

Diabetic Retinopathy Severity Detection using Convolutional Neural Network

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Abstract. Diabetic Retinopathy is one of the most prominent eye diseases and is the leading cause of blindness amongst adults. Automatic detection of Diabetic Retinopathy is important to prevent irreversible damage to the eye-sight. Existing feature learning methods have a lesser accuracy rate in computer aided diagnostics; this paper proposes a method to further increase the accuracy. Machine learning can be used effectively for the diagnosis of this disease. CNN and transfer learning are used for the severity classification and have achieved an accuracy of 73.9 percent. The use of XGBoost classifier yielded an accuracy of 76.5 percent.

Keywords: Convolutional Neural Networks, Hypertensive Retinopathy, Arteriosclerotic Retinopathy, Machine learning, Transfer Learning, EyePacs

1 Introduction

Diabetic Retinopathy (DR) is a disease which occurs due to damage to the retina. It is a leading cause of blindness [15]. Diabetic Retinopathy has different levels of severity. Severity level is a crucial aspect in Diabetic Retinopathy. It not only tells us about the risk of blindness but also dictates whether it can be cured or not. People diagnosed with diabetes have a higher probability of getting diagnosed with DR. Hence regular screening of diabetic patients for DR helps in early detection and therefore treatment.

Early detection is an important aspect in Diabetic Retinopathy. Diabetic retinopathy affects up to 80 percent of those who have had diabetes for 20 years [1] or more. It often has no early warning signs, but if detected early it can be cured 90 percent of the time [15]. DR can be classified into three categories [3]: 1.Hypertensive Retinopathy 2.Arteriosclerotic Retinopathy 3.Retinopathy of prematurity

This paper focuses on Hypertensive and Arteriosclerotic retinopathy. Hypertensive retinopathy is caused by high blood pressure [3]. The high blood pressure causes damage to blood vessels in the retina. This puts pressure on the optic nerve which can limit the retina function leading to blindness. Arteriosclerotic retinopathy is caused by Arteriosclerosis [4]. Thickening of walls of arteries in the eye occurs in this condition. Hence the blood flow is partially blocked which causes vision impairment. If this condition remains untreated can cause swelling or even burst-

ing of blood vessels. Hence the early detection and treatment of Diabetic Retinopathy is necessary.

In hospitals and clinics the analysis is performed by an ophthalmologist manually. The retina scan is captured by retinal scanners. These scans are observed and analyzed. The ophthalmologist looks for signs such as hemorrhages, swelling of blood vessels, clots, the color of the retina and many more [5]. This entire process is manual and thus takes a significant amount of time. Besides this there's always the element of human error which cannot be predicted. These factors can collectively lead to misdiagnosis.

If Diabetic Retinopathy is misdiagnosed and accurate treatment isn't provided it can cause irreversible damage to the retina and might result in permanent blindness. Thus an accurate diagnosis is necessary. Computerizing the whole detection is one way to prevent misdiagnosis.

A neural network is a set of algorithms loosely modeled after the structure of the human brain [16]. Neural networks are designed to recognize patterns. Hence we can make such a network that'll help us identify the cases of diabetic retinopathy. A tool to determine the severity of the DR would be incredibly useful so doctors can diagnose it faster and more accurately.

Several algorithms have been proposed for DR detection and severity analysis. However these algorithms have a lower rate of correct diagnosis. To address this low accuracy problem, we used different neural networks but mainly Convolutional Neural Network (CNN). CNN is a type of neural network mostly used to analyze visual imagery. CNNs consist of multilayer perceptrons [16]. Multilayer perceptrons are fully connected networks. The name 'Convolutional Neural Network' implies that the network is performing convolution function. In CNN

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the input is a tensor with a definite shape. This shape is 'number of images x image width x image height x image depth' After the image passes through these layers a feature map is created. This way each layer performs convolution and passes the result to the next layer.

