

Marathwada Shikshan Prasarak Mandal's  
**Deogiri Institute of Engineering and Management Studies,**  
**Aurangabad**

**Seminar Report**

**On**

**Diabetic Retinopathy**

Submitted By

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**(2019- 2020)**

**Seminar Report**  
**On**  
**Diabetic Retinopathy**

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**In partial fulfillment of**  
**Bachelor of Technology**  
**(Computer Science & Engineering)**

Guided By

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**Aurangabad**  
**(2019- 2020)**

## **CERTIFICATE**

This is to certify that, the Seminar entitled “**Diabetic Retinopathy**” submitted by **Aditya Sharma** is a bonafide work completed under my supervision and guidance in partial fulfillment for the award of Bachelor of Technology (Computer Science and Engineering) Degree of Dr. Babasaheb Ambedkar Technological University, Lonere.

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## **Contents**

<b>List of Figures</b>	<b>i</b>
<b>1. INTRODUCTION</b>	<b>1</b>
1.1 Diabetic retinopathy	1
1.2 Anatomy	3
1.3 Classification	4
<b>2. LITERATURE SURVEY</b>	<b>5</b>
2.1 Supervised Classification	5
2.2 Background	7
<b>3. BRIEF ON SYSTEM</b>	<b>9</b>
3.1 Proposed Methodology	9
3.2 Data Augmentation	10
3.3 Preprocessing	10
3.4 CNN Classification	10
<b>4. CONCLUSION</b>	<b>13</b>
4.1 Conclusion	13
4.2 Application	13
<b>5. REFERENCES</b>	
<b>6. ACKNOWLEDGEMENT</b>	

## **LIST OF FIGURES**

<b>Figure</b>	<b>Illustration</b>	<b>Page No.</b>
1.1	Anatomy of eye	4
3.1	Flow Chart	11
3.2	CNN Model Image	12

## **Abstract**

A recent development in state-of-art technology machine learning plays a vital role in image processing applications such as biomedical, satellite image processing, Artificial Intelligence such as object identification and recognition and so on. In Global, diabetic retinopathy suffered patients growing vastly. And the fact is the earliest stage could not diagnose the normal eye vision. The increasing the necessity of finding diabetic retinopathy as earliest would stop vision loss for prolonged diabetes patient although suffered youngs'. The severity of diabetic retinopathy disease is based on the presence of microaneurysms, exudates, neovascularization, Haemorrhages. Experts have categorized that diabetic retinopathy into five stages such as normal, mild, moderate, severe Nonproliferative(NPDR) or Proliferative diabetic retinopathy patient(PDR). A proposed deep learning approach such as Deep Convolutional Neural Network(DCNN) gives high accuracy in the classification of these diseases through spatial analysis. A DCNN is a more complex architecture inferred more from human visual prospects. Amongst other supervised algorithms involved, the proposed solution is to find a better and more optimized way to classifying the fundus image with little pre-processing techniques. Our proposed architecture deployed with dropout layer techniques yields around 94-96 percent accuracy. Also, it tested with popular databases such as STARE, DRIVE, kaggle fundus images datasets are available public.

# 1.INTRODUCTION

## 1.1Diabetic Retinopathy

Diabetic retinopathy also known as diabetic eye disease is when damage occurs to the retina due to diabetes. It's a systemic disease, which affects up to 80 percent of all patients who have had diabetes for 20 years or more. Despite these intimidating statistics, research indicates that at least 90% of these new cases could be reduced if there were proper and vigilant treatment and monitoring of the eyes. The longer a person has diabetes, the higher his or her chances of developing diabetic retinopathy. According to the International Diabetes Federation, the number of adults with diabetes in the world is estimated to be 366 million in 2011 and by 2030 this would have risen to 552 million. The number of people with type 2 diabetes is increasing in every country 80% of people with diabetes live in low-and middle-income countries. India stands first with 195%(18 million in 1995 to 54 million in 2025). Previously, diabetes mellitus(DM) was considered to be present, largely, among the urban population in India. Recent studies clearly show an increasing prevalence in rural areas as well. Indian studies show a 3-fold increase in the presence of diabetes among the rural population over the last decade or so (2.2% in 1989 to 6.3% in 2003). In India, Study shows the estimated prevalence of type 2 diabetes mellitus and diabetic retinopathy in a rural population of south India are nearly 1 of 10 individuals in rural south India, above the age of 40 years, showed the evidence of type 2 diabetes mellitus. There is five major levels of clinical DR severity. Many patients have no clinically observable DR early after DM diagnosis, yet there are known structural and physiologic changes in the retina including slowing of retinal blood flow, increased leukocyte adhesion, thickening of basement membranes, and loss of retinal pericytes. The earliest clinically apparent stage of DR is mild non-proliferative diabetic retinopathy(NPDR) characterized by the development of microaneurysms. The disease can progress to moderate NPDR where additional DR lesions develop, including venous caliber changes and intraretinal microvascular abnormalities. The severity and extent of these lesions increased in severe NPDR and the retinal blood supply becomes increasingly compromised. As a consequence, the non-perfused areas of the retina send signals stimulating new blood vessel growth, leading to proliferative diabetic retinopathy(PDR).

