

Diabetic Retinopathy Detection using Fundus Photography



Hritik Rao, Pranjay Bajaj, Kanmani Sivagar

Abstract— Patients suffering from prolonged diabetic conditions are prone to Diabetic Retinopathy (DR) which leads to vision impairment if left untreated. Diabetic Retinopathy has been on the rise across the globe due to an increase in the number of diabetic patients. Diabetic Retinopathy detection in early stages has become vital to prevent permanent vision impairment and avoid arduous medical treatment in the later stages. Diabetic Retinopathy (DR) causes damage to the retina and gradual loss of sight and in severe cases permanent vision impairment eventually leading to blindness. An early analysis of Diabetic Retinopathy helps in controlling the progress of the disease and increases the chances of recovery. An automated classification of Diabetic Retinopathy using images is a difficult job due to the microscopic variability of the appearance of different classes and the lack of a standard data infrastructure by medical professionals. One of the major deterrents in automated Diabetic Retinopathy (DR) detection is the identification of the essential features in the fundus image. Techniques like Gaussian Blur and auto-cropping has been used for feature extraction and noise removal. Through this paper, we aim to classify various fundus images of the eye into various classes of diabetic Retinopathy and automate the screening process.

Keywords— Diabetic Retinopathy, Retina, fluorescein angiography, Convolutional Neural Network, radial, Optical coherence tomography, preprocessing.

I. INTRODUCTION

Over the years there has been a drastic increase in the number of people affected by diabetes. Diabetes is complemented by various other diabetic conditions which generally affect people who have had extended suffering from diabetes. Diabetic Retinopathy is a condition caused by perpetual suffering from diabetes. It is the major leading cause of blindness in this present day and age. It has affected almost 93 million people in the world. It causes gradual loss of sight which leads to blindness in the long run. All kinds of diabetic patients are affected by diabetic retinopathy in due course. The patients suffering from type 1 diabetes generally tend to feel the effects of DR at a later stage whereas in the case of type 2 diabetic patients it is the contrary.

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Diabetic Retinopathy causes the blood vessels present in the eye to leak blood and other fluids around the retina. As the severity of Diabetic Retinopathy increases, it causes the blood vessels to get blocked hence the retina stops receiving proper nourishment. The retina starts to become unhealthy which eventually leads to loss of sight. Early diagnosis is of the essence in the treatment of Diabetic Retinopathy. If we can analyze the Diabetic Retinopathy early, then there is a great possibility of containing the disease and hence avoiding further escalation. Conventional methods to detect diabetic retinopathy require regular screening of the eye. In the current scenario, there is a lot of expert manpower required for the present screening facilities that are needed for this purpose. Therefore, there is a need to place an automated screening technique in its place. By doing this it will drastically reduce the workload and give quicker outcomes and hence plays a helping hand to the ophthalmologists. With advancements in machine learning, various algorithms are being used to generate an automated system to carry out the screening process. However, in recent times, various techniques such as CNN, transfer learning have brought in drastic changes in the field of medical science. Researchers have started utilizing deep learning as a method to perform image segmentation and classification of Diabetic Retinopathy. Deep learning is a method that emulates the functioning of the human brain which gathers all the data and creates a knowledge base. Using this knowledge it extracts various information like patterns and takes decisions on it. The deep learning model is first trained on a certain set of labeled and structured databases and then tested onto the other set of databases. Hence, deep learning helps in deploying a computer model that helps in classifying data into different categories. These data could be anything from sounds to texts to images. Deep learning model has proven to have high computational powers as well as has been able to extract a multitude of features from the given labeled dataset. Hence various deep learning methods like convolutional neural networks are being used in various medical institutes, banking, and corporate world. Hence deep learning algorithms have had a greater impact in today's classification and detection model of image processing, text processing or sound processing systems.

II. LITERATURE SURVEY

The current methodology of research employs various machine learning algorithms for the diagnosis of diseases along with the help of available medical records for the classification and detection of various diseases. An intensive survey was carried out to gain knowledge on the methods applied by researchers and to expand our knowledge of various preprocessing methods.

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This survey also helped us know about various data augmentation procedures that could help in getting more generalized datasets. The approach used by Ankita Gupta and Rita Chhikarab [1] divides their detection of DR into two different approaches. The first approach focuses on Blood Vessel Segmentation and the second on the Identification of lesions. This paper helps us in understanding and gaining knowledge about various results like sensitivity, AUC, the accuracy that was derived when different machine learning algorithms were used such as Improved Match Filtering, Ensemble Classifier, etc.