Our dataset was created using retinal scans provided by EyePacs. This dataset contained normal retina scans as well as retina scans of people diagnosed with DR. The dataset had retinal scans with varying severity of DR. The severity of Diabetic Retinopathy was on a scale of 0 to 4, 0 being the absence of DR and 4 being proliferative DR. Using these images neural network was trained to look for features such as shape, size, color etc. Using these parameters the network gave the result. The output of CNN was the indication of the severity of the DR.

Firstly, pre-processing was performed in order to fine tune the dataset. This included cropping of the retinal scan, suppressing the noise etc. We make use of VggNet, ResNet and inception V3 to obtain a more accurate result. The use of XGBoost trainer classifier further increased the accuracy.

We illustrated dataset, pre-processing and algorithm in section 3 and in section 4 we illustrated the testing results and accuracy of the various models.

2 Literature Survey

In the (DRSS) Diabetic Retinopathy Severity Score manual [14], Bob Wilkes explains how diabetic retinopathy is detected from retina scans of the eyes. The manual explains how the early signs of diabetic retinopathy which are abnormal blood vessels, retinal detachment and swelling of the retina. These signs are looked for in a patient's retinal scans to check if there is any danger to the patient's eyesight. Bio-inspired nano-sensor-enhanced CNN visual computer, elaborated on image recognition, stabilization, and pattern detection can be done using a CNN [12]. In [15] demonstrates the effectiveness in the detection of lesions in retinal images using CNNs.

In [13], the resourcefulness of transfer learning models was illustrated. Google's inception V3 has been used after cleaning the dataset via transfer learning. While training a validation split of 0.1 was introduced and the model used the Softmax classifier and Inception v3 is a widely-used image recognition model that has been shown to attain greater than 78.1 percent accuracy on the ImageNet dataset.

The use of a combination of datasets is explained in [6], and one of those was maintained by EyePacs. The other dataset was named Messidor-2 and is publicly available. While training the model, Pre-initialization and batch normalization was used to improve training speed and accuracy. The model used 80 percent of the images for optimizing network weights and 20 percent to optimize hyperparameters. The model accuracy was 70.7 percent.

In [7], during their pre-processing stage they performed color normalization using the OpenCV package. They trained the network using stochastic gradient descent with Nesterov momentum. They performed analysis to grade the severity of Diabetic Retinopathy and vali-

dated their result by verifying from an expert ophthalmologist. [9] explained the advantages of GoogleNet, ResNet, AlexNet etc. The accuracy of the used VggNet-s model classification was 95.68 percent.

Pires et al. in their research have demonstrated how a multi-resolution training approach works [10]. In this model the weights from the previously trained network can be utilised in order to increase accuracy and boost the efficiency. So this used multiple CNNs. The weights from the first CNN at the end were used as the initial weights of the second CNN. In "Modified Alexnet architecture for classification of diabetic retinopathy images" the images were split in RGB channels [11]. Using these channels the images were refined. As different channels have different advantages their added collective benefit increased the model accuracy to 96 percent. By reading all these papers on Diabetic Retinopathy detection using the Convolutional Neural Network we created our own model based on that knowledge.

3 Proposed Algorithm

The retinal scans we used in the dataset were maintained by EyePacs, a California based foundation that actively works on Diabetic Retinopathy screening programs. There were a total of 35126 retinal scans in the training data. These images were in pairs having a left and right retinal images of every subject and it was named accordingly. A trained clinician-rated the presence of Diabetic Retinopathy and included the same for every individual image in a .csv file. The CSV file contained the severity graded from 0-4 of its corresponding retinal image.

Class Name	Degree of DR	Numbers
Class 0	Normal	25810
Class 1	Mild	2443
Class 2	Moderate	5292
Class 3	Severe	873
Class 4	Proliferative	708

Since the images had a different resolution we had to reshape them to a standard resolution to make the dataset. The standard resolution we chose was 1024x1024. So keeping that in mind we resized all the images to that resolution. While doing so we changed the aspect ratio of all images to 1:1. This made the dataset more uniform. The image below shows the difference between a normal retina and a retina of a person diagnosed with Diabetes.

