Study on Machine Learning for Diabetic Retinopathy Disease Grading

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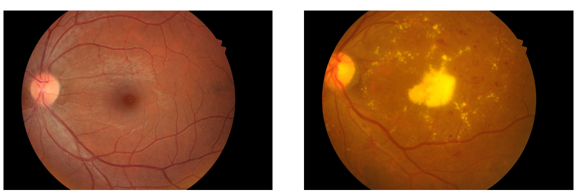
I. INTRODUCTION

Diabetes mellitus has been found as worldwide disease that continues to grow in the future. The average number of estimated growth for people with diabetes developing countries from 2010 to 2030 is around 69% [1]. This disease also complicates to diabetic retinopathy, which potentially drives blindness in the adult in 20-69 age group [2]. Thus, the normal screening process to perform early detection of diabetic retinopathy is important to anticipate the treatment for the disease. However, the screening process needs experts' effort and a hefty amount of time. This can be easily aided by automatically grading of the diabetic retinopathy using computers. Using retinal fundus images of the subjects, computers can perform computer-vision based machine learning tasks to identify the grade of diabetes. The sample of the healthy and severe diabetic retinopathy disease fundus image can be seen in Figure 1.



(a) (b)

Fig. 1. Sample retinal fundus image with (a) no apparent diabetic retinopathy and (b) severe diabetic retinopathy

Several studies on automated detection and grading of diabetic retinopathy involve methods of feature extractions and machine learning, i.e. t-SNE with bagged ensemble classifiers (BEC) [3], lesion feature extraction with neural network [4], convolutional neural network without feature extraction [5], deep feature learning with decision tree classifier [6], and transfer learning-based convolutional neural network [7]. Non-deep learning classifiers [3][4][6] require some features to be extracted first, while deep learning based classifiers [5][7] do not need preprocessed features to perform the classification. This is because convolutional neural networks, which is well-known for image based deep learning tasks, only takes whole full image as its input rather than few meaningful attributes that used by classical machine learning methods. However, some deep learning methods needs a large amount of dataset and significant time to train their model, which can be put as disadvantages regardless of their high performance.

On the other hand, all of the learning methods requires image preprocessing before going to feature extraction or classification step. The image preprocessing studied for diabetic retinopathy disease grading ranges from simplest one such as resizing, grayscale color transformation, data augmentation [3][5][6], auto-cropping, contrast adjustment and normalization [4][7]. Effects of each preprocessing method are proved to be useful to help improve the quality of diabetic retinopathy grading.

Thus, in this study, we will propose an investigation about the diabetic retinopathy grading using different machine learning and image preprocessing methods. We will try to see if there is any trade-off between the quality of the model according to their training and execution time. Dataset used in this study is the IDRID dataset [8], which can be considered new and still rarely used in known diabetic retinography research. We will discuss about the performance regarding the quality of the model and the efficiency.

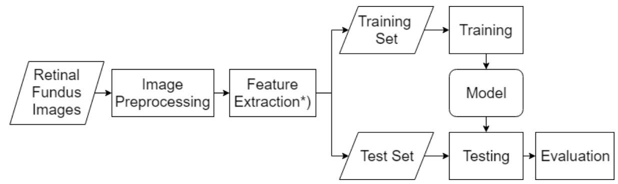


Fig. 2. Basic implementation flow for proposed method

II. PROPOSED METHOD

Our basic work flow for the implementation of machine learning for Diabetic Retinopathy disease grading is presented in Figure 2. However, deep learning models will not perform feature extraction, thus they will directly train and test using after the image preprocessing step. Each process will be explained in the following subsections.

A. Image Preprocessing

Based on research that conducted in [9], we will use the Fractional Max-Pooling to obtain retinal fundus image that used for feature extraction. These are the steps that we perform in preprocessing phase:

1) Rescale the images to have the same radius (300 pixels or 500 pixels)
2) Subtracted the local average color and mapped into 50% gray
3) Clipped the images to 90% size to remove the boundary effects

B. Feature Extraction

After the image preprocessing step, we will try to extract attributes that explains the image instead of raw pixels. In

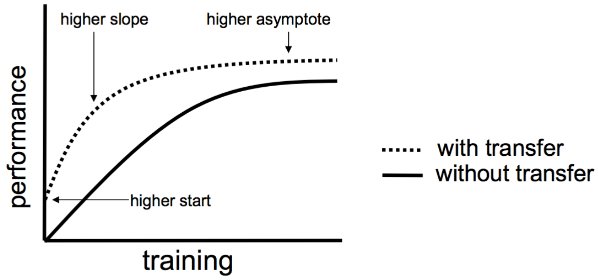


Fig. 3. Performance Comparison of Transfer Learning

this case, we will use combination of Principal Component Analysis (PCA) [10], t-Distributed Stochastic Neighbor Embedding (t-SNE) [11], and their combination.

Both PCA and t-SNE will reduce the features from the full dimension of the images to only a handful meaningful features. Thus, these extracted features capture the characteristics of the diabetic retinopathy severity.

C. Non-Deep Learning-Machine Learning Methods

We will perform ensemble machine learning method for the diabetic retinopathy using previously extracted features. We will use combination of two different classifiers: Support Vector Machine [12] and Decision Trees [13]. We extend those classifiers to be more robust using bagging style ensemble methods [3]. This ensemble method will assign the predicted label of each instance by the majority vote of its member classifiers.

D. Convolutional Neural Network

Finally we will examine the Diabetic Retinopathy dataset using Convolutional Neural Networks (CNN). It has been proved that CNN is the most suitable deep learning architecture for image classification.

Instead of training a deep network from scratch, we will use a model trained on a different domain (such as ImageNet) and adapt it for Diabetic Retinopathy dataset. Pre-trained model has learned to pick out features from images that are useful in distinguishing one image (class) from another. The network contains convolution blocks with activation on the top layer that defines complex functional mappings between inputs and response variable, followed by batch normalization after each convolution layer [7]. Figure 3 shows how transfer learning approach achieves a better performance compare to traditional model. Moreover, it reduces significantly the training process since we don't need to train all component within the network.

III. DATASET

The dataset used in this research is Indian Diabetic Retinopathy Image Dataset [8] of Diabetic Retinopathy grading. This dataset contains 516 images with 5 different severity of DR, which 0 stands for no DR and 4 for severe DR. Those 516 images are separated into 413 images of training set and 103 test set.

IV. EXPERIMENTAL SETUP

In this study, we will perform the classification of diabetic retinopathy grading case using different feature extraction and classification techniques as described before. We will experiment using the variation of feature numbers and classification methods (deep learning and non-deep learning approach). All of the modules will be implemented in Python.

V. EVALUATION METRIC

To measure the quality of our prediction model, we will use the Mean Squared Error (MSE). MSE will measure how far a single predicted label $\hat{y}_j$ to its ground truth y_j are apart. The formula of MSE for dataset with N instances is described by Eq.1. We use MSE as the labels have the value from 0 to 4 where each value corresponds to severity in the term of rank.

$$MSE = \frac{1}{N}\sum_{j=1}^{N}(y_j - \hat{y}_j)^2 \tag{1}$$

Additionally, we will also measure the time needed to preprocess, train, and estimate the grade of the diabetic retinopathy on whole dataset.

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