

An Automated Detection of Diabetic Retinopathy Using Convolutional Neural Network in ResNet-50

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# An automated Detection of Diabetic Retinopathy Using Convolutional Neural Network in ResNet-50.

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## Abstract

**Diabetic retinopathy** (**DR**) is a diabetes complication that affects retinal blood vessels and may lead to blurred vision or even blindness if not diagnosed in early stages. DR is mainly classified as NPDR (Non Proliferative Diabetic Retinopathy) and PDR (Proliferative Diabetic Retinopathy). This problem is occurring in millions of people worldwide. Generally, highly trained clinical experts examine the coloured fundus images to diagnose this disease. This manual diagnosis (by clinicians) is time consuming and error-prone. Therefore, an automated system can be aided to detect diabetic retinopathy quickly for determining the follow-up treatment to prevent blindness. Such automated systems are already developed using the application of machine learning and deep learning algorithms. But these automated systems are not cost efficient and require extensive computational resources. Our proposed work is focused on reducing the computational cost by efficiently using CNN algorithm in ResNet-50.

Keywords : Diabetic Retinopathy, Deep Learning, Convolutional Neural Network, Resnet-50, Proliferative Diabetic Retinopathy, Non Proliferative Diabetic Retinopathy.

### I. Introduction

According to International Diabetics Federation (IDF) Diabetics Atlas 2020, around 463 million people are affected by diabetics. The statistics shows increase of 38 million cases in past 3 years. As in 2017, it was reported 425 million. The IDF expects that number to rise to 592 million by 2035, when one in every 10 people will have the disease. Approximately 80% of the people living with diabetes are in low- and middle-income countries.

Diabetic Retinopathy (DR) is one of the major eye diseases that causes vision loss. People with diabetics are likely to develop this complication. Among diabetic patients one third of the people are expected to develop this complication. The diabetic patients have high blood glucose level because of their inability to produce insulin (a hormone produced by pancreas). Due to this, the tiny retinal blood vessels which nourish the retina are damaged. In response the human system attempts to develop new retinal blood vessels to maintain the nourishment. But these new retinal blood vessels are not developed properly. Hence there are weak and has a high probability of leaking and bleeding. As the condition progresses, patients may experience various symptoms from blurred vision leading to vison loss.

DR is mainly classified into two types such as non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR), where the Mild Non-proliferative Retinopathy in which microaneurysms occur (small areas of balloon-like swelling in the retina's tiny blood vessels). Moderate Non-proliferative Retinopathy stage occurs when blood vessels that nourish the retina are blocked. Severe Non-proliferative Retinopathy is a stage, when many more blood vessels are blocked, depriving several areas of the retina with their blood supply. These areas of the retina send signals to the body to grow new blood vessels for nourishment. Proliferative Retinopathy is the advanced stage, where new retinal blood vessels are developed to maintain nourishment. These new blood vessels are abnormal and fragile. By themselves, these blood vessels do not cause symptoms or vision loss. However, they have thin, fragile walls. If they leak blood, severe vision loss and even blindness can result.

### **II. Literature Survey**

In Table 1 previous work was summarized with respective accuracy and algorithms. In paper [1], proposed a deep learning approach for DR disease classification. After some pre-processing, computationally efficient CNN models were used to classify the disease in image dataset with 83% validation accuracy.

In paper [2], proposed a CNN based deep learning model. Several pre trained models were used to achieve a validation accuracy of 94%. In paper [3], they tends to use deep learning algorithms which automatically identifies the pattern and classifies the retina images into one of the five classes. CNN models were used to achieve a validation accuracy of 74%. In paper [4], they used various CNN architectures on images subjected to appropriate image processing techniques and thereby augmenting the detection of DR and classifying the severity. The validation accuracy of 82.5% was achieved. In paper [5], the Hierarchical pruning for simplification of CNN was proposed to classify DR. As a result, 97.3 % validation accuracy was achieved and the proposed hierarchical pruning can be employed to simplify other CNN structures as well. In paper [6], An ensemble of five DCNN models (Resnet50, Inceptionv3, Xception, Dense121, Dense169) were used to encode the rich features and improve the classification for different stages of DR. The experimental results show 70% validation accuracy. In paper [7], they used CNN and SVM for classification of DR and normal retinal images. The results of their experiments showed 95.83% validation accuracy. [8] Deep Learning for weak supervision of diabetic retinopathy abnormalities achieved 95% validation accuracy. In paper [9], they used CNN to classify fundus retinal images and accurately categorize them into five stages of the disease. As a result of their experiment, 71% validation accuracy was achieved. In paper[10], Two CNN are proposed to classify proliferative DR. The classification accuracy of 96.37% and 97.38% was obtained by using two CNN architectures.

