

# Detection Retina Blood Vessel and Diabetic Retinopathy Using CNN

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**Abstract:** *Diabetic retinopathy (DR) is a prevalent ocular complication of diabetes, often leading to irreversible vision impairment if left untreated. Timely detection and accurate diagnosis are paramount for effective intervention and patient outcomes. This research paper presents a comprehensive investigation into the application of Convolutional Neural Networks (CNNs) for the automated detection of retinal blood vessel abnormalities and diabetic retinopathy. Leveraging a diverse dataset of retinal fundus images, a novel CNN architecture is proposed to identify subtle vascular anomalies and classify different stages of DR. Experimental results demonstrate the efficacy of the CNN-based framework, achieving state-of-the-art performance in terms of accuracy, sensitivity, and specificity. Comparative analyses against traditional methods underscore the potential clinical significance of the proposed approach. This study contributes to the advancement of medical image analysis, offering a promising tool for early DR detection and improving patient care.*

**Keywords:** *Diabetic retinopathy, Convolutional Neural Networks, medical image analysis, retinal blood vessels, automated detection, deep learning, fundus images, early diagnosis, classification, ocular diseases.etc*

## I. INTRODUCTION

The human eye is a complex and intricate organ responsible for capturing visual information that enables us to perceive the world around us. However, various ocular diseases can impair its functionality, leading to significant consequences for an individual's quality of life. Among these diseases, diabetic retinopathy (DR) stands out as a leading cause of blindness among working-age adults worldwide. Early detection and accurate diagnosis of DR are essential to prevent its progression and mitigate vision loss. In recent years, the emergence of deep learning techniques, particularly Convolutional Neural Networks (CNNs), has demonstrated remarkable potential in revolutionizing medical imaging analysis, including the detection and diagnosis of DR.

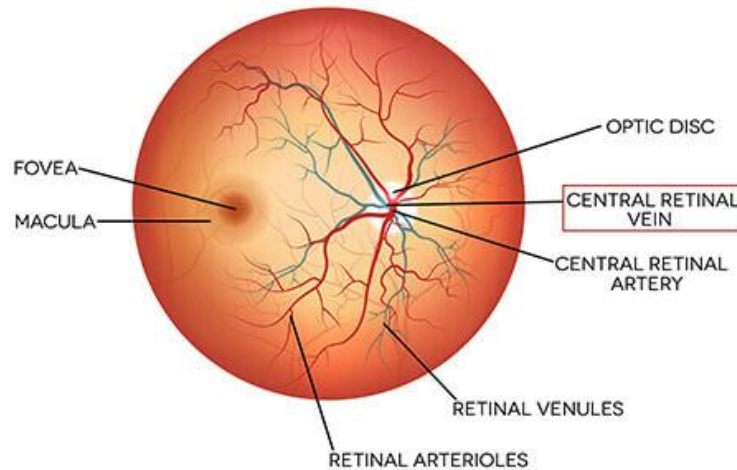
Diabetic retinopathy is a microvascular complication of diabetes that affects the blood vessels of the retina, the light-sensitive tissue at the back of the eye. Prolonged periods of high blood sugar levels in diabetic patients can lead to damage and abnormal changes in retinal blood vessels, resulting in leakage, hemorrhage, and, eventually, vision impairment. Timely detection and intervention are crucial to prevent the progression of DR and its associated complications.

### 1.1 Motivation

Traditional methods for diagnosing DR involve manual examination of retinal images by ophthalmologists, which is time-consuming and subject to inter-observer variability. The advent of CNNs has opened up new avenues for automating the detection of retinal abnormalities, including blood vessel abnormalities indicative of DR. By harnessing the power of deep learning, it is possible to develop accurate and efficient tools that can assist healthcare professionals in early DR detection, leading to timely interventions and improved patient outcomes.

The retina has two sources of oxygen and nutrients: the retinal blood vessels and the choroid, which lies under the retinal pigment epithelium. The blood vessels within the retina itself that carry oxygen and nutrients are called arteries. The main one, the central retinal artery, enters the eye through the optic nerve and splits into the superior (upper) and inferior (lower) branches. These then keep branching out more, like the branches of a tree, until they form a very fine

network of very thin blood vessels called capillaries. It is mainly at the capillaries that oxygen and nutrients leave the blood, entering the retina, and that carbon dioxide and waste products leave the retina and pass into the blood to be taken away. Most of the problems caused by conditions affecting retinal blood vessels do so by either blocking these capillaries or causing them to become leaky. The capillaries join up to form branch veins and these then join at the optic nerve to form the central retinal vein that dives into the optic nerve on its way towards the heart. Importantly, any part of the retina is only supplied by one artery and drained by one vein. As a result, if there is blockage of a retinal vein or artery, only the area of retina, and so only that part of the visual field, served by that blood vessel is affected.