The progression from no retinopathy to PDR can take 2 decades or more, and this slow rate enables DR to be identified and treated at an early stage. The development and progression of DR are related to duration and control of diabetes. DR in its early form is often asymptomatic but amenable to treatment. The Diabetic Retinopathy Study and the Early Treatment of Diabetic Retinopathy Study (ETDRS) showed the treatment with laser photocoagulation can more than halve the risk of developing visual loss from PDR. The main difficulty faced by DR affected patients is that they are unaware of the disease until the changes in the retina have progressed to a level that treatment will in turn tend to be less effective. Automated screening techniques for the detection purpose have great significance in saving cost, time and labour. The screening of diabetic patients for the development of diabetic retinopathy can reduce the risk of blindness by 50%. With the increase in the rate of the patients affected by the disease there is all the more need for automated systems to take the charge since the number of ophthalmologists is also not sufficient to cope with all patients, especially in rural areas or if the workload of local ophthalmologists is substantial. Therefore, automated early detection could limit the severity of the disease and assist ophthalmologists in investigating and treating the disease more efficiently. There may exist different kind of abnormal lesions caused by diabetic retinopathy the most frequent being exudates, hemorrhage, microaneurysm. A handful of researches have been presented in the literature for Diabetic Retinopathy using various methods. Recently, the use of automation method using fundus images for DR have received a great deal of attention among researchers. A brief review of some recent researches is presented here. Previous studies [5] indicated that the importance of developing several automated methods for detecting abnormalities in fundus images. The purpose of those studies was to improve their automated hemorrhage detection method to help diagnose diabetic retinopathy. They found a new method for preprocessing and false positive elimination in the present study. The brightness of the fundus image was changed by the nonlinear curve with brightness values of the hue saturation value (HSV) space. In order to emphasize brown regions, gamma correction was performed on each red, green, and blue-bit image. Subsequently, the histograms of each red, blue, and blue-bit image were extended. After that, the hemorrhage candidates were detected. The brown regions indicated hemorrhages and blood vessels and their candidates were detected using density analysis.



The sensitivity and specificity for the detection of abnormal cases were 80% and 88%, respectively. Those results indicate that the new method may effectively improve the performance of their computer-aided diagnosis system for hemorrhages. Researchers have described that Diabetic retinopathy, an eye disorder caused by diabetes, was the primary cause of blindness in America and over 99% of cases in India. India and China currently account for over 90 million diabetic patients and are on the verge of an explosion of diabetic populations. That may result in an unprecedented number of persons becoming blind unless diabetic retinopathy can be detected early. The automated diabetic retinopathy problem was a hard computer vision problem whose goal was to detect features of retinopathy, such as hemorrhages and exudates, in retinal color fundus images. They described their initial efforts towards building such a system using a range of computer vision techniques and discuss the potential impact on early detection of diabetic retinopathy. Another study subscribed that Diabetic retinopathy (DR) was an important cause of visual impairment in industrialized countries. Automatic detection of DR early markers can contribute to the diagnosis and screening of the disease. The aim of that study was to automatically detect one of such early signs: red lesions (RLs), like haemorrhages and micro aneurysms. To achieve that goal, they extracted a set of colour and shape features from image regions and performed feature selection using logistic regression. Four neural network (NN) based classifiers were subsequently used to obtain the final segmentation of RLs: multilayer perceptron (MLP), radial basis function (RBF), support vector machine (SVM) and a combination of those three NNs using a majority voting (MV) schema.