Hemorrhages, Aneurysm and abnormal growth of blood vessels can be observed in the second retina scan. We pre-processed our data to enhance these features of the retina scan so that they can be easily detected. We tried Ben Graham's insightful way of improving lighting in the images so that the lesions, hemorrhaging are visible clearly in the image.

In this method we convert the image into gray-scale to reduce the layers of the image to reduce computing time. Next we add another image to the image, this added image is called the Gaussian Blur effect. It adds an image

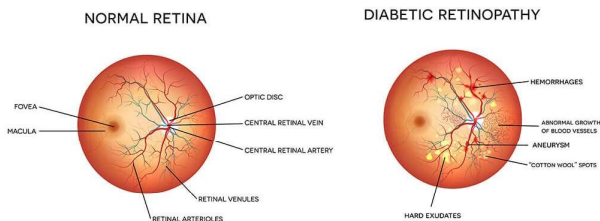


Figure 1. Normal eye vs affected eye

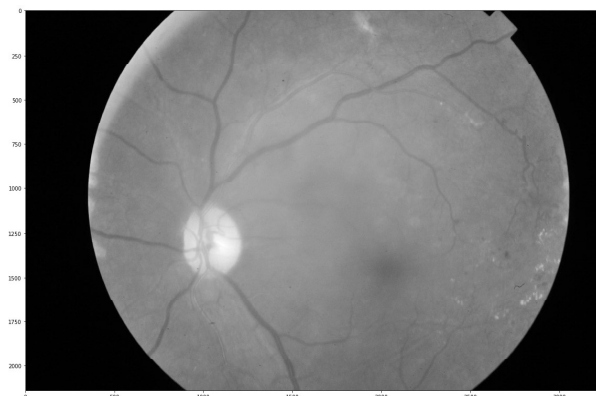


Figure 2. Gray scale image

which is considered as white Gaussian Noise which suppresses the non-vital regions in the image. It has its own sigma level adjustments and alpha-beta-gamma filter levels to adjust the levels of the Gaussian Blur.

We have also cropped out the non relevant black areas in the background of the scans by using a cropping algorithm that crops out the areas without any information and keeps only the areas which contain the retinal scans. However the method used by us is applicable only for gray-scale images. The preprocessed images were then converted to datasets to be used by the models that will be further developed by us.

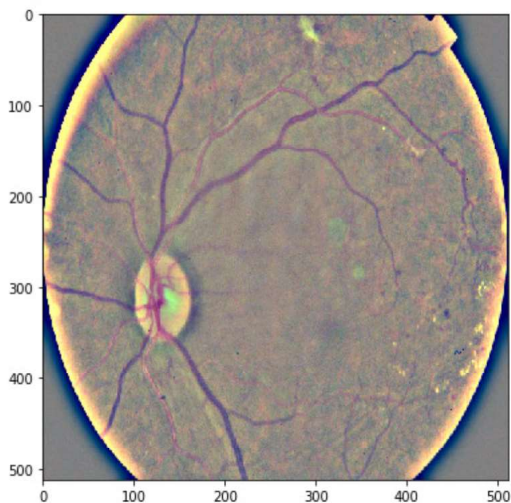


Figure 3. Image with Gaussian Blur

We have developed a Convolutional Neural Network of 7 layers that extract the features from the images and help the network to classify the images more accurately. The network runs for 10 epochs and gives accuracy in the range of 70-80 percent. Another method used in this paper is the XGBoost library which uses Booster models for classification problems. This method works very well for imbalanced datasets like the ones used for this problem. They have block structure implementation to support parallelization of tree structure. This ensures a very high accuracy in the training process.

We have employed two transfer learning models as well to gauge the accuracy of the detection under some of the established learning algorithms. Transfer learning is an approach that involves storing knowledge acquired from solving a problem and using that knowledge to solve another pertinent problem. For instance, the knowledge gained while learning to identify cars could be used to design a model that would recognize trucks.

