retinal data input. This may increase the kappa's value considering retinal bleeding is a sign of diabetic retinopathy. Additionally, the added channel may be an exudates channel which is also a sign of diabetic retinopathy.

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