## **1.2 Anatomy**

The retina is a multi-layered sheet composed of neurons, photoreceptors, and support cells. It is one of the most metabolically active organs in the body, and as a result, it is extremely sensitive to ischemia and nutrient imbalances (Frank 2004). A perfused retina is a happy retina. The outer one-third of the retina receives its blood supply from the choriocapillaris, a vascular network that lies between the retina and sclera. The inner two-thirds of the retina is supplied by branches of the central retinal artery, which comes from the ophthalmic artery (the first branch off of the internal carotid artery).

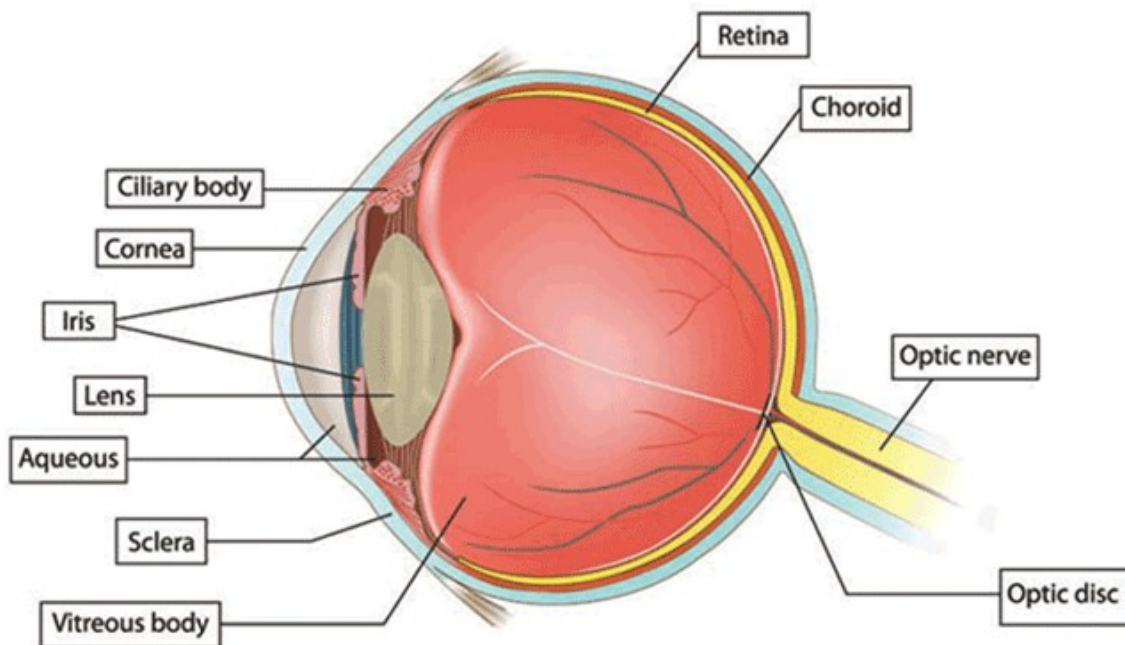


Fig. 1.1 Anatomy of eye

### 1.3 Classification

Diabetic retinopathy falls into two main classes: non proliferative and proliferative. The word “proliferative” refers to whether or not there is neovascularization (abnormal blood vessel growth) in the retina. Early disease without neovascularization is called nonproliferative diabetic retinopathy (NPDR). As the disease progresses, it may evolve into proliferative diabetic retinopathy (PDR), which is defined by the presence of neovascularization and has a greater potential for serious visual consequences.

