Diabetic Retinopathy Detection Using Machine Learning

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Abstract

Diabetic retinopathy is a disorder induced by long-term diabetes that can result in total blindness if not addressed. As a result, early detection of diabetic retinopathy is critical, as is the medical treatment to prevent its adverse effects. Manual ophthalmologist detection takes longer and produces considerable discomfort during examination. Machine learning has recently become one of the most popular strategies for improving performance in a variety of sectors, including medical picture analysis and classification. As a result, an automated system aids in the early detection of diabetic retinopathy. Using a combination of neural networks, this research offers the extraction of exudates, haemorrhages, and micro-aneurysms and classification by machine learning.

Keywords: Diabetic Retinopathy (DR), Neural Network Algorithm, Retinal Dataset

1. Introduction

Diabetic retinopathy is an eye complication caused by hyperglycemia, also known as diabetes. It can cause vision loss and, in extreme cases, total blindness. Blurred vision, dark areas of vision, cloudy eyes, and difficulty recognizing colors are early symptoms of diabetic retinopathy. The early detection of diabetic retinopathy is critical in preventing total blindness. Around one-third of the world's estimated 285 million diabetics have diabetic retinopathy. The global prevalence of diabetic retinopathy is expected to rise from 126.6 million in 2010 to 191 million by 2030. Non- proliferative diabetic retinopathy (NPDR) is a form of early retinal disease characterized by small red spots. The appearance of various

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types of lesions on retinal images indicates the presence of DR. These are microaneurysms (MA), haemorrhages (HM), soft and hard exudates.

1.1 Haemorrhages

Bleeding Appears as large spots on the retina, over 125 µm in size, and irregular edges. Flame (surface HM) and Stain (deep HM) are the two types of HM.

1.2 Micro-Aneurysms

Due to the weakness of the vessel wall, a small red circle appears on retina, and it is the sign of DR. It is less than 125 µm in size and has sharp edges.

1.3 Exudates

There are two types, which are soft and hard exudates.

1. Soft Exudates: “Also called cotton wool, it appears as white spots on the retina due to swelling of 4,444 nerve fibers” [5]. The shape is oval or circular.

2. Hard Exudates: “Pale-yellow spots appear on the retina due to Plasma leaks” [5]. They have sharp edges and are in the last layer of the retina.

2. Related Work

Garcia et al. CNN has proposed procedures to apply individually to both the right and left eyes (Alex net, VGGnet16, etc.). Preprocessing and expansion steps have been applied to the dataset to improve image contrast. The accuracy was 93.65 percent, the sensitivity was 54.47 percent, and the accuracy was 83.68 percent. The DR stage, on the other hand, was not specifically categorized by its work.

Hagos et al. Using the pre-trained Inception V3 framework, developed a model to classify images into two class of DR using Kaggle DR recognition challenge dataset consisting of 2500 fundus photographs. bottom. They used the SGD Optimizer on their models and got 90.9% accuracy and 3.94% loss.

[Farrikh Alzami, 2019] This diabetic retinopathy grade classification system is based on fractal analysis Random Forest and the MESSIDOR dataset. Your computer system segmented the image and used a function to calculate the fractal dimension. They couldn't tell the difference between mild and severe diabetic retinopathy.

[Qomariah 2019] Convolutional Neural Network and support Vector Machine classification of diabetic retinopathy and normal retina images (SVM). Exudate, bleeding, and microaneurysms are among the features. The proposed system was divided into two parts by the author. The first section used neural network-based feature extraction, and the second section classified using SVM.

H. Wang et al. The hard exudate lesions on the Eophtha and HEIMED records were detected by combining the properties of a handmade custom CNN with a random forest classifier. Clipping, colour normalisation, camera shutter changes, and candidate recognition using morphological configuration and dynamic thresholding were applied to these datasets. Following that, patches of size 32 * 32 will be gathered and expanded. To identify patch features, the custom CNN has three CONV layers, three pooling layers, and an FC layer. For the Eophtha and HEIMED datasets, this work achieved sensitivity of 0.8990 and 0.9477, and AUC of 0.9644 and 0.9323, respectively.

3. Dataset and Technique

3.1 Dataset

Using a publicly available Kaggle dataset, this study detected diabetic retinopathy. The database was built using images from publicly available records to detect retinopathy. There are 1000 images in the Kaggle dataset. 300 diabetic retinopathy images and 700 normal images are chosen from the total number of images. Exudate, bleeding, and microaneurysms were among the abnormal images chosen.

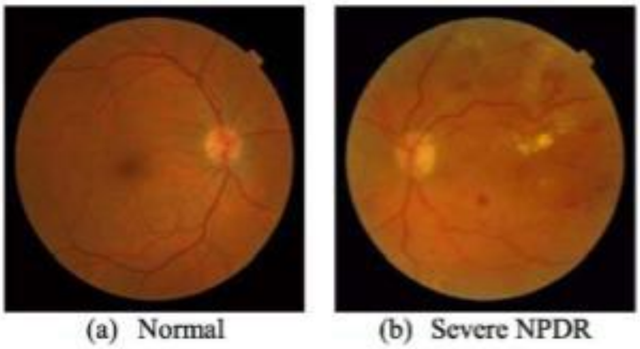

Figure 1. Normal image and an abnormal image

Appearance, number, distribution and size, exudate area, Microaneurysms and bleeding are all the factors present in DR as shown in Figure 1. Exudate is a bright area of yellowish appearance that is slightly different in color from the nipple. The ruptured blood vessels contain lipids and exudate appears.