The algorithm applied by Yuchen Wu and Ze Hu [2] uses the Migration Learning Approach which is one of the new machine learning approaches. There are four different approaches to implement this method. They have used Feature-based Transfer Learning. The pre-training model they used is based on ImageNet. Since there was a requirement of data augmentation which involved the usage of imageDataGenerator which is a class present in Keras. Hence Keras was primarily used. They used the pre-training model for feature extraction that was required to develop the final model to detect DR.

The results obtained by using CNN has been projected by the paper published by Shuang Yu, Di Xiao and Yogesan Kanagasigam [3] It uses pixel-wise exudate image patches. The accuracy that was obtained was off 91.92%. The Framework for exudate detection with deep learning includes three main procedures before the image is sent to the DR model that was established using CNN. The three major steps are Removal of Optic Disc Detection, Removal of Retinal Vessels, and Ultimate Opening. The images are entered in the form of 64*64 patches.

There have been various modern screening approaches that have been used to diagnose Diabetic Retinopathy. S.D. Shirbahadurkar, V. M. Mane and D. V. Jadhav[4] have tried to use decision trees to diagnose DR. This algorithm can classify the fundus image into various DR. Hence this algorithm is holentropy enabled. The above method uses activities like grey scaling (converts image into a pixel driven image that a computer understands), optic disc segmentation and blood vessel segmentation to detect DR. The following steps include feature extraction and hence a feature extraction vector to which appropriate weights are assigned to different features which help in detecting DR.

There also have been various approaches for detecting proliferative DR. This research was published by Anaswara Chandran, Prof. Nisha K K and Dr. Vineetha S [5]. The ability to handle higher dimensional feature sets was essential for the classification process. Hence, Random-Forest Classifier was used here. Different patches of the dataset are used to train various decision trees. The patches are extracted from the image sets. The patches undergo two distinct extraction processes namely Texture Feature Extraction and Vessel Feature Extraction. The decision trees after giving various decisions its output is fed forward to random forest classifier which uses a rule-based approach to classify the images to reach a certain result.

The research methodology employed by Mamta Arora and Mrinal Pandey of Manav Rachna University [6] shows the various stages involved in using deep neural networks for the diagnosis of diabetic retinopathy detection. They

followed a two-step process which includes step 1: data preprocessing and augmentation and step2: convolution layer. The convolutional layer was further divided into a 5 step process that involved the convolutional layer which is the basic building block of Convolutional neural extracting weights, Pooling Layer, connecting layer and logistic classifier.

Placing emphasis on non-proliferative DR, SVM algorithm was used for the diagnoses. This is shown by Handayani Tjandrasa et al. [7] and Enrique V. Carrera et al. [8]. The main features of this paper were exudate segmentation, feature extraction and the classification of NPDR severity level. The extracted features were finally trained and tested using soft margin SVM as a classification model.

III. PROPOSED WORK

The overall framework for Diabetic Retinopathy detection has been illustrated in fig 1. The database consists of fundus images of the eye. These images are obtained using the fundus camera. Once obtained, the data is labeled by a professional ophthalmologist. The labeled data constitutes the training dataset that is required to train the neural network. The training database then undergoes data preprocessing techniques like removal of padding, Gaussian blur, and Feature extraction. The data preprocessing techniques help to eliminate noise and realize the important features of the eye in the fundus image. Due to the small size of the dataset, data Augmentation was performed using Keras ImageDataGenerator. It helps in providing new data by applying various transformations on the training set. The image dataset is then fed to the Convolutional Neural Network and Resnet for training the model. The model essentially extracts important features and apply commensurate weights. These extracted features hold the key to detecting Diabetic Retinopathy more accurately. The model is then generated which can be used for automated detection of Diabetic Retinopathy. Integrated to a web app using FLASK.