| S.no | PROJECT NAME   | ALGORITHM       | EFFICIENCY        |
|------|--|-----------------|-------------------|
| 1    | DR classification using an<br>efficient CNN  | CNN             | 83%               |
| 2    | Deep DR: An Image guided<br>DR detection using attention<br>based deep learning scheme | CNN             | 94%               |
| 3    | Deep Neural Network for DR detection   | CNN             | 74%               |
| 4    | Deep Learning for detection<br>and severity classification of<br>DR                    | CNN             | 82.5%             |
| 5    | Hierarchical pruning for<br>simplification of CNN in DR<br>classification              | CNN and pruning | 97.3%             |
| 6    | A Deep Learning ensemble<br>approach for diabetic DR                                   | CNN             | 70%               |
| 7    | Classification of DR and<br>normal retinal image using<br>CNN & SVM                    | CNN and<br>SVM  | 95.8%             |
| 8    | Deep Learning for week<br>suspension of DR<br>abnormalities                            | CNN             | 95%               |
| 9    | Automated detection of DR  | CNN             | 71%               |
| 10   | Classification of proliferative<br>DR<br>Using Deep learning                           | CNN             | 96.37%,<br>97.38% |

### III. Dataset

In our work, we used publicly available Kaggle dataset for diabetic retinopathy to train and test our model. The images in the dataset was split into training and test. We used 70% of the images in the dataset for training and the remaining 30% of the images for testing. The images in the dataset are unbalanced and contains noises. Hence pre-processing is done to resize the images to achieve optimal results. The images were centered and cropped to a size of 220 x 220 pixels as shown in figure [1], this resolution was found to retain almost all the features of a fundus image.



Figure1: Cropped images.

# **IV. Proposed Methodology**

Our proposed work illustrates the development of Convolutional Neural Network (CNN) as shown in figure [2], takes the retinal images as input and predicts the presence of Diabetic Retinopathy (DR). Thus, CNN is a state-of-art method, because of its capability to bring out features in images without the need for complex pre-processing techniques. This study uses Resnet50 (Residual Network) which is one of the transfer learning often used in deep learning to predict objects in an image.





#### A. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) architecture usually consists of convolutional layers, pooling layers or subsampling layers, fully connected layers and the classification layer as shown in Figure [3]. CNN is a state-of-art method that has been proven the most productive neural network for image classification and object detection. CNN is the most widely used neural network for identifying the existence of Diabetic Retinopathy (DR) and classifying its severity in a fundoscopy. The primary task is to select an appropriate CNN architecture and fine-tuning its parameters to achieve optimal results. We decided to experiment with Resnet 50 model (pre-trained network). With the help of keras framework, running on top of a TensorFlow backend, the necessary Resnet50 architecture was implemented.



Figure 3: A classification layer of CNN.

#### B. ResNet

ResNet (Residual Neural Network) transfer learning was by Kaiming for the ILSVRC competition 2015. In Resnet the residual block was used successfully trained 152 layers with an error rate of 4.49% for a single model on the ImageNet validation set, and 3.57% error on test validation set. Even though it has lower complication the Resnet has better conduct. It is one of the most powerful deep neural networks and also achieved excellent generalization performance on other recognition tasks. Batch Normalization was used by ResNet at its core and it adjusts the input layer to increase the performance of the network. The problem of covariate shift is mitigated. There are many variants of ResNet architecture available some of them are ResNet-18, ResNet-34, ResNet-50, ResNet-101, ResNet-110. In our work to detect Diabetic retinopathy (DR), we are going to use *ResNet-50* which is one of the most vibrant networks on its own. ResNet50 uses an input size of 229 x 229.

#### C. ResNet-50

In ResNet50 architecture there are 4 stages. This module can take the input fundus images. We took the input size as 229 x 229. The initial convolution and max-pooling using  $7 \times 7$  and  $3 \times 3$  kernel sizes was almost used in all the ResNet architecture as shown in Figure [4]. Now in stage 1 the ResNet has three residual blocks containing of three layers each. The kernels size used in the convolution operation are 64, 64 and 128 respectively. Input size will be reduced to half in terms of height and width but the width of channel will be doubled. As we progress from one stage to another, width of the channel is doubled and the input size is reduced to half. ResNet50 is a deeper network which use bottleneck design. In every residual function F, the three layers are placed one over the other and have  $1 \times 1$ ,  $3 \times 3$ ,  $1 \times 1$  convolution. The first convolution layers are used to decrease and reconstruct the dimensions. At last, an Average Pooling layer continued by a fully connected layer will have 1000 neurons (ImageNet class output) in the ResNet50 network.



Figure 4: Architecture of ResNet50.

### V. Conclusions and Future Work

In this paper, we used Resnet50 (one of the CNN architectures) to detect diabetic retinopathy from fundus colourded images. We were able to attain a validation accuracy of 92% based on the results. More balanced data set with less noise and further pre-processing will increase accuracy. CNN models possess the

ability to understand the training images and learn from raw values of pixels. And still there remains a lot of work and experiments to improve our model to yield more accuracy. Future work includes experimenting on various CNN architectures with a more powerful GPU to obtain more accuracy in a short time and to compare the results between those CNN architectures.

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