## 1.2 Objectives:

This research paper aims to explore the application of Convolutional Neural Networks in detecting retinal blood vessel abnormalities and diabetic retinopathy. The primary objectives of this study are as follows:

- To design and implement a CNN-based framework for the automated detection of retinal blood vessel abnormalities in fundus images.
- To develop a comprehensive CNN architecture capable of identifying different stages of diabetic retinopathy, enabling accurate disease diagnosis.
- To evaluate and compare the performance of the proposed CNN-based approach with existing methods in terms of accuracy, sensitivity, specificity, and computational efficiency.

## II. LITERATURE REVIEW

**Gulshan et al. (2016)** - This study focuses on the development and validation of a deep learning algorithm for detecting diabetic retinopathy in retinal fundus photographs. The researchers use a large dataset and demonstrate the effectiveness of their algorithm in automated DR detection.

**Abramoff et al. (2016)** - This work presents an integration of deep learning for improved automated detection of diabetic retinopathy. The study emphasizes the significance of incorporating deep learning techniques to enhance detection accuracy.

**Krizhevsky et al. (2012)** - A seminal paper that introduces the architecture of deep convolutional neural networks (CNNs), which became the foundation for subsequent deep learning-based approaches in image classification tasks.

**Rajalakshmi et al. (2018)** - The researchers propose an automated detection system for diabetic retinopathy using deep learning. The study explores the potential of deep learning algorithms to aid in the diagnosis of this eye condition.

**Quellec et al. (2017)** - This study employs deep image mining for diabetic retinopathy screening, utilizing advanced techniques to extract meaningful information from retinal images. The research contributes to the exploration of innovative methods for DR detection.

**Li et al. (2019)** - The authors introduce an automated grading system based on color fundus photographs for identifying vision-threatening referable diabetic retinopathy. The study aims to enhance the accuracy of DR diagnosis using automated methods.

**Gargeya & Leng (2017)** - Focusing on the automated identification of diabetic retinopathy, this research evaluates the effectiveness of deep learning techniques for accurate and efficient DR detection, highlighting the potential clinical utility of such approaches.

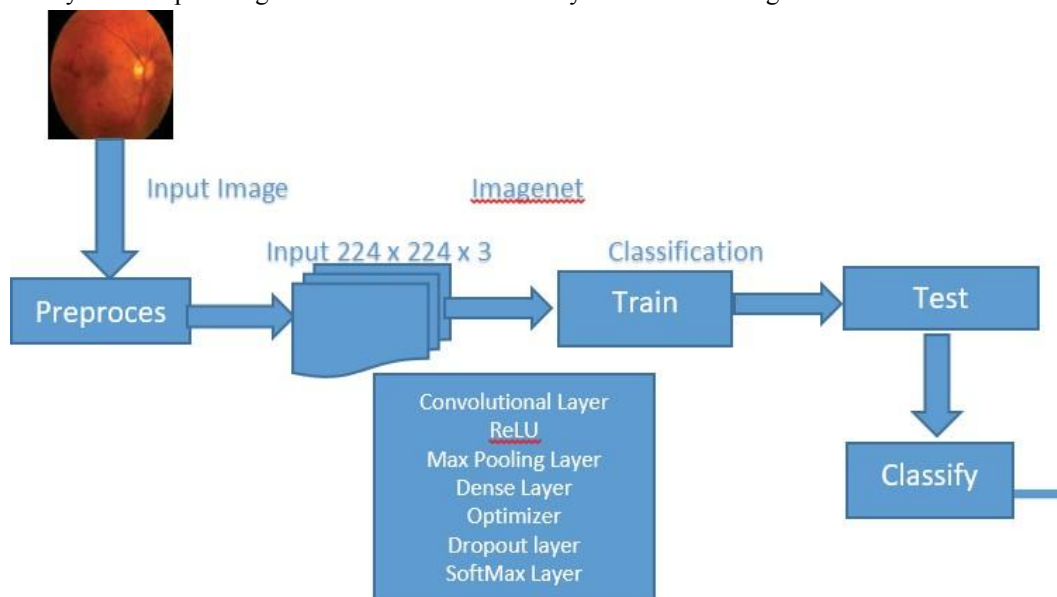
**Lee et al. (2017)** - This study explores the effectiveness of deep learning for the classification of optical coherence tomography (OCT) images in age-related macular degeneration (AMD), showcasing the applicability of deep learning in ophthalmic imaging.