## 2. LITERATURE SURVEY

### 2.1 Supervised classification

It is based on classifying the test image dataset from the training data with labeled classes. In general, classification is done by extracting the features from the images followed by identifying the categorized classes based on the trained data with labeled classes. In Classification, the extracted features listed out the severity of the diabetic retinopathy diseases. There are five categories of diabetic retinopathy classification from nonproliferative diabetic retinopathy to proliferative diabetic retinopathy are classified based on extracted feature values. Some of the popular methodologies well utilized to do feature extraction and classification of diabetic retinopathy analysis are: S.Wang, et al, using a convolutional neural network performs as a trainable hierarchical feature extractor and Random Forest(RF) as a trainable classifier. It has 6 stacked layers of convolution and followed by subsampling layers for feature extraction. Random Forest algorithm is utilized for classifier ensemble method and introduced in the retinal blood vessel segmentation. This architecture is used in the DRIVE, STARE databases and achieved around 0.98 and 0.97. Mrinal Haloi et al, a new deep learning-based computer-aided system for microaneurysm detection. Comparing another deep neural network, it required less preprocessing, vessel extraction and more deep layers for training and testing the fundus image dataset. It consists of five layers which include convolutional, max pooling and Softmax layer with additional dropout training for improving accuracy. It achieved a low false-positive rate. And the performance measured as 0.96 accuracies with .96 specificity and .97 sensitivity. M.Melinscak et al[3], automatic segmentation of blood vessels in fundus images. It contains deep max-pooling convolutional neural networks to segment blood vessels. It is deployed 10-layer architecture for achieving a maximum accuracy but worked with small image patches. It contains a preprocessing for resizing and reshaping the fundus images. It carried around 4-convolutional and 4-max pooling layer with 2 additional fully connected layers for vessel segmentation. Also, this method achieved an accuracy of around 0.94. Gardner et al, a pioneering method of diabetic retinopathy screening tool using an artificial neural network with preprocessing techniques. This method learned features from the sub-images. It heavily relied on a backpropagation neural network.

For automated detection, novel two-step hierarchical binary classification is used. For classification of lesions from non-lesions proposed GMM, SVM, KNN and ADABOOST methods are used. They take 30 top features like are, variance of Ired channel, Igreen channel, I sat of object, major and minor axis length, Mean pixels for Igreen, Ired and intensity, solidity etc. The DREAM system 100 percent sensitivity, .5316 specificity achieved. Also, carried out average computation time for DR severity per image from 59.54 to 3.46s. overall feature reduction effects the average computation time. JayakumarLachure et al, retinal microaneurysms, hemorrhages, exudates, and cotton wool spots are the abnormality find out in the fundus images. Detection of red and bright lesions in digital fundus photographs. Preprocessing, morphological operations performed to find microaneurysms and features are extracted such as GLCM and structural features for classification. This SVM classifier optimized to 100 percent and 90 percent sensitivity. R.Priya, P.Aruna et al, to diagnostic retinopathy used two models like Probabilistic Neural network(PNN) and Support Vector Machines. The input color retinal images are pre-processed using grayscale conversion, adaptive histogram equalization, discrete wavelet transform, matched filter and fuzzy C-means segmentation. The classification of preprocessed images features were extracted.It achieved an accuracy of 89.6 percent and SVM of around 97.608 percent. Giraddi et al, detection of the exudates in the color variability and contrast retinal images. Comparative analysis made for SVM and KNN classifier for earliest detection. They utilized the GLCM texture features extraction for obtaining the reduced number of false positives. Eventually the true positive rates for SVM classifier around 83.4 and KNN classifier around 92%.As a result, KNN outperforms SVM with color as well as texture features. Srivastava et al, a key idea of randomly drop units along with their connections during the training. His work significantly reduces the over fitting and gives improvements over other regularization techniques. Also, improves the performance of neural networks in vision, document classification, speech recognition etc. Overall other methods, to identifying the microaneurysm, Exudates, vessels segmentation for maximizing the accuracy rate is the key objective.

## 2.2 Background

The main difficulty faced by DR affected patients is that they are unaware of the disease until the changes in the retina have progressed to a level that treatment will in turn tend to be less effective. Automated screening techniques for the detection purpose have great significance in saving cost, time and labour. The screening of diabetic patients for the development of diabetic retinopathy can reduce the risk of blindness by 50%. With the increase in the rate of the patients affected by the disease there is all the more need for automated systems to take the charge since the number of ophthalmologists is also not sufficient to cope with all patients, especially in rural areas or if the workload of local ophthalmologists is substantial. Therefore, automated early detection could limit the severity of the disease and assist ophthalmologists in investigating and treating the disease more efficiently. There may exist different kind of abnormal lesions caused by diabetic retinopathy the most frequent being exudate's, hemorrhage, micro aneurysm. A handful of researches have been presented in the literature for Diabetic Retinopathy using various methods. Recently, the use of automation method using fundus images for DR have received a great deal of attention among researchers. A brief review of some recent researches is presented here. Previous studies [5] indicated that the importance of developing several automated methods for detecting abnormalities in fundus images. The purpose of those studies was to improve their automated hemorrhage detection method to help diagnose diabetic retinopathy. They found a new method for preprocessing and false positive elimination in the present study. The brightness of the fundus image was changed by the nonlinear curve with brightness values of the hue saturation value (HSV) space. In order to emphasize brown regions, gamma correction was performed on each red, green, and blue-bit image. Subsequently, the histograms of each red, blue, and blue-bit image were extended. After that, the hemorrhage candidates were detected. The brown regions indicated hemorrhages and blood vessels and their candidates were detected using density analysis. They removed the large candidates such as blood vessels. Finally, false positives were removed by using a 45-feature analysis. To evaluate the new method for the detection of hemorrhages, they examined 125 fundus images, including 35 images with hemorrhages and 90 normal images. The sensitivity and specificity for the detection of abnormal cases was were 80% and 88%, respectively.