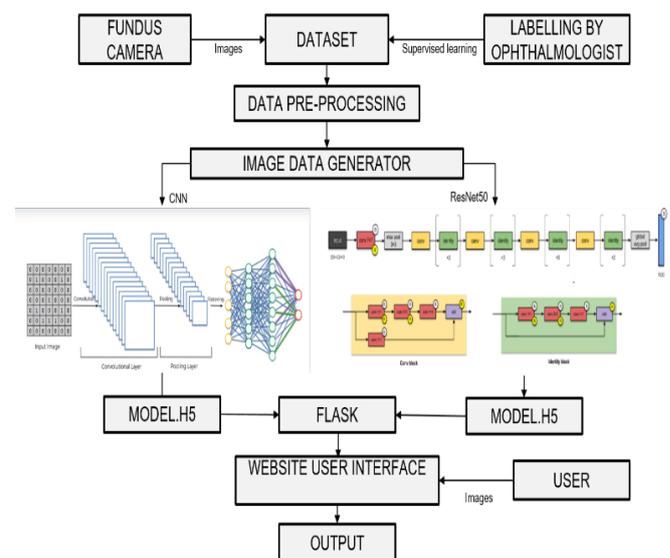


Figure 1. Architecture

A. Data Introduction

The dataset consists of fundus images of the eye which were obtained through various medical professionals. For the development of dataset, macula-centered fundus images were obtained from EYEPACS which is a U.S. based private organization and three other hospitals in India. The dataset consisted of fundus images from various patients with varying levels of illumination and other physical parameters leading to inconsistencies with the data even in the same class. The dataset consists of three categorical classes of Diabetic Retinopathy. The classes being No DR, Non-proliferative DR, proliferative DR.

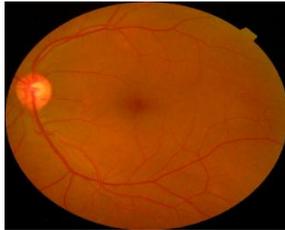


Figure 2 NO DR



Figure 3 Non-Proliferative DR



Figure 4 Proliferative DR

B. Data Preprocessing

Padding (Removal):

The input data consists of fundus images in various dimensions. The image is encapsulated with noise in the form of padding of blackened pixels. The removal of the padding layer reduces the noise present in the input image while focusing on the essential components of the data. The input data is resized to a predefined size of 256x256 which provides uniformity and stability in applying pre-processing operations on the dataset being fed to the neural network.

Gaussian Blur:

Gaussian Blur is a mathematical function used to extract essential features present in the image. Gaussian Blur helps in blurring the edges and reducing the contrast. It further enhances the essential features of the input data. This helps the algorithm to differentiate between essential and nonessential features present in the image.

Feature Extraction (Circular Crop):

The pre-processed (Gaussian blur filters) image still consists

of nonessential components in the form of noise around the corners of the image due to the spherical shape of the eyeball. Auto cropping is a data pre-processing approach that was applied to the dataset to remove the background noise and realize all the essential feature parameters present in the fundus dataset. Auto Cropping perceives the major portion of the eye required by identifying the circular component of the image where the eye is located. The remaining portion which consisted of nonessential features was blackened out to remove any intrusion to the neural network by the noise. Auto Cropping helps in eradicating the noise as well as extracting all the important features of the eye present in the image.

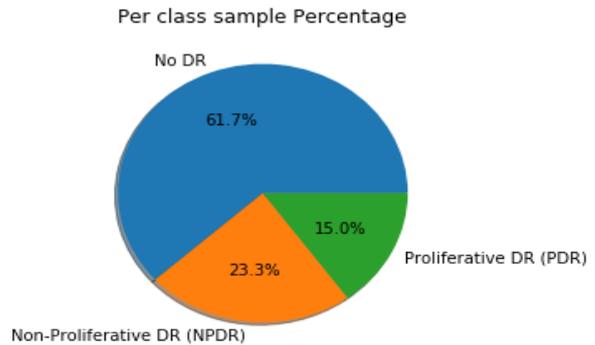


Figure 5 Dataset in each class

C. Data Augmentation

Keras ImageDataGenerator is a data augmentation function that is used to increase the dataset size and helps generate a more normalized input for the network. The training data is fed as a batch of images to the network. The ImageDataGenerator takes the training data as input which undergoes certain transformations like horizontal_flip, vertical_flip, rotation_range, zoom_range, validation_split, etc. The new set of images along with the previous dataset realizes to be the new dataset for the system improving the normalization of the model.

D. Neural Network and Transfer Learning

Convolutional Neural Network:

CNN consists of three distinct layers such as a convolutional layer, pooling layer, and the fully-connected dense layer. All the features are extracted with the use of various convolutional and pooling layer. The high dimensional features which were extracted from the last pooling layer are fed into the fully connected layer for final optimization.