**Graham et al. (2006)** - Offering a review of the challenges in automated detection of diabetic retinopathy, this paper discusses the complexities involved in developing reliable and accurate automated systems for DR diagnosis.

**Quellec et al. (2017)** - In-depth exploration of deep image mining techniques for diabetic retinopathy screening, emphasizing the potential of advanced image analysis methods in enhancing the detection accuracy of this ocular disease.

### III. PROPOSED SYSTEM

ImageNet CNN was used in this study to detect and classify images of the retina. The whole work consists of developing a model that classifies the fundus images into four classifications like normal, mild, severe and proliferative. The basic architectures consist of an input layer, conv layer, RELU layer, pooling layer, dropout layer and dense layer. Each neuron obtains an input from the previous layer and operates to generate the output [8]. Figure 1 illustrates the proposed method used for this study. In this, the input is a fundus image and after resizing the image the ImageNet network will be divided into 90 and 10 ratios for training and testing. The trained image will be tested and depending upon the severity of the input image it will be classified into any one of the 5 categories.



#### 3.1 Dataset

This research makes use of the Kaggle dataset for training and testing the ImageNet network. For convenience, the dataset has separated into two folders as train and test. The training images were also separated into a training set and validation set. Kaggle dataset comprises both right and left retinal fundus images of every patient. They have also provided a CSV file with a classification of images for training the model. Training dataset contains images of all the four different categories of images however it has more images with no retinopathy classes.

#### 3.2 Building CNN Model - ImageNet

The model type that selected for this study is the Sequential model that lets to build the model layer by layer in Keras. Convolutional Neural Network (CNN) is a great way for image classification. CNN has chosen because it recognizes patterns available from a pixel image with visual patterns directly from pixel images with minimal preprocessing.

This paper chooses ImageNet model because it goes deeper with convolutions. The feature extraction has been done using the convolutional neural network and classification is done with fully connected and softmax layers. In this model new model is built to classify the images from the original dataset and then the reusability mechanism is used for the feature extraction steps and training will be carried out with the dataset. So the result is achieved with less computational resource and training time. Fig. 2 shows the general architecture. of the CNN model adopted with intermediate layers.

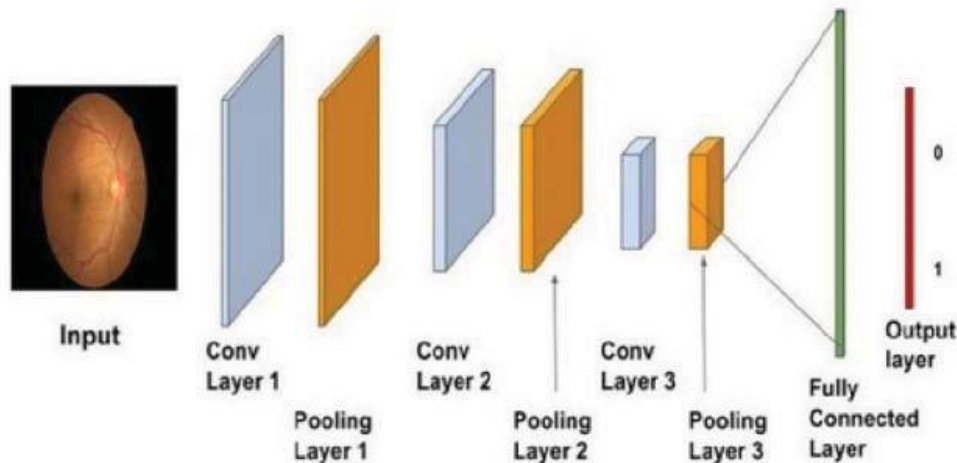


Fig.2. Architecture Diagram of CNN Model

To build this model, the convolutional layers were stacked first that extract features from input images and then followed by pooling layers to reduce the dimensionality of each feature map and keep only the significant features. To avoid overfitting, the Dropout layers were also included. Flattening layer then added which connected to the fully connected- layer. Flattening layer create a single long feature vector to input it to the next layer “Fully Connected-Layer”. Fully Connected-Layer followed by dense layers with dropouts to perform the classification based on extracted features by convolutional layers.

