INTERNATIONAL JOURNAL
OF TECHO-ENGINEERING

ISSN : 2057-5688

# Diabetic Retinopathy Using Sequential Model in Deep Learning

**Dr. R .Durga M.C.A., M.Phil., Ph.D.**
Associate Professor
Department of Computer Science,
Vistas, Chennai

**P. Hariharan (MSC Cs)**
Department of Computer Science,
Vistas, Chennai

**Abstract:** Diabetic retinopathy (DR) is an eye disease that commonly affects diabetics and can result in permanent blindness if not treated promptly. A membrane called Retina covers the back of the human eye and is extremely sensitive to light. The retina converts light into electrical signals, which are then transported to the brain by the Nervous System. The human eye's sensation of sight is enabled by this mechanism, which produces visual images. Diabetic retinopathy causes vision distortion due to fluid leaks from damaged blood vessels inside the eye. Doctors are now using retinal scans to evaluate the level and intensity of blindness in individuals. Due to the microscopic size of the lesions and their complexity in contrast, this task is tedious, time-consuming, and takes a great amount of effort. A deep-learning-based solution can be used to tackle this problem. We proposed a strategy to detect diabetic retinopathy using deep learning sequential models in our model.

## 1. INTRODUCTION

Diabetes mellitus causes diabetic retinopathy, which is a passive disease. It has a number of negative impacts on the naked eye that, if not addressed, might result in blindness. It took multiple surgeries to heal and restore the eye after it became infected. This concept simplifies things by preventing illness spread by diagnosing the infection as soon as feasible and administering the necessary medication. The model uses a powerful algorithm to precisely determine the phases and infection. As a result, the model aids in recognizing and informing about the patient's infection level. This is a user-friendly model in which the trained data set runs the deep learning algorithm to determine the degree of infection in the eye.

**RETINOPATHY: A DIABETIC DISORDER**

Diabetes is one of the world's most debilitating diseases. Diabetes mellitus affects the majority of the elderly population. The increase in sugar levels in the body causes a slew of horrible diseases. It also reduces the body's inherent strength. Diabetes causes a slew of additional serious illnesses. Diabetic Retinopathy is one such condition caused by diabetes mellitus. Diabetic retinopathy is caused by high blood sugar levels. It is a condition in which the eye sight gradually deteriorates until it completely disappears at one point. Diabetic retinopathy is a vision problem caused by diabetes. It can occur as a consequence of diabetes-related high blood sugar levels.

Too much level of glucose can affect blood vessels in