The Use of Deep Learning Algorithms for the Detection of Diabetic Retinopathy

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1 Introduction

Diabetic retinopathy (DR) is a medical condition that causes damage to the eye's retina due to diabetes mellitus [1]. Worldwide, there are over 450 million diabetic patients that are at risk for the disease [2]. DR is the leading cause of blindness in the working age population in the United States, and thus, detection through the use of novel artificial intelligence algorithms serves to inform clinical treatment of this disease [3].

The detection of retinal damage in high-risk diabetic patients can assist with clinical decision making, where there are no clear early warning signs for diagnosis [3]. At present, clinicians must examine the patient in-person through a dilated eye examination in order to screen for DR. In many parts of the world, a dilated eye examination is not available since the process can be costly, time-consuming and require medical photograph graders that are unable to keep pace with patient volume [2].

Features of the retina, such as blood vessels, can be extracted to study the extent of the disease's spread. Through the use of an automated tool for screening of retinal fundus images, we propose a detection process that can be made more efficient, by accelerating disease detection and thus, treatment. Deep learning strategies have been implemented (such as Google's work in diabetic eye disease deep learning and computer vision) [2].

2 Background

2.1 Biomarkers

The medium is the retina of the eye. Clinically, the back of the eye must be examined and rated for disease presence and severity. Disease severity is ranked by the type of lesions present, including microaneurysms, hemorrhages and hard exudates. The presence of lesions can indicate that the eye is bleeding or leaking fluid, as can be seen in Figure 1. [2]

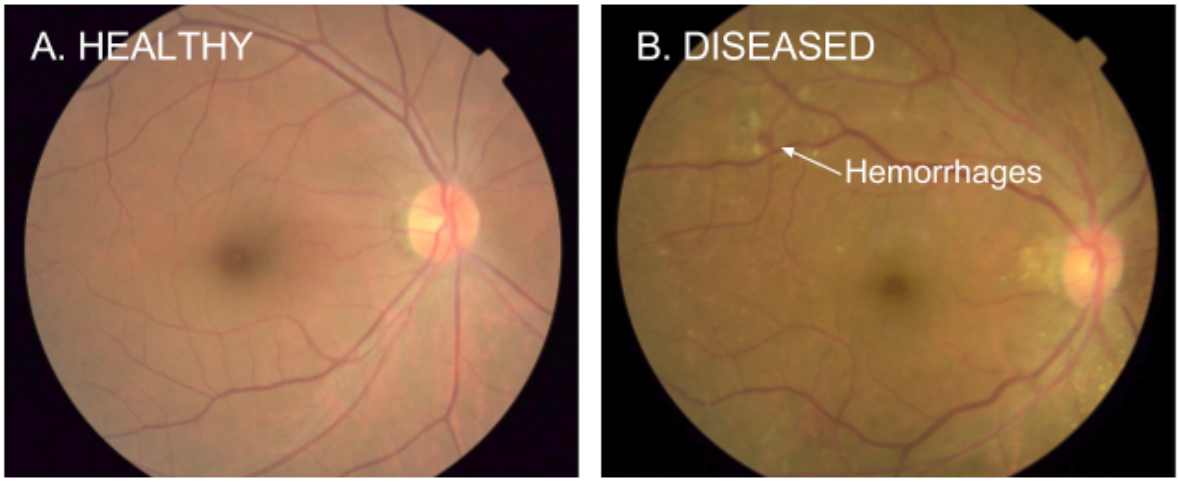

Figure 1: (A) Healthy retina, (B) Retina with hemorrhages present [2]

DR can be subclassified into proliferative and non-proliferative pathology subtypes [1]. Non-proliferative DR is the most common, early stage of DR marked by the presence of edema and hard exudates, which is lipid that has leaked from the blood vessels. Additionally, the patient will typically experience central vision blurring due to the presence of the hard exudate at the central part of the retina. During later stages of the disease, called proliferative DR, there is increased presence of abnormal blood vessels and scar tissue on the retina's surface. Vitreous hemorrhaging can occur at this stage when the scar tissue attached to the vitreous humor begins to pull at the blood vessels and cause them to bleed. This hemorrhaging can lead to sudden vision loss in the patient. Usually, this hemorrhaging will heal on its own, however, the progression of the disease is marked by increased hemorrhaging that can severely affect the quality of life of the patient. Thus, it is crucial to detect and classify the current state of the disease, such as whether it is proliferative or not. Through the image capture of the retina, and specific image classification that relies on distinct features of the retina, such as the presence of abnormal blood vessels that mark the proliferative diabetic retinopathic patient, image classification techniques can be used to help quickly assess the disease progression in the patient. Although treatments exist for both stages of the disease, early detection is the best means of reducing the progression of vision loss. Using high resolution retina images from the left and right field of the subject, an automated analysis system will be created that can classify each image as shown below:

0	no DR
1	mild
2	moderate
3	severe
4	proliferative DR

2.2 Artificial Intelligence

Artificial intelligence is a subdiscipline of computer science that studies a specific intelligence generated by machines, unlike natural human intelligence. The intelligent agents are studied for their potential to learn or problem solve, akin to human cognitive processes [4]. Learning is conducted by splitting the data into train-validate segments and having the model ”train” on samples of data that are then compared to ”labels” to validate the model.

Deep learning, a type of artificial intelligence technique, uses multi-layer neural networks that takes an input from a previous layer and refines based on algorithms that improve accuracy and minimize error. The network ”learns” to perform a specified task [5]. In medicine, deep learning can be used to detect medical anomalies in radiology images or features in ultrasounds. In this project, images will be classified by neural networks to diagnose DR.

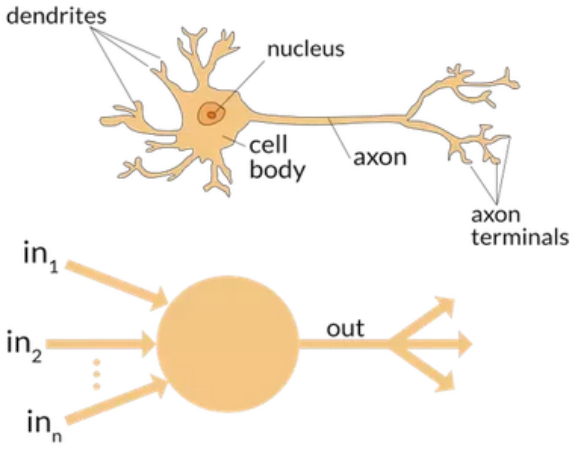

Figure 2: Simplified model of a human neuron as a basis for simple neural network [5]

A neural network was initially modeled after the brain’s neuronal organization, shown in Figure 2. Neural networks today can conduct parallel distributed processing. [5]

2.3 Training Procedures and Data Input

The APTOS 2019 Blindness Detection data set of size 3662 images will be used [6]. For each training sample, a diagnosis will be made that categorize the image at 0, 1, 2, 3, or 4 according to the stated classifications.

```
from PIL import Image
im = Image.open(df['path'][1])
width, height = im.size
im.show()
```

Figure 3 shows a sample image.

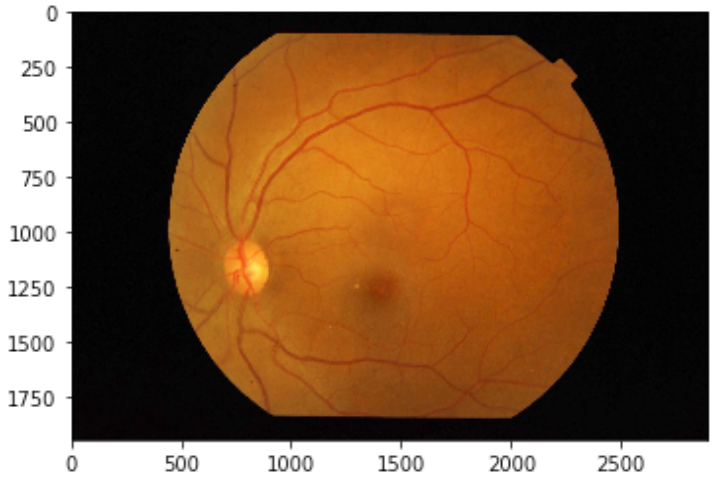

Figure 3: Example image from the dataset

2.4 Image Acquisition

Retinal images can be captured using a retinal camera called the Topcon NW400 shown in Figure 4 [7]. A camera has silicon sensors that are composed of photosensitive pixels (”pixel element”) that detect photons. Depending on the angle of view, spatial, tonal and temporal sampling occurs whereby photons are converted into photoelectrons via the photoelectric effect. Electrons are released and stored in a potential well during the exposure, which is proportional to the number of photons that hit the sensor. As the electric charge accumulates, the analog voltage is digited by an analog-to-digital converter, produces a digital image. [8]