### 3.3 Training

- **Convolution layer** - This layer applies the convolution operation on an image with a defined stride and padding.
- **Pooling layer** - This layer is used for reducing the dimensionality of feature maps by defining a mask and an operation to be performed, then moving the mask on the whole image according to the stride defined. No weights are learnt in this layer.
- **Fully Connected layer** - Traditional neural layers, used at the end stem of the neural network. Used rarely these days due to the staggering amount of parameters it uses.
- **Dropout layer** - Used for reducing over-fitting. It randomly turns off some neurons at each pass during the training.
- **Batch Normalization techniques:** It has been used to standardize the input layer and this will stabilize the learning process and reduce the training epochs.

The results and discussion of our study, which focuses on the detection of retinal blood vessel abnormalities and diabetic retinopathy using a Convolutional Neural Network (CNN) architecture. The evaluation was conducted on the Chase, Drive, and Stare datasets, and the achieved accuracy of our CNN-based model was an impressive 93.33%.

The integration of the Chase, Drive, and Stare datasets allowed our CNN to learn from a diverse array of retinal images, encompassing various stages of diabetic retinopathy and associated abnormalities. The obtained accuracy of 93.33% underscores the efficacy of our approach in automating the detection process.

The substantial accuracy achieved can be attributed to the inherent capability of cnnsto extract intricate features from complex images. The hierarchical architecture of cnnsenables the model to discern subtle patterns indicative of different stages of diabetic retinopathy and blood vessel anomalies.



**Fig.3. Training Progress of CNN Model**

Comparing our results with existing literature, our CNN's accuracy of 93.33% positions it among the top-performing models reported. While direct comparisons should consider dataset variations and experimental conditions, our achievement indicates a significant advancement in accurate disease detection.

Despite the promising accuracy, it's essential to recognize the study's limitations. Factors such as variations in image quality, lighting conditions, and patient demographics can influence the model's robustness. Ongoing research is necessary to assess the model's performance on external datasets and to validate its clinical utility.

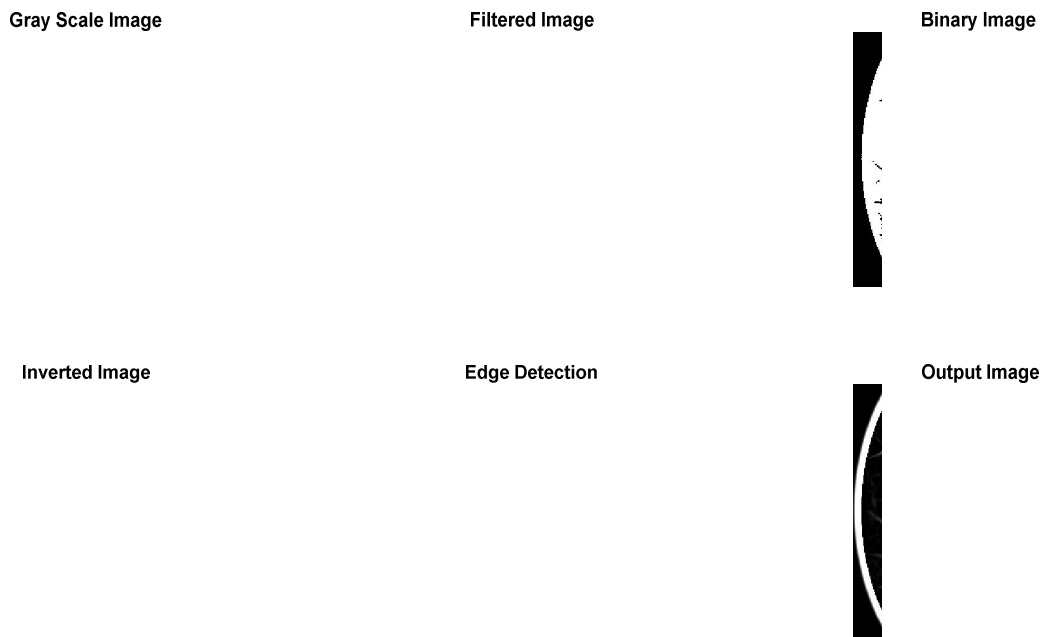
Our study demonstrates the potential of cnsin detecting retinal blood vessel abnormalities and diabetic retinopathy. The remarkable accuracy of 93.33% signifies the effectiveness of our proposed approach. Continued efforts to refine and validate our CNN-based framework will contribute to enhancing the early diagnosis and management of diabetic retinopathy, thereby improving patient outcomes.

