Project Proposal: Diabetic Retinoplasty Detection Using Convolutional Neural Networks

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Abstract

Diabetic retinopathy is a disease where the retina of the eye is damaged as a result of diabetes and if left untreated, can eventually lead to blindness. Using data made available by the California Healthcare Foundation and EyePACS as part of a competition hosted by Kaggle [6], we plan to explore diabetic retinoplasty detection using techniques borrowed from computer vision, signal processing, pattern recognition, and machine learning. Specifically, we will apply convolutional neural networks to the problem.

1. Introduction and Problem Statement

Diabetic retinopathy (DR) is a disease of the eye where the blood vessels of the retina, the light-sensitive area located in the back of the eye, are damaged from diabetes, a metabolic disease characterized by the body's failure to produce or properly interact with insulin [10] [8]. If left untreated, diabetic retinopathy can lead to blindness. In fact, diabetic retinopathy is the number one cause of blindness in the working-age population in developed countries, currently affecting over 93 million people [6]. The current method for detecting diabetic retinopathy requires specially trained clinicians carefully examining fundus photographs of the retina, a very time-intensive, human-centric process. As a result, the California Healthcare Foundation has sponsored a Kaggle competition to automate this process, and we have elected to participate in this competition [6].

The goal of the Kaggle competition is to take a high-resolution image of the retina as input and output a predicted score based on how a trained clinician would rate the severity of the disease. The severity is rated as belonging to one of the following classes: “No”, “Mild”, “Moderate”, “Severe”, or “Proliferative” DR.

2. Literature Review

A great deal of work has been done on the topic of automatically analyzing digital images of eyes for diabetic retinopathy. Walter et al. focused on detecting retinal exudates, fluids emitted within the retina, as a first step for diagnosis of DR by looking at variations in gray-level, finding contours using morphological operators, and applying a segmentation algorithm [11]. Exudate detection was a focus of Zhang et al. as well. Similar to Walter, they used a morphological segmentation algorithm but performed more complex pre-processing by normalizing and denoising the image while also detecting image artifacts and reflections. A random forest algorithm was used for classification [13].

Franklin and Rajan were another team to explore exudate detection [2]. Their contribution was to use the Luv colorspace and apply feature extraction techniques borrowed from image processing. A neural network was used for binary classification on a per-pixel level. Like Franklin, Gardner et al. used an artificial neural network to train a classifier, but instead of only focusing on only exudates, they tried to predict whether image patches represented normal eye tissue, blood vessels, exudates, or hemorrhages [4].

Sinthanayothin et al. focused on detecting DR before it lead to full blindness. They pre-processed color images of the eye, identified landmark points (namely, the optic disc, blood vessels, and the fovea), and then performed segmentation of lesions related to DR [9]. While Gardner focused on detecting non-proliferative DR, Welikala et al. focused on the opposite case. One key feature for proliferative DR is neovascularization, “the growth of abnormal new vessels” [12]. Welikala used a line operator to detect lines in the image and segment blood vessels. They extracted features along these vessels and used an SVM to classify vessels as “pre-existing” or “new” [12].

Ganesan et al. extracted features using trace transforms and then applied SVMs and probabilistic neural networks for detecting early stage DR [3]. Trace transforms are generalizations of the radon transform, and the mathematical details can be found in [3]. Antal and Hajdu examined combining six existing automated DR screening systems and classifiers into one system using an ensemble of classifiers [1]. A survey on other existing techniques and systems for various stages of the DR detection pipeline was authored by Mookiah et al. [7].

3. Methodology

3.1. Technical Details

We are developing our system in Python. We are relying on the OpenCV and Caffe libraries. Our solution is hosted on Amazon EC2.

3.2. Dataset

The dataset consists of a large set of high-resolution retina images provided by the California Healthcare Foundation and EyePACS. There are several inconsistencies among the images that must be controlled. These include differences in lighting, model, and type of camera. According to the California Healthcare Foundation, images may contain artifacts, be out of focus, be underexposed, be overexposed, or be taken from one of two viewpoints: anatomically or inverted (what one sees during a typical live eye exam). A left and right field is provided for every subject.

Our training dataset consists of 35,127 images of various size, quality, orientation, eye positioning, and exposure. The test/validation dataset consists of 53,577 images.

3.3. Data Pre-Processing

Image pre-processing is required as the images come from different models and types of camera and as a result, may have differing image dimensions and different image quality. Some images are inverted while others are shown anatomically. We will require a robust mechanism for unifying image sizes, centering the eyeballs, and dealing with other miscellaneous noise and variance inherent in the image classification problem (*e.g*. differences in illumination and contrast).

3.4. Feature Extraction and Classification

We plan on investigating using convolutional neural networks (CNN) for learning and extracting features as well as for classification. We are using the Caffe library with Python bindings for working with convolutional neural nets [5]. CNNs have been proven to be very effective tools for recognition- and detection-related tasks in computer vision. However, CNNs require careful design decisions and tuning of hyper-parameters. Some of the issues we will have to deal with as we progress include:

- Designing the network architecture (*e.g*. depth of the net, the size and types of layers, size and number of filters, pooling method, activation layer type, loss type, output layer classifier type, etc.)
- Selecting and tuning the optimization method for back-propogation
- Reducing overfitting (*e.g*. using dropout)
- Dealing with issues related to computationally heavy tasks (*e.g*. using the GPU for training)

3.5. Experiments and Evaluation

We plan to first focus on smaller subsets of the dataset as we design our network architecture and eventually grow to working with the whole dataset. We will split the training set provided by Kaggle into a training and validation set, and only use the test set with our final model. We will evaluate our model on the metric provided by Kaggle as well as with standard metrics used in machine learning. The Kaggle competition performance metric is described below.

Each training image is labeled by a pair of graders with score i belonging to a human grader and j belonging to an automated grader. These scores fall in $\{0, 1, 2, 3, 4\}$. The difference in scores is calculated as

$$w_{i,j} = \frac{(i-j)^2}{(N-1)^2}$$

where N is the total number of possible combinations of scores. Histograms of the number of witnessed score combinations O and expected ratings for each score combination E are computed, and the evaluation criteria, the quadratic weighted kappa, is computed as:

$$\kappa = 1 - \frac{\sum_{i,j} w_{i,j} O_{i,j}}{\sum_{i,j} w_{i,j} E_{i,j}}$$

We will also explore other metrics such as the traditional accuracy rate.

4. Timeline and Plan

- Proposal and Literature Review **March 18**
- Setup development environment and download images to server: **March 18** - Kevin
- Image pre-processing: **March 21 - April 1**
- Design and implement prototype CNN: **April 2 - 8**
- Tune and modify CNN: **April 9 - 22**
- Obtain results from test set and submit code to Kaggle: **April 23 - 25**
- Finish writing report (add implementation details, results, discussion, and conclusion) **April 26 - May 1**
- Final project including presentation **May 2 - 5**

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