# Deep Learning For Diabetic Retinopathy stage prediction

**Surua Garikapati** ( garikapatisurya12345@gmail.com )
**Venkata Saiteja Yarlagadda**

**Research Article**

**Keywords:**

**Posted Date:** May 12th, 2022

**DOI:** https://doi.org/10.21203/rs.3.rs-1633698/v1

# Abstract

Diabetic Retinopathy (DR) is a prevalent issue among diabetic individuals, resulting in a constructive loss of vision in such people. If this problem is not diagnosed early on, there is no therapy available to restore vision. As a result, the only way out of this unreversible condition is to diagnose the sickness early on and cure it. The ophthalmologists use the "fundus images" of the patients' eyes, which are the retinal pictures of the patients, to maintain their eyesight. However, detecting an abnormality in a human eye with the naked eye of another person takes time, money, and can occasionally lead to misjudgment owing to subjective differences and concerns among ophthalmologists. As a result, we employ "Deep Learning" algorithms to diagnose diabetic retinopathy using fundus pictures in this article. As a result, a computer-aided diagnosis system is established, which leads to a reduction in misdiagnosis. Deep learning approaches have recently become the most popular ways for improving image recognition or feature detection systems' accuracy for both classification and regression. In this study, we employ Convolutional Neural Networks (CNN) for image identification, training the neural network model with retinal pictures, and achieving excellent accuracies. In this work, the difficulties of various methodologies as well as faults with existing methods were examined.


# I. Introduction

There are around 420 million diabetics worldwide, and all of these individuals are at risk of Diabetic Retinopathy (DR). This condition is predicted to continue to rise in the future, resulting in an increase in the number of people who are susceptible to diabetic retinopathy. Furthermore, the fact that this condition (i.e., DR) is incurable adds to its dreadfulness, and the prospect of vision loss terrifies everyone . Early detection, which is crucial for therapy, is the sole answer to this condition. This is the difficult step, since it highlights the old techniques' lack of skilled hands and facilities. Furthermore, conventional or mature DR screening approaches encourage disagreement among readers and their subjective opinions. Finally, with the rise in diabetes and its retinal problems throughout the world, manual techniques of diagnosis may not be able to keep up with demand for screening services.

In order to solve these issues, automated diabetic retinopathy diagnosis approaches are required. While deep learning for binary classification has obtained excellent validation accuracies in general, the results for "multi-stage classification," especially for early-stage illness, are less spectacular.

We provide an automated DR grading system capable of identifying photos based on disease pathology at a few severity levels in this work. This suggested approach employs a "Convolutional Neural Network" (CNN), which convolves a picture as input into a predetermined weighted matrix to extract certain image properties without sacrificing spatial arrangement information (also known as "Feature extraction"). For the binary classification problem, we first assess multiple CNN designs to select the best performing network model among them, with the goal of achieving the best performance. We next proceed to train multi-class models, which increase sensitivity for mild or early stage classes by using different data processing and data augmentation strategies to improve test accuracy. The CNN architecture models are

then trained and tested. Several strategies, like as dropout and learning rate regulations, are used to modify them to perform optimum on a training dataset. The dataset is a publicly available Kaggle dataset with hundreds of fundus photos divided into five categories (normal, mild, moderate, severe, end stage). The goal of this research is to develop a more effective method of identifying and categorising early stage diabetic retinopathy into different phases for clinical benefit.

# Ii Background And Domain Knowledge

Deep Learning (DL) is a subset of Machine Learning (ML) that gives systems the ability to learn on their own and improve performance based on experience without the need for human intervention. DL uses the concept of a neural network in the human brain, which copies the methodology of training itself by learning [7]. Deep Learning focuses on the creation of computer algorithms that can exploit data to learn and train themselves to perform with high accuracies on data that is new to the model or data that is unlabeled [6].

The major goal is for the systems to learn on their own, without any need for human assistance, and to enhance their activities as a result.

Deep Learning has been extremely effective in constructing networks that can learn from unsupervised training, unlabeled, or unstructured data. PEAS is a set of stages used by most systems.

P- Performance

E- Environment

A-Actuators

S- Sensors

The computer trains itself and increases accuracy via "back propagation" using these elements, and deep neural networks, which are made up of multiple neurons, are made up of these technologies.