That may result in an unprecedented number of persons becoming blind unless diabetic retinopathy can be detected early. The automated diabetic retinopathy problem was hard computer vision problem whose goal was to detect features of retinopathy, such as hemorrhages and exudates, in retinal color fundus images. They described their initial efforts towards building such a system using a range of computer vision techniques and discuss the potential impact on early detection of diabetic retinopathy. Another study subscribed that Diabetic retinopathy (DR) was an important cause of visual impairment in industrialized countries. Automatic detection of DR early markers can contribute to the diagnosis and screening of the disease. The aim of that study was to automatically detect one of such early signs: red lesions (RLs), like haemorrhages and micro aneurysms. To achieve that goal, they extracted a set of colour and shape features from image regions and performed feature selection using logistic regression. Four neural network (NN) based classifiers were subsequently used to obtain the final segmentation of RLs: multilayer perceptron (MLP), radial basis function (RBF), support vector machine (SVM) and a combination of those three Nns. using a majority voting (MV) schema. Their database was composed of 115 images. It was divided into a training set of 50 images (with RLs) and a test set of 65 images (40 with RLs and 25 without RLs). Attending to performance and complexity criteria, the best results were obtained for RBF. Using a lesion-based criterion, a mean sensitivity of 86.01% and a mean positive predictive value of 51.99% were obtained. With an image based criterion, a mean sensitivity of 100%, mean specificity of 56.00% and mean accuracy of 83.08% were achieved. There are various explorations [1] stating that the automated analysis of human eye fundus image was an important task. Diabetes was a disease which occurs when the pancreas does not secrete enough insulin or the body was unable to process it property. That disease affects slowly the circulatory system including that of the retina. As diabetes progresses, the vision of a patient may start to deteriorate and lead to diabetic retinopathy. The main stages of diabetic retinopathy were non-proliferative retinopathy (NPDR) and Pro-liferative retinopathy(PDR).In that paper, they have approached a computer based approach for the detection of DR stages using color fundus images.

### **3.BRIEF ON SYSTEM**

#### **3.1 Proposed Methodology**

In recent years most of the image processing researchers indulged in the development of machine learning especially deep learning approaches in the field of Hand-written digit recognition such as MNIST dataset, image classification by IMAGENET. Our proposed methodology strongly emerged based on these key aspects of diseases severity classification from the fundus images. Convolution neural network is a subset of deep learning neural network. It is mainly used for image classification and image analysis. The goal behind CNN is to mimic how human brain analyzes the image. Convolution neural network is comprised of one or more convolutional layers and then followed by one or more fully connected layers. The CNN consist of input, hidden and output layer. The input layer basically consist of arrays of pixels. The hidden layer is the most important layer as it plays the main role in image computation. Hidden layer comprises of activation functions and biases. The output layer helps us to determine the class score. The benefit of CNN's is that they are easier to train with providing high accuracies.

In general, especially classification of diseases with the proposed architecture a DCNN[add citation] following these basic steps to achieve maximum accuracy from the images dataset are i) Data Augmentation ii) Pre-processing iii) Initialization of Networks iv) training v) Activation function selections vi) Regularizations vii) Ensemble the multiple methods. In our proposed diabetic retinopathy classification model in Fig.3.1, an architecture are condensed and its building blocks are :

- a. Data augmentation
- b. Preprocessing
- c. Deep Convolutional Neural Network Classification

### **3.2 Data Augmentation**

The fundus images are obtained from the different datasets are taken under different camera with varying field of view, non-clarity, blurring, contrast and sizes of images different. In data augmentation, contrast adjustment, flipping images, brightness adjustments are made.