Once the doctor uploads the patient’s images to a cloud server, our software will analyze the images and provide the doctor with a diagnostic evaluation. TopCON is fully automated,

utilizing auto-focus and auto-capture for produce high resolution color images of the retina. A color sensor captures 45° field of view, with 9 internal fixation targets for wide angle retina views. The Topcon facilitates USB storage of images and well as uploading to cloud servers or electronic medical records. [9]

Figure 4: Topcon NW400 retinal image acquisition system [9]

3 System Description

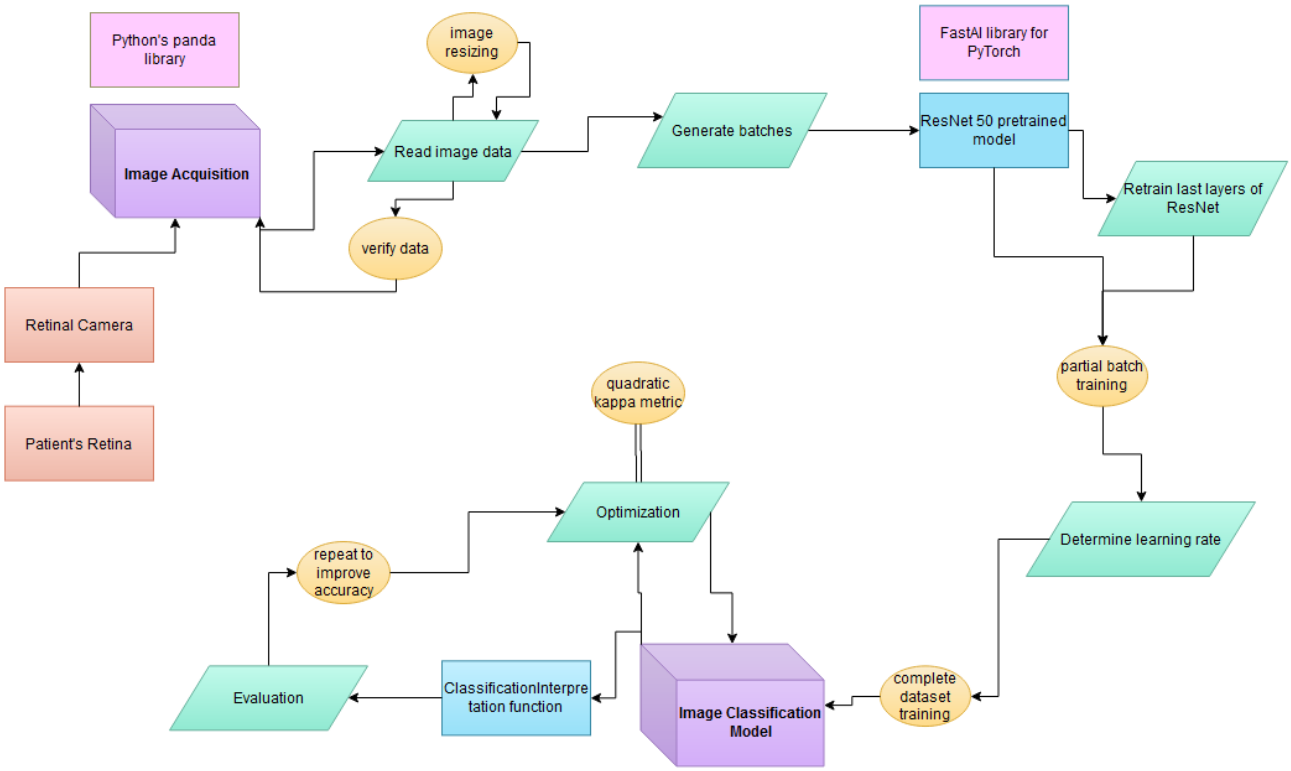

Figure 5: Image Classification System Design

The design of the image acquisition and classification system, including use of retinal camera and deep learning libraries, is shown in Figure 5.The FastAI deep learning library for PyTorch will be used to build the image classification system. An example of the training code is shown below:

```
learn = cnn_learner(data,
    base_arch=models.resnet50, metrics = [quadratic_kappa])
```

9 image batches of the dataset will be created to feed into PyTorch framework's neural network to process the data. The ResNet50 architecture is used. Pretraining occurs on the ImageNet database (depth of 152 layers) to enhance deep learning as learning residual functions with reference to layer inputs.