# Iii. Problem Description

In identifying and evaluating the deviations in the DR fundus photos from the non DR fundus images (i.e., the input data), sophisticated deep learning algorithms are employed to predict the phases of diabetic retinopathy. The traditional method of detecting DR is time-consuming, and it necessitates the employment of highly experienced and talented ophthalmologists to identify the important aspects, disease-causing alterations in retinal pictures [10]. The automated technique for diagnosing diabetic retinopathy might aid individuals with diabetes, as well as the professionals who treat them, in recognising the signs early on. The CNN processes are heavily implemented for the application of this worldview. This CNN model contains a number of hidden layers (the number changes depending on the

demand), which convolve the picture, extract its features, and other information needed for further processing. The classification layer provides the output of this CNN model.

# Iv. Problems In Existing System

When a patient is diagnosed with diabetes, we might notice abnormalities in their vision; the cause of this visual impairment is the effect that diabetes has on the retina, resulting in Diabetic retinopathy [3]. Typically, ophthalmologists or clinical professionals view the retinal pictures with their naked eye, which results in misdiagnosis, inaccuracy, time consumption, and cost to the patients. Existing automated systems, on the other hand, rely on an expert system with a large number of business rules, which takes more time and money, as well as a lengthy coding process. When dealing with a huge number of picture inputs, some coding approaches may not be very efficient. The irregularity of the input dataset is also a disadvantage of the current system, resulting in lower accuracy and hospitals continuing to rely on old procedures. [4]

These expert systems employ statistical techniques that are often employed for textual and numerical data, but are inefficient for picture datasets.

Disadvantages of existing system:

- Inaccurate
- Expensive
- It takes more time
- Much coding
- Mostly statistical approach
- In accurate training

# V. Methodology Of Proposed Work

The suggested methodology employs a deep learning technique called Convolutional Neural Network (CNN) to handle the irregular and unlabeled, large number of fundus pictures, as we have already supplied with issues in the existing system. Meanwhile, deep learning algorithms and methodologies are built on human-like approaches that are dependable, cost-effective, and time-effective. When working with unlabeled picture data, CNN algorithms are widely renowned for their accuracy [8]. When training the architecture with fundus pictures, the sensitivity is likewise quite high while compared to other models when considering accuracy (unlabeled data as well).

# Vi. Dataset

The dataset used to train the model and obtain the model's outcome is accessible from Kaggle, a public resource. We employed multiple fundus photos in this study, and their labels were stored in a csv file

named Training Labels, which contained the labels for the fundus images as well as their severity scale, which was one of [0,1,2,3,4]. This dataset will be used to train the model, and predictions will be made on the data to be tested based on previous experiences (i.e., the CNNmodel developed from training the data). [9]

# Vii. Image Processing And Analysis

From the above histogram obtained from the dataset, we can see that there is class imbalance in the training data-set with most cases having value of ‘0’ and least in ‘3’ and ‘4’ classes.

# Viii. Pictorial Representation Of Convolutional Network

**STEPS FOR BUILDING A CNN MODEL:**

- Import libraries
- Preprocessing
- Initialize neural network model
- Add input layer
- Add hidden layers
- Add output layer
- Compile neural network model

**LIBRARIES REQUIRED:**

- Pandas
- PIL
- OS
- Numpy
- Random
- Sklearn
- Matplotlib
- Keras

# Ix. Preprocessing

It is usually important to do preprocessing before executing any job involving photos in order to make the images more acceptable as input data. Converting photos from JPEG or PNG files into useful data for neural networks, for example. The collection comprises mostly of fundus photography pictures of the retina of the eye. As can be seen, photos have artefacts, with some being out of focus, underexposed, or overexposed, among other things. Furthermore, some of the photographs have poor brightness or low

lighting circumstances, making it harder to judge the differences between them and increasing the danger of making a mistake.

**Image Resizing**:

Images of various sizes will be included in the picture dataset. It is necessary to transform all of them to a standard dimension; in this case, the data is converted to the dimensions 256x256. This may be accomplished by resizing or scaling the image.

**Convert image into Green Channel**:

As photos contain a variety of points, they are transformed to green channel. There are a few with high densities and a few with low densities, however when pictures are transformed to green channel, the densities of all spots in the image are moderated.

**Augmentation of images**:

It is done by applying numerous changes to a picture depending on some random function in order to develop the model using a large number of images, despite the fact that we only collected a small dataset.

The result after the preprocessing and application of green channel looks like the above images

# X. Initialize Neural Network Model

**Sequential Neural Network**:

Through their consecutive layers, Neural Networks build high-level features in a sequential manner. A novel neural network model is proposed, in which each layer is coupled with a list of possible mappings. It's a layer stack that runs in a straight line.

