Diabetic Retinopathy using Deep Learning

Chandresh Phirke[1] Divya Patidar[2] Gourav Sharma[3] Ritesh Khedekar[4] Kavita Namdev[5]
[1,2,3]Student [4,5] Assistant Professor
[1,2,3,4,5]Department of Computer Science and Engineering
[1,2,3,4,5]Acropolis Institute of Technology and Research, Indore, India

Abstract— Diabetes is a metabolic disorder or more precisely Diabetes Mellitus (DM) happens because of the high level of blood sugar or say blood glucose in the body. Eye deficiency also is known as Diabetic Retinopathy (DR) is created by disease Diabetes which causes major vision loss. For successful treatment of Diabetic Retinopathy, it is very important to perform early detection which is one of the most essential challenges of its proper treatment. Even for trained clinicians or popular labs, the classification task of retinal images is found to be a tedious task. In many adjacent subjects, for diagnosis and treatment of diabetic retinopathy, a Convolutional neural network (CNN) have been used successfully. On the ImageNet Large Scale Visual Recognition Competition (ILSVRC), Deep convolutional networks have been achieving high-performance results on image classification challenge. Inception-V3 model is an example of a Deep Convolutional image recognition model. The unique feature of Inception-V3 is the extraction of different sized features of input images convolution level which is performed using Inception modules. We have used a pre-trained Inception-V3 model in this work because its Inception modules have many advantages for Diabetic Retinopathy Detection.

Keywords: Deep Convolutional Networks, Inception Modules, Transfer Learning, Diabetic Retinopathy, Training Data Insufficiency

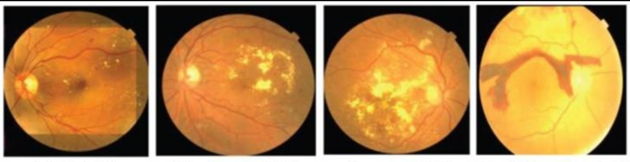
I. INTRODUCTION

A. *Diabetic Retinopathy*

Diabetic retinopathy happens when due to diabetes damage occurs to the retina and causes blindness. When millions of people across the globe are suffering from diabetes, estimated around 18-28% are prone to Diabetic Retinopathy, whose severity is classified into four categories.

Healthy Eye Fundus Image

– Mild non-proliferative retinopathy- This is the first stage that shows mild symptoms that most people ignore in this stage only microaneurysms occur.
– Moderate non-proliferative retinopathy- At this stage blood vessels lose their ability to transfer blood to all the regions due to their distortion and swelling with the progress of the disease.
– Severe non-proliferative retinopathy- This stage occurs when the retina is completely deprived of blood due to the increased blockage of more blood vessels.
– Proliferative diabetic retinopathy- This is the most advanced stage, in which growth features secreted by the retina activate proliferation of the new blood vessels.



Mild DR Moderate DR Severe DR Proliferative DR

Each stage has its own characteristics and particular properties, so doctors possibly couldn't take a number of them under consideration once, and thus make arise a possibility of incorrect diagnosis. So this results in the thought of the creation of an automatic solution for Diabetic Retinopathy Detection. The clinical grading process consists of detection of certain subtle features, like microaneurysms, exudates, intra-retinal hemorrhages and sometimes their position relative to every other on images of the Retina.

B. *Deep Learning*

Artificial intelligence (AI) may offer a solution to this problem. Deep learning (DL) can be used for an accurate assessment of unprocessed medical images to produce a prediction. Transfer learning is the re-training of deep learning models that are pre-trained on huge datasets. A convolutional neural network is a type of Deep Learning architecture that is more suited to work with multiple matrices such as images and videos. Deep Learning needs a huge amount of training dataset to correctly work and predict the output on unseen data. The absence of enough training data has been identified as one of the key challenges of applying Deep Learning in healthcare and other similar fields. Transfer learning, on deep convolutional neural networks, has gained traction due to the insufficiency of proper training data in building models. Transfer learning can be used to reduce the training data required and minimize the model training time.

Here transfer learning has been used on a Deep Convolutional Neural Network model that was pre-trained on a subset of the ImageNet's dataset. We train this neural network using a high-end graphics processor unit (GPU) on the Colab platform using the available Kaggle dataset and demonstrate impressive results, particularly for a high-level classification task. On the data set of 80,000 images used our proposed Neural Network model achieves a sensitivity of 94% and an accuracy of 72% on 1000 validation images.

II. Related Work

Many works have been done related to automatic DR detection in the last decade alone. Feature extraction based classification and DL has been used mostly to classify DR. A higher-order spectra technique was used in Acharya et al. to extract features from 300 fundus images and provided it to a Support Vector Machine classifier; it classified the images into 5 classes with a sensitivity of 82% and specificity of 88%.