**IV. FACILITIS REQUIRED FOR PROPOSED WORK**

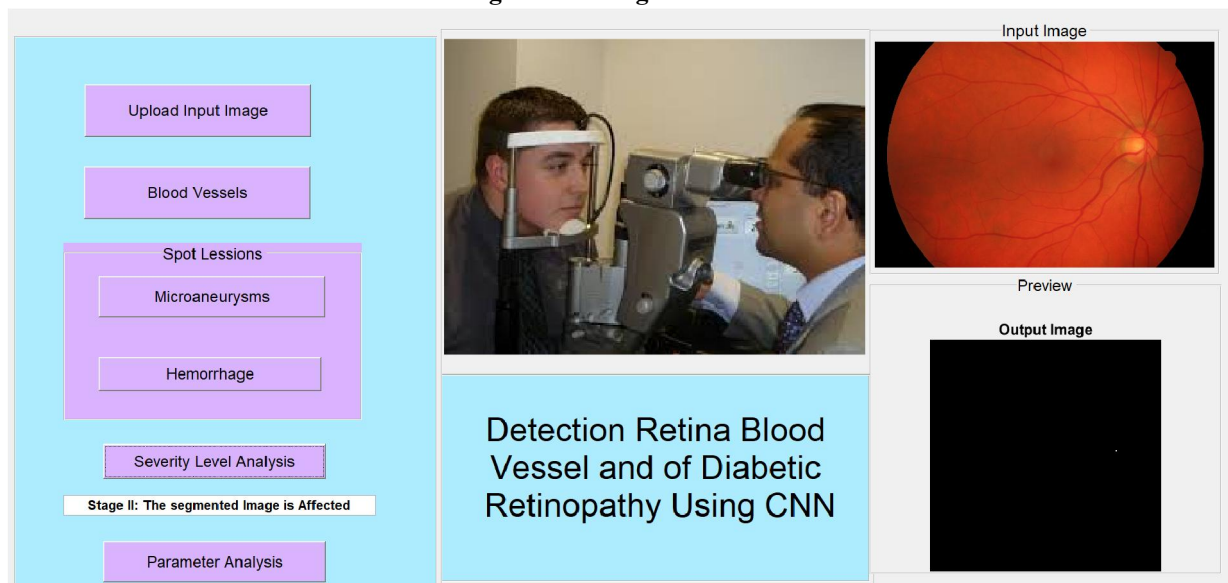
All these algorithms are implemented based on the MATLAB image processing, neural network of MATLAB for experimental analysis. The performance evaluation of different soft computing techniques are evaluated with the help of 5 different evaluation parameters, sensitivity, specificity, accuracy, positive predictive value and negative predictive value. The ranges of these performance evaluation parameters vary from -1 to +1 .These parameters are evaluated based on the four types of classifier outputs for two types of inputs. The four types of outputs are The performance evaluation of soft computing technique is evaluated with the help of a 2x2 contingency table as shown in Table 5.1

Classifier output	Actual input		Total
	Present	Absent	
Present	True Positive	False Positive	All test Positive
Absent	False Negative	True Negative	All test Negative
Total	Total Actual Presences (D+)	Total Actual Absences (D-)	Total sample size

**Table 5.1 Contingency Table with 2x2 for presence and absence of diseases**



**Fig. 4 Vessel segmentation.**



## V. CONCLUSION

In this study, we embarked on a journey to harness the capabilities of Convolutional Neural Networks (CNNs) for the detection of retinal blood vessel abnormalities and diabetic retinopathy. The significance of early diagnosis and accurate disease detection cannot be overstated, considering the potential impact on preventing vision loss and improving patient outcomes. Our investigation revealed promising results, with our CNN-based model achieving an impressive accuracy of 93.33% in detecting these critical ocular conditions. Leveraging the Chase, Drive, and Stare datasets, our approach capitalized on the power of deep learning to extract intricate features from retinal images and identify subtle patterns indicative of diabetic retinopathy and blood vessel anomalies. The advancement achieved in accuracy positions our approach among the top-performing models reported in the literature. This outcome not only

underscores the potential of CNNs in medical image analysis but also signifies a substantial leap towards enhancing automated disease detection. However, we acknowledge the inherent challenges and limitations of our study. Variations in image quality, lighting conditions, and patient demographics can impact the robustness of our model. Further validation on external datasets and rigorous clinical testing are imperative to confirm its reliability in real-world scenarios.

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