**ADD INPUT LAYER:**

The input shape, which is a function that defines the input image's size, has been declared. This is the CNN model's input. It's a convolution layer with 32 filters and a 3x3 kernel, and the activation and padding arguments are set to "ReLU" and "same," respectively.

**ADD HIDDEN LAYERS:**

Three layers are concealed in our model. A convolution layer with 32 filters and a 3x3 kernel is the first hidden layer, followed by a max pooling layer and one dropout layer. The second hidden layer is a convolution layer with 64 filters and a 3x3 kernel, and the activation and padding arguments are set to "ReLU" and "same," respectively. A convolution layer with 64 filters and a kernel of size 3x3 is the third

hidden layer, followed by a max pooling and a dropout layer. Then, to feed the data to the next layer, we apply the "Flatten" model to the data in a 1-dimensional array.

**ADD OUTPUT LAYER:**

The network's last layer, the output layer, is a Dense layer with 512 neurons that also includes a ReLU activation function and is followed by a dropout layer. The softmax function is used as the activation property in the following dense model, with units set to "5".

**COMPILE NEURAL NETWORK MODEL:**

Finally, the framework is designed using the Keras optimizer, with a learning rate of 0.0001 and accuracy as metrics. The categorical bridge between an output tensor and a target tensor (categorical crossentropy) is the first attribute of model.compile.

# Xi. Results Obtained

On the processed picture data, however, the training accuracy for 10 epochs was 73 %, for 15 epochs was 79 %, and for 50 epochs was 83.6 % after employing the aforesaid CNN model. The greatest accuracy for the test set was 86 %, because to the small number of neurons used. This demonstrates that increasing the complexity of the neural net by increasing the number of both epochs and neurons or hidden layers increases the model's accuracy. It's worth noting that "this model's accuracy score lowers after preprocessing." We believe this is because critical picture characteristics are lost during median filter. This strategy should be investigated further to see if we can improve these models' sensitivity to very sensitive and very mild class DR.

# Xii. Comparitative Analysis

There are a variety of strategies for detecting diabetic retinopathy automatically; in this study, we employed Convolutional Neural Networks (CNN) to improve accuracy and minimise complexity. Many alternative strategies for detecting DR, on the other hand, are already in use. These are some of the methodologies:

- Decision Support System (DSS)

It's a method for making decisions, making judgements, and deciding on a course of action in a system. It analyses data and compiles information in order to solve an issue or make a conclusion. The accuracy of this approach on DR detection is 67 percent. [8]

- Statistical Classification

The observations from training the dataset are used to categorise the data into its relevant category using this approach. This technique is 79.62 percent accurate in identifying DR. [8]

- Fuzzy CMeans (FCM) Clustering

FCM is a type of clustering that divides data into numerous related clusters and outputs the most likely alternative based on the likelihood of a given point in all clusters. Clustering using FCM has a 66 percent accuracy rate. [8]

As a result, CNN is one of the very few approaches that produces great picture data accuracy.

# Xiii. Conclusion

Automated screening systems, also known as detection systems, are utilised to drastically shorten the time it takes to identify diagnoses, saving ophthalmologists time and money while also allowing patients to be treated more quickly. Automated Diabetic Retinopathy Detection Systems play a critical role in diagnosing or detecting retinopathy at an early stage. The DR phases are determined by the type of retinal defects that develop. CNNs have recently been suggested as a possible addition to the range of algorithms used to test for diabetes illness by researchers. CNNs are always an effective strategy for leveraging a huge number of pictures collected by ophthalmologists for diagnosis, but with varying pixel sizes and irregularity. Because of the high variance and low bias of these models, CNNs may be able to identify a wider spectrum of non-diabetic disorders [11], and such innovative approaches are being used to change  the medical business and assist both physicians and patients.