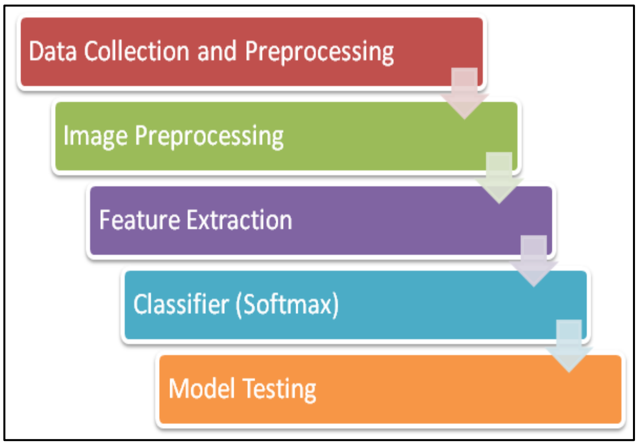
Traditionally the process involves three stages, preprocessing, feature extraction and image classification. Using feature extraction for classification needs expert knowledge and experience to set the right parameters in order to detect the specific features. Hence it becomes a time-consuming process that involves feature selection, identification, and extraction. It is known that Deep Learning especially the Convolutional neural network performs better than feature-based methods when it comes to classification.

Pratt et al. trained a CNN using a stochastic gradient descent algorithm to classify DR into 5 classes, and it achieved 95% specificity, 75% accuracy and 30% sensitivity using a training dataset that includes 70,000 fundus images. A Convolutional neural network was trained from scratch to classify fundus images from the dataset into different classes, and it scored a sensitivity of 96.2% and an accuracy of 66.6%.

The above processes were time-consuming because models were trained from scratch, to avoid the time and resource to such extent, Mohammadian et al. used transfer learning on Inception-V3 and Xception pre-trained models to classify the dataset into two classes by using data augmentation to balance the dataset, and was able to score the accuracy of 87.12% on the Inception-V3, and 74.49% on the Xception model. One research suggested that an Inception-V4 model-based Diabetic Retinopathy classification scored higher sensitivity as compared to human expert graders on 25,326 retinal images of patients with diabetes from Thailand.

The Kaggle dataset [8], which contains 35126 labeled fundus images has been most popularly used for Neural network-based classification of Diabetic Retinopathy research purposes. To solve the problem of medical training data insufficiency for DL, The proposed model was trained on a subsample of 3500 fundus images and tested it on 15000 previously unseen fundus images.

III. Methodology



A. *Data Collection and Preparation*

In this work, we have used the Kaggle DR detection challenge dataset. This dataset contains color fundus images. These images are labeled as 0,1,2,3 or 4 for normal, mild, moderate, severe and prolific DR, respectively. For model training and testing, we have used a smaller subset of size 2500 from the publicly available Eyepacs dataset that is uploaded on the Kaggle DR Detection challenge. We created two classes, healthy class, and unhealthy class, for model training and model testing. For model training, for the healthy class, we used 1250 images from normal fundus images dataset and for the unhealthy class, 250 images were selected each from mild, moderate, severe and prolific DR classes. For model testing, for the healthy class, we used 1000 images from normal fundus images dataset and for the unhealthy class, 1000 images were selected each from mild, moderate, severe and prolific DR classes.

B. *Image Preprocessing*

The fundus images contain black surrounding pixels. To remove the black surrounding, we used Opencv Python to crop that black surrounding pixel from the input images. The images then were resized to 300x300.

C. *Features Extraction*

The convolutional part and classifier part are the two basic parts in the architecture of a deep CNN. Convolution is a mathematical operation used to merge two sets of information. This is applied on input data to extract the characteristics of different classes. To classify the input data based on collected characteristics, the classifier part is used.We have used the pre-trained convolutional part of the Inception-V3 model proposed by Szegedy et al.[7].

D. *Classifier Training*

To classify the extracted features, we added a Relu activated layer followed by a Softmax classifier on top of the pre-trained models. The cosine loss function was used to calculate the error. The softmax function was used for the output layer. Stochastic Gradient Descent (SGD) was used for training with an ascending learning rate of 0.0005.

E. Model Testing

The model is tested on a dataset of 5000 fundus images that we did not use for training. The accuracy of our model is 89.9% and 4.34% loss.

IV. CONCLUSION

In this work, we implemented transfer learning to classify Diabetic Retinopathy in two classes i.e. healthy and unhealthy. As training data is limited in healthcare therefore this implementation is done using comparatively less training data. The training of a deep learning model is designed in such a way that it performs efficiently by learning from small datasets. To compare performances of another pre-trained model in DR classification, experiments should be done.

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