Hyperparameters help us decide the neural structure and determine how the network behaves during training and testing. These parameters are set to optimize the stability and accuracy of the model.

Transfer Learning with ResNet50

Transfer learning is one of the machine learning techniques which helps the model by incorporating model weights file in the neural architecture. It is a popular deep learning technology which helps in the optimization and improvement of the learning process in a neural network. In a classification model such as ResNet50 reducing computational overhead is very cost-effective transfer learning becomes a major benefit.

IV. EXPERIMENTAL RESULTS

In this paper, the proposed methodology contains a series of simple yet effective preprocessing techniques like removal of padding, auto-cropping and Gaussian blur which has shown a great effect.

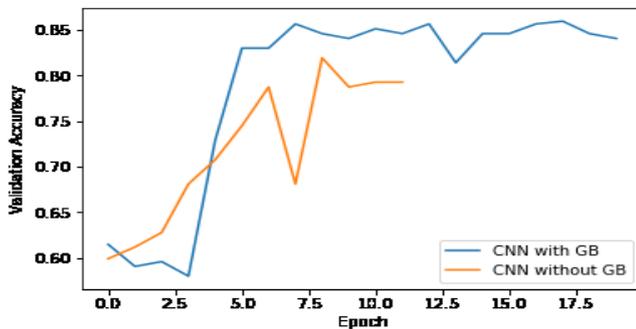


Figure 6 Comparison

As seen with the accuracy curve of the CNN model, from the comparison of CNN layers with and without Gaussian Blur where the former came out to be triumphed by a significant improvement in the overall stability and precision of the model. Auto cropping and Gaussian Blur removes the irrelevant portions captured in a fundus image and keeps the vital part of the eye to be used for the detection and classification of the Diabetic retinopathy.

As seen with the accuracy curve of the CNN model, Gaussian Blur helps to improve the accuracy of Diabetic Retinopathy detection. CNN was only able to achieve about 81% but with Gaussian blur added as a preprocessing technique, the model was able to achieve an accuracy of about 86%. This shows how valuable Gaussian blur is as a preprocessing technique for Fundus Images. The loss score obtained when using CNN architecture without Gaussian Blur is approximately 0.18 whereas when Gaussian Blur was applied we were able to achieve a loss score of 0.14.

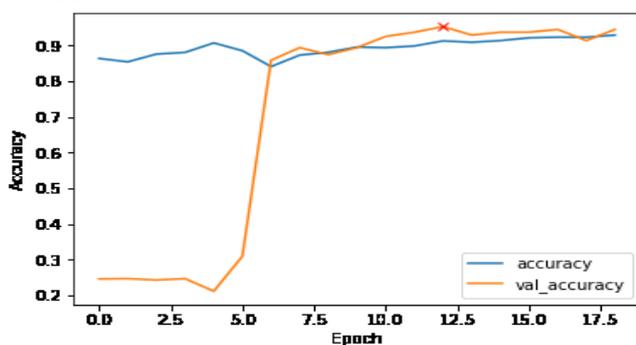


Figure 7 ResNet50 Accuracy

ResNet50 was the most successful architecture. ResNet was able to achieve this with the help of transfer learning which greatly reduces computation time and other preprocessing techniques which resulted in an optimal score of 96.16%. The loss score attained using transfer Learning with ResNet50 is 0.0002.

Name	CNN Model Without Gaussian Blur	CNN model with Gaussian Blur	ResNet50 Model with Gaussian Blur
Validation	81.91%	86.16%	94.15%

Accuracy			
Testing Accuracy and Loss function	69.19% & 0.1893	78.67% & 0.1425	93.99% & 0.0002

After applying further optimization on classification, the specificity of PDR is about 99.1%, MPDR is approximately 92.3% and that of NPDR is 93.4%. This shows that it is capable of detecting Diabetic Retinopathy in real-time.

V. CONCLUSION

The results achieved in this study are consistent with the other works that have been done with deep convolutional neural networks. The results obtained by our proposed model are in accordance with the current res and display that better results are obtained by models that are deeper. The results verify the proposal that features learned by pre-trained models help to learn features for a completely different domain dataset, in our case the Diabetic Retinopathy images dataset. The use of transfer learning models for feature extraction is a high performance-yielding technique for medical image analysis. Additionally, fine-tuning and data augmentation are important parameters for a better model.

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