# Xiv. References


1. Abràmoff M. D., Reinhardt J. M., Russell S. R., Folk J. C., Mahajan V. B., Niemeijer M., Quellec G. Automated early detection of diabetic retinopathy. Ophthalmology, 2010;117(6):1147–1154. [PMC free article] [PubMed] [Google Scholar]
2. Antal B., Hajdu A. An ensemble-based system for microaneurysm detection and diabetic retinopathy grading. IEEE transactions on biomedical engineering, 2012;59(6):1720–1726. [PubMed] [Google Scholar]
3. Chan J. C., Malik V., Jia W., Kadowaki T., Yajnik C. S., Yoon K.-H., Hu F. B. Diabetes in asia: epidemiology, risk factors, and pathophysiology. JAMA, 2009;301(20):2129–2140. [PubMed] [Google Scholar]
4. Congdon N. G., Friedman D. S., Lietman T. Important causes of visual impairment in the world today. Jama, 2003;290(15):2057–2060. [PubMed] [Google Scholar]
5. Decenciere E., Zhang X., Cazuguel G., Lay B., Cochener B., Trone C., Gain P., Ordonez R., Massin P., Erginay A., et al. Feedback on a publicly distributed image database: the messidor database. 2014;33:231–234. [Google Scholar]
6. Gardner G., Keating D., Williamson T., Elliott A. Automatic detection of diabetic retinopathy using an artificial neural network: a screening tool. British journal of Ophthalmology. 1996;80(11):940–944. [PMC free article] [PubMed] [Google Scholar]

7. Gargeya R, Leng T. Automated identification of diabetic retinopathy using deep learning. Elsevier. 2017 [PubMed] [Google Scholar]
8. Goh J. K. H, Cheung C. Y., Sim S. S., Tan P. C., Tan G. S. W, Wong T. Y. Retinal imaging techniques for diabetic retinopathy screening. Journal of diabetes science and technology, 2016;10(2):282–294. [PMC free article] [PubMed] [Google Scholar]
9. Graham B. Kaggle diabetic retinopathy detection competition report. 2015 [Google Scholar]
10. Gulshan V., Peng L., Coram M., Stumpe M. C., Wu D., Narayanaswamy A., Venugopalan S., Widner K., Madams T., Cuadros J., et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA, 2016;316(22):2402–2410. [PubMed] [Google Scholar]
11. Huang L. C., Yu C., Kleinman R., Smith R., Shields R., Yi D., Lam C., Rubin D. Opening the black box: Visualization of deep neural network for detection of disease in retinal fundus photographs. The Association for Research in Vision and Ophthalmology. 2017 [Google Scholar]

# Figures


**Figure 1**

5 stages of DR

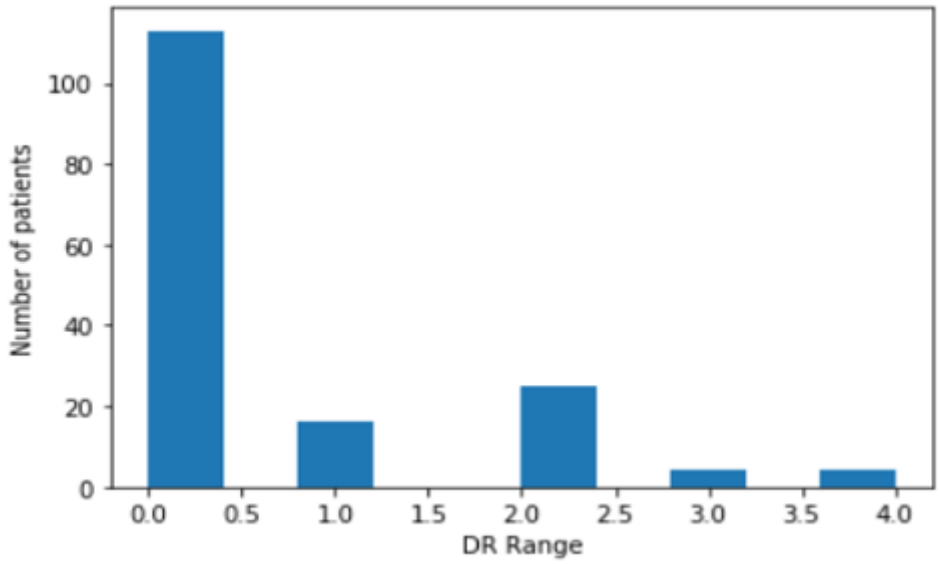



**Figure 2**

Class distribution of output variable:

Histogram to represent patients ranging within five stages of DR

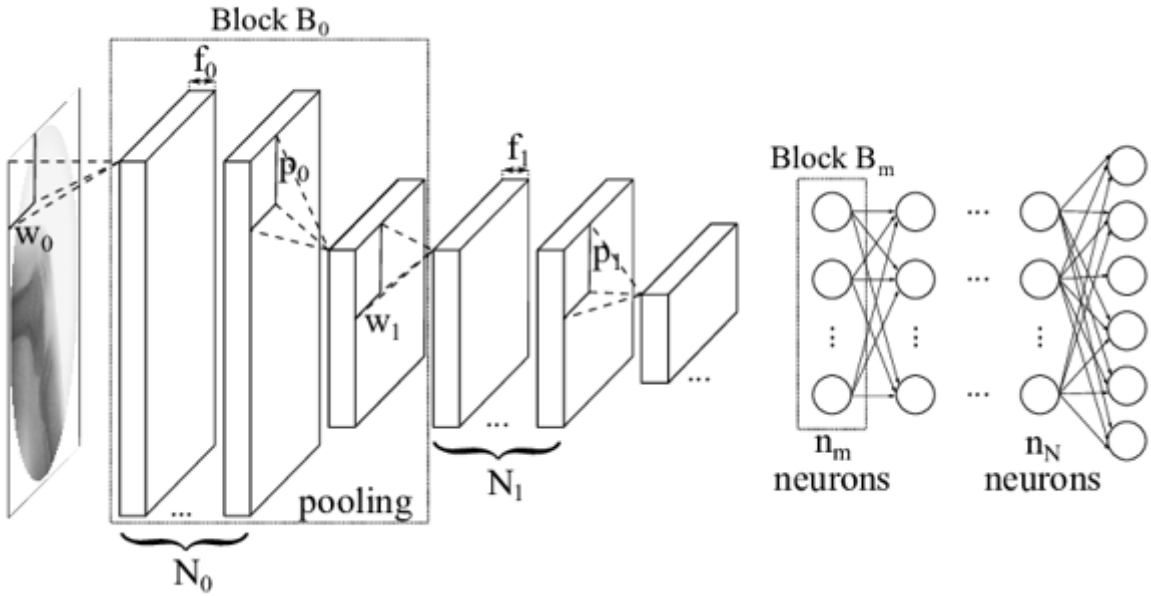
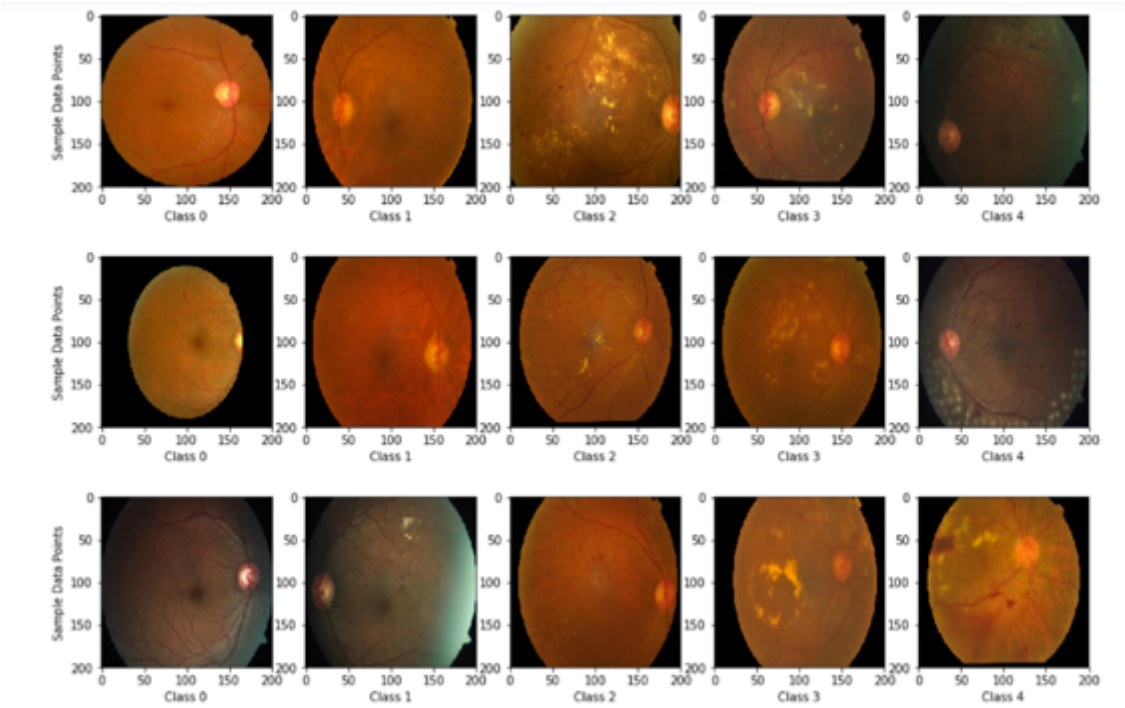



**Figure 3**

Pictorial representation of convolutional network




## Figure 4

Dataset of fundus images before pre-processing  Hence, we image processing to overcome these problems.