From a practical standpoint, transferring information from previously trained models or tasks for the learning of distinct and newer tasks has the potential to significantly boost the performance of a reinforcement learning agent. Three possible benefits to look for when using transfer learning as stated by Lisa Torrey and Jude Shavlik in their book under the chapter of transfer learning are [20]: "Higher start. The initial skill (before refining the model) on the source model is higher than it otherwise would be. Higher slope. The rate of improvement of skill during the training of the source model is steeper than it otherwise would be. Higher asymptote." The overall capability of the the transferred model is better than a model that would be designed from scratch.

We have used the following three pre-trained models to implement transfer learning: Google’s Inception V3 model and Microsoft’s ResNet

4 Results

Vision loss can be prevented if diabetic retinopathy is diagnosed at an early stage. The algorithm proposed focuses on developing an accurate model to detect the severity of the disease. Deep learning is one of the most widely used techniques for countering classification problems with higher efficiency. Meticulously designed Convolution Neural Networks providing accurate classification will be helpful in the diagnosis. The class with the highest probability score is called the winning class.

Algorithm	Classifier	Performance
CNN	Sigmoid	73.9%
ResNet50	Relu	73.9%
InceptionV3	Relu	73.9%
XGBoost	XGBClassifier	76.5%

There were a total of 35126 images available for training. The CNN Model developed by us yields an accuracy of 73.9 percent, whereas the value accuracy for the model is 75.1 percent. The XGBoost classifier trainer gives us a

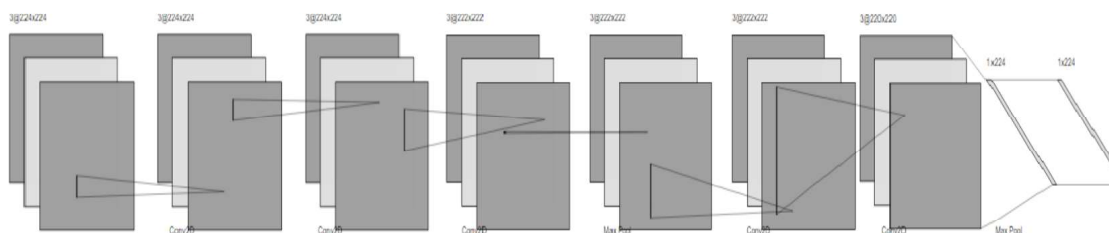


Figure 4. CNN Architecture

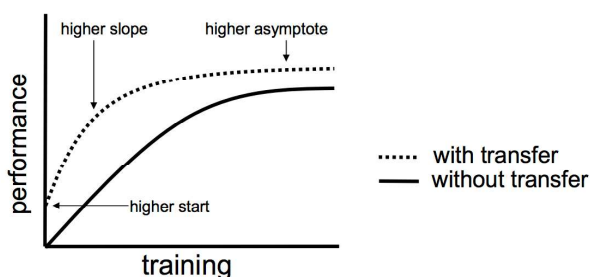


Figure 5. Advantages of transfer learning

better accuracy of 76.5 percent since it uses a scaling tree boosting system which uses a recursive learning system to rectify the errors. The ResNet50 model yielded a 75.3 percent accuracy and uses around 24,113,421 total parameters out of which 24,060,541 are trainable and 53,120 are non-trainable parameters. The Inception V3 is the algorithm developed by Google which is widely used for image recognition and gives us an accuracy of 76.2 percent.

Name	Technique	Accuracy
Xiaoling Wang et. al. [17]	Inception V3	63.23%
Kwasigroch et. al. [18]	CNN	51%
Hare S.S. et. al. [19]	CNN	74.04%
Proposed	XGBoost	76.5%

5 Conclusion

In this paper we introduced a CNN architecture designed to detect and identify the cases of Diabetic Retinopathy. This method was used to classify a retina scan into different classes from 0 to 4, class 0 indicating absence of DR and class 4 being proliferative DR. This architecture yielded an accuracy of 73.9 percent, and on using XG-Boost the accuracy rose to 76.5 per cent. Further research can improve the accuracy.

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