Cohen's kappa coefficient will be used as a metric to determine inter-rater agreement of the categorical classification. Pseudo-code of implementation is as follows:

```
from sklearn.metrics import cohen_kappa_score
```

```
def quadratic_kappa(y_hat, y):
    return torch.tensor(cohen_kappa_score(torch.round(y_hat),
    y, weights='quadratic'), device='cuda:0')
```

Only the last layers of ResNet50's pre-trained neural network will be retrained. PyTorch's learning rate finder will be used on a short run to improve performance and ensure fast convergence.

```
learn = cnn_learner(data, base_arch=models.resnet50,
metrics=[quadratic_kappa])
learn.lr_find()
```

Next, the network will be trained and batches will be plotted against loss. Classification will occur was mentioned in the 0, 1, 2, 3 or 4 numbered categories, using if-else structure, shown in the below code:

```
def predict(self, X, coef):
        X_p = np.copy(X)
        for i, pred in enumerate(X_p):
            if pred < coef[0]:
                X_p[i] = 0
            elif pred >= coef[0] and pred < coef[1]:
                X_p[i] = 1
            elif pred >= coef[1] and pred < coef[2]:
                X_p[i] = 2
            elif pred >= coef[2] and pred < coef[3]:
                X_p[i] = 3
            else:
                X_p[i] = 4
        return X_p
```

FastAI's ClassificationInterpretation class will be used to interpret model performance, such as the top losses metric.

```
interp = ClassificationInterpretation.from_learner(learn)
losses,idxs = interp.top_losses()
len(data.valid_ds)==len(losses)==len(idxs)
```

Furthermore, the model can be evaluated for accuracy using the following code:

```
interp = ClassificationInterpretation.from_learner(learn)
```

```
losses,idxs = interp.top_losses()
len(data.valid_ds)==len(losses)==len(idxs)
```

4 System Accuracy

Quadratic weighted kappa was used to score the model (also known as Cohen's kappa, κ). κ-metrics is commonly used to assess measure of similarity between categorical ratings. κ varies from -1 to 1, being 0 for random agreement between raters (that is, the agreement expected by chance), 1 for complete agreement between raters and -1 for complete disagreement between two raters.

The possible categorical scores for a given image in the set are 0, 1, 2, 3 or 4 (see Table 2.1). Every image is described by a tuple (e_A, e_B) where e_A is a true score (Rater A) and e_B is score predicted by the model (Rater B). To evaluate κ, a 5×5 confusion matrix O of true and predicted scores was constructed. $O_{i,j}$ then corresponds to the number of images that scored i with Rater A and j with Rater B. A 5×5 wight matrix W is then constructed based on the proximity of scores i and j.

A 5×5 matrix of expected values is constructed as $E = v_A \otimes v_B$, where $\langle \otimes \rangle$ is vector outer product, and v_A and v_B are two 5-element vectors with v_i being the number of elements with score i given by the specified rater (A or B, respectively).

Then, the quadratic weighted similarity score is

$$\kappa = \frac{\sum_{i,j=1}^{5} W_{i,j} O_{i,j}}{\sum_{i,j=1}^{5} W_{i,j} E_{i,j}} \tag{1}$$

The model was evaluated on to have to κ score of 0.88.

5 Possible System Shortcomings

The dataset labels are imbalanced, since most of the labels are 0 (no DF) relative to the other levels. Furthermore, only 3662 images were used, which is a small amount of data. Future work can look to increase the number of images used during training and adjust testing parameters to improve system accuracy. Furthermore, the use of a 2D fundus image does not consider other variables that contribute to diagnosis, which can be improved through 3D imaging technology [2]. By incorporating the work of this project into 3D images, machine learning models can be trained to make high accuracy diagnostic classifications of DR.

6 Conclusion

Diabetic retinopathy (DR) is a disease with the potential to affect millions of individuals worldwide. Through the design and implementation of an automated system of retinal image classification using neural network techniques, efficiency and ease of DR detection and diagnosis can be improved. By improving detection, patients can receive treatment earlier and thus mitigate the retinal damage that occurs due to the disease. Thus, our proposed work is important to the development of efficient disease detection and draws upon the cutting-edge fastAI library using PyTorch to efficiently optimize and implement deep learning algorithms.

References

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