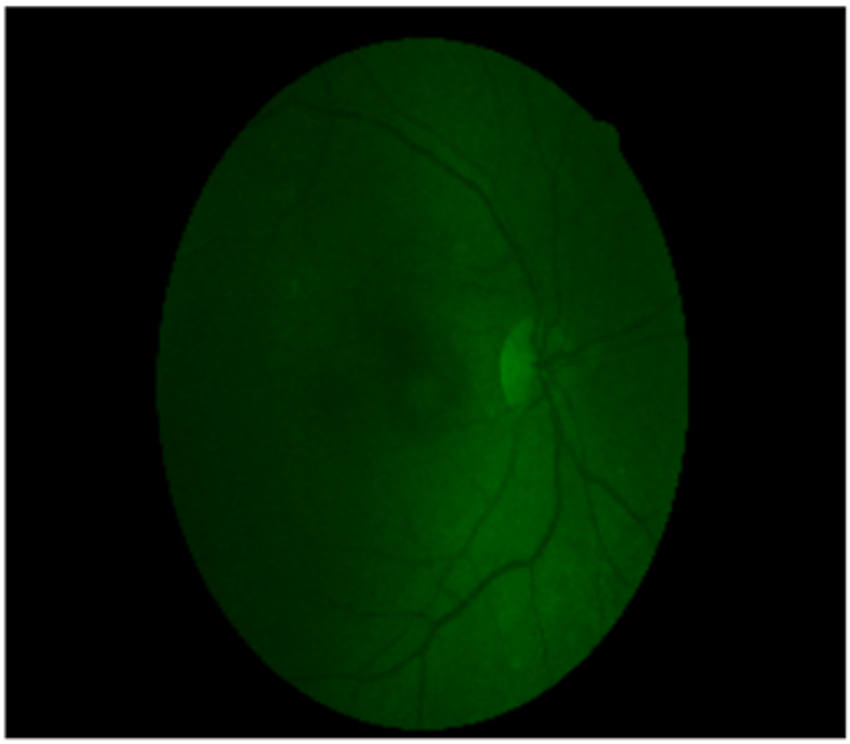


**Figure 5**

After applying green channel

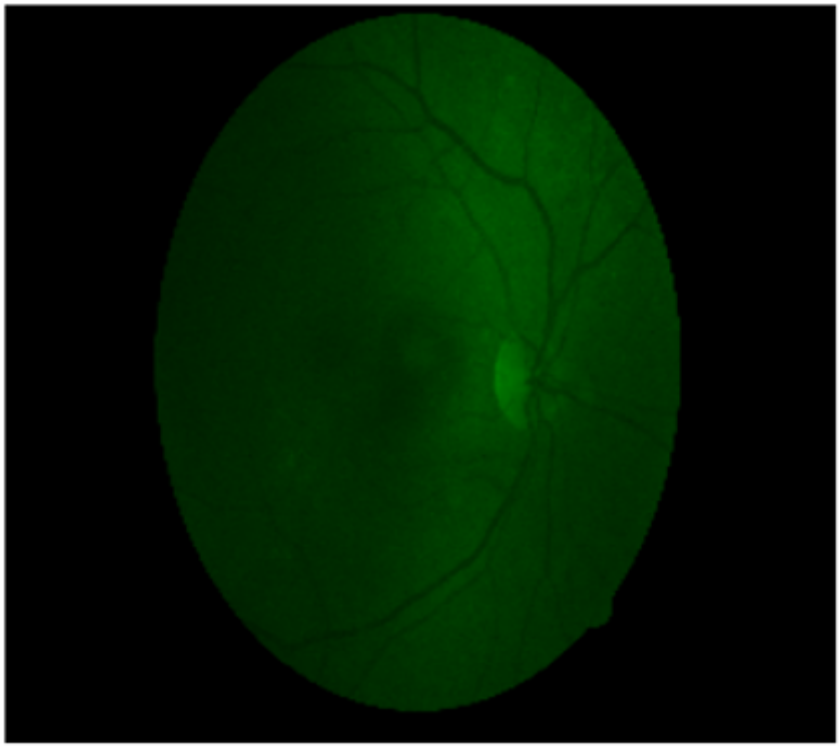


**Figure 6**

After applying green channel