### **3.3 Preprocessing**

For Deep convolutional neural network worked on spatial data of the fundus images. A primary steps involved in the preprocessing is resizing the images. Before feeding into the architecture for classification, convert the images in to gray scale. And then, convert in to the L model. It is a monochrome images which is used to highlights the microaneurysms, and vessels in the fundus images. And flatten the images in single dimensional for processing further.

### **3.4. CNN Classification**

In Image recognition, a Convolutional Neural Network(CNN) is a type of feed-forward artificial neural network in which the connectivity pattern between its neurons is inspired by the organization of animal visual cortex, whose individual neurons are arranged in such a way that respond to overlapping regions tiling the visual field. In deep learning, the convolutional neural network uses a complex architecture composed of stacked layers in which is particularly well-adapted to classify the images. For multi-class classification, this architecture robust and sensitive to each feature present in the images. Common layers deployed in making Deep Convolutional Neural Network architecture(DCNN) are shown in Fig. 3.2



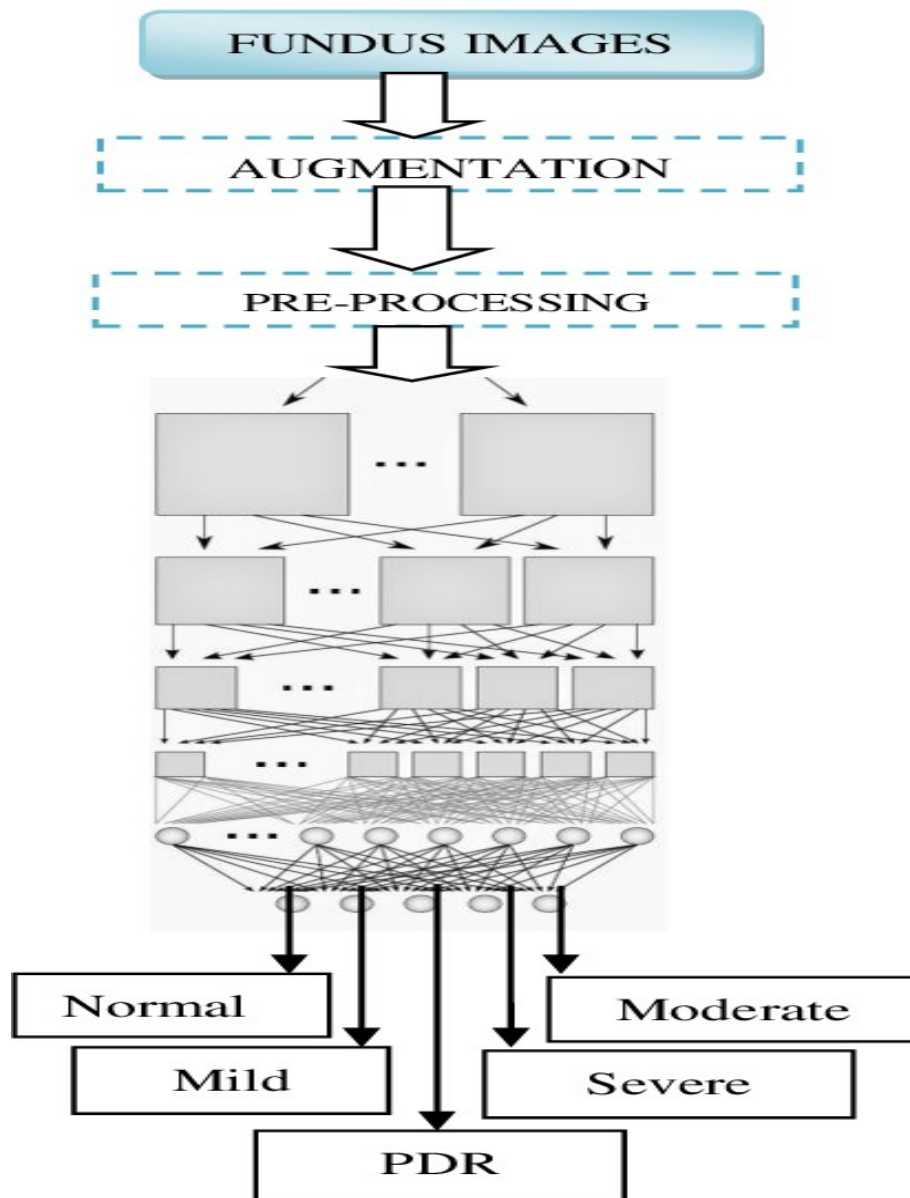


Fig 3.1 Block diagram of the proposed model

1. Convolution Layer
2. Pooling Layer
3. ReLU Layer
4. Dropout layer
5. Fully connected Layer
6. Classification Layer