3.2 Methodology

Dataset Analysis

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Image Preprocessing

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Feature Extraction

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Training & Testing

↓ ↓

Normal Abnormal

3.3 Pre-Processing and Feature Extraction

Image preprocessing to find exudate first converts the image from the dataset to an HSV image. Color space conversion transforms an image displayed in one color space into another. For red, blue, and green, the saturation and value are channelized to hue in the specified image. When converting RGB to HSV, From the RGB image, the extraction of yellow exudate is useful. Next, edge zero padding and median filtering are performed. Figure 2 shows the image before preprocessing, and Figure 3 as after image preprocessing.

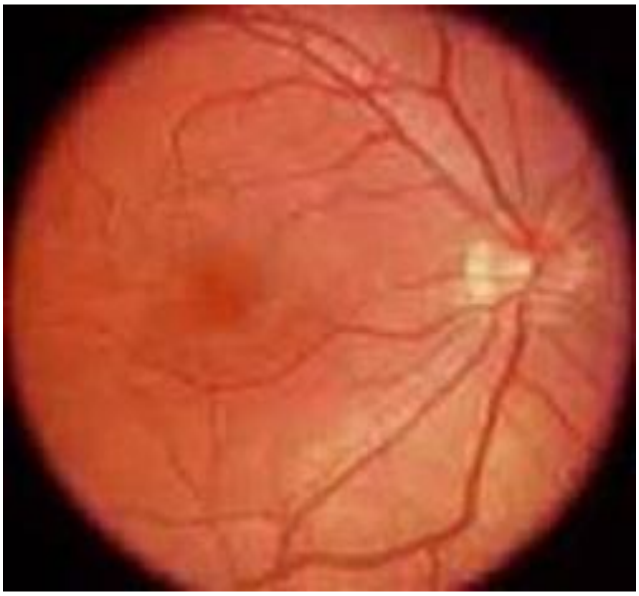

Figure 2. Before Preprocessing

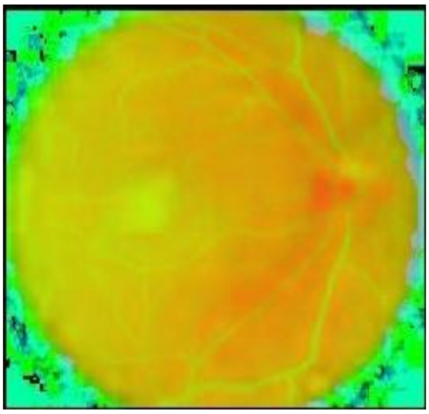

Figure 3. After Preprocessing

3.4 Feature Extraction

Binary classification uses two functions here. With the number of exudates as the first parameter bleeding and microaneurysms as the second parameter. Count the number of white pixels in the preprocessed one divide the image by the total number of pixels present in the image.

3.5 Model Training

Trained models with over 20 epochs. An epoch is a loop across a training dataset of a convolutional neural network. Training neural networks usually takes a lot of time. The model was trained with the ADAM optimizer. The optimizer is a technique or tool that adapts neural network properties such as learning rate and weights to minimize losses. ADAM is the best optimizer because it is very efficient and takes very little time to train the model. The model is trained with a cross-entropy loss function, an activated softmax layer, and a batch size of 16. A learning rate of 0.001, which is Adam's standard parameter is used.

3.6 Model Testing

The model was tested with a brand-new set of 200 retinal images that were not included in the 1000 images that the model was trained on. Image preprocessing and feature extraction are performed while the model is being tested. With 20 epochs, 91.5 accurate and loss 3.8%.

4. Performance Parameters

Accuracy: “Accuracy is the percentage of total accurate predictions which are based on the positive and negative classes” [1]

$$accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

where TP, TN, FP and FN are true positive, true negative, false positive and false negative respectively.

Recall/Sensitivity: "Sensitivity is also called TPR (True Positive rate)" [1], which can be calculated as follows:

$$recall = \frac{TP}{TP + FN}$$

Precision: "It is the ratio of a truly classified number of samples and the given sum of True positive and False positive" [1]:

Precision = TP/TP+FP

F1-Score: It is "the harmonic mean of recall and precision" [1]:

$$F1 = \frac{2\ (Precision)\ \ (recall)}{Precision + recall}$$

5. Results and Discussion

Table 1. Experimental result of the proposed work

Size of dataset	1000 Images
Optimizer used	ADAM
Class mode	Categorical
Epochs	20
Loss	3.8%
Accuracy	91.5%

The results suggest that the use of this model may be an effective method for early detection of diabetic retinopathy. They also suggest that such models can be developed to detect other eye-related medical conditions. This model produced an accuracy rating 0.8441, recall score 0.9147, f1 Measure score 0.8798. While this model looks like an easy way to identify the disease, it is not 100% and is an alternative for doctors as it can only be used as a way to help doctors diagnose diabetic retinopathy.

6. Conclusion

Diabetes is the fastest growing illnesses in recent years. According to studies, diabetics have a 30% risk of developing diabetic retinopathy. If the disease is not diagnosed early, it can lead to floater, blurred vision, and ultimately blindness. Manual diagnosis of these photographs is time consuming, complex and requires highly qualified professionals. A convolutional neural network model has been successfully created using the VGG19 framework that detects diabetic retinopathy and provides information on the severity of the disease. The accuracy of the model achieved is 92%. This model helps doctors diagnose the disease more quickly. Similar models can be developed to diagnose other diseases, especially those that affect the eye. This helps identify such illnesses early and avoid permanent blindness.

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