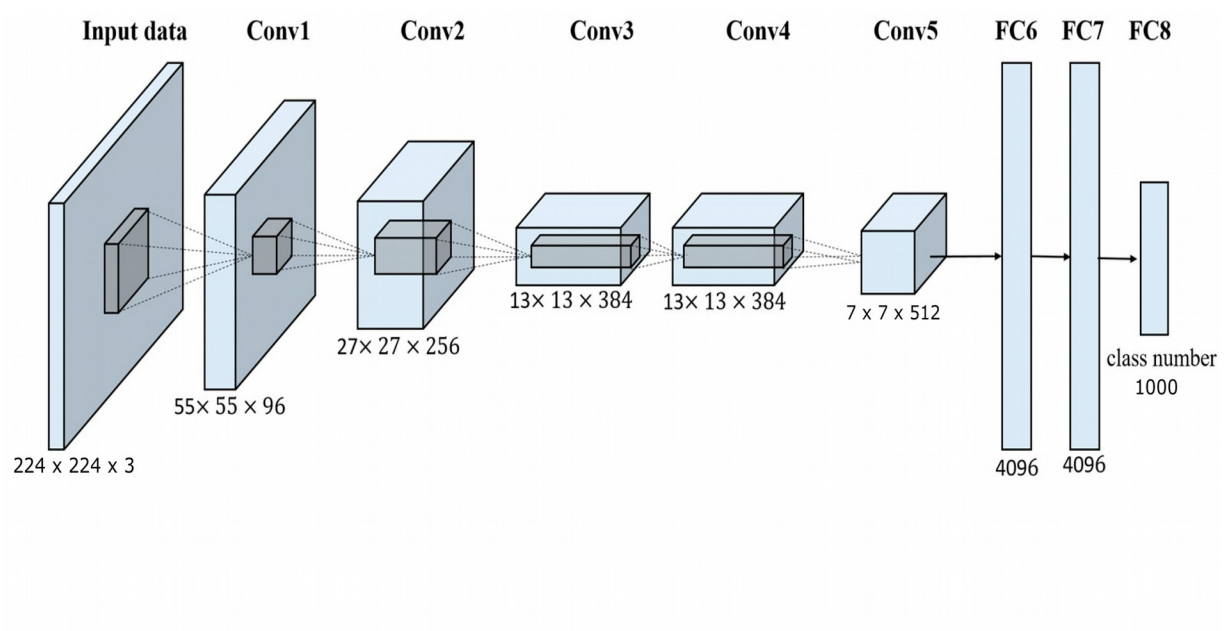


Fig 3.2 Deep Convolutional Neural Network (DCNN) Architecture

## CONCLUSION

### 4.1 Conclusion

Among other existing supervising algorithms, most of them are requiring more pre-processing or post-processing stages for identifying the different stages of diabetic retinopathy. Also, other algorithms mandatorily requiring manual feature extraction stages to classify the fundus images. In our proposed solution, Deep Convolutional Neural Network(DCNN) is a wholesome approach to all levels of diabetic retinopathy stages. No manual feature extraction stages are needed. Our network architecture with dropout techniques yielded significant classification accuracy. True positive rate(or recall) is also improved. This architecture has some setbacks are: An additional stage augmentation is needed for the images taken from different cameras with different fields of view. Also, our network architecture is complex and computation-intensive requiring a high-level graphics processing unit to process the high-resolution images when the level of layers stacked more.

### 4.2 Application

**Diabetic retinopathy** is the most common complication of **diabetes**. It's screening with fundus photography **uses** a lot of resources. The University of Oulu is involved in a project that aims to automate **retinopathy** screening through machine learning.

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### **Signature of Student**

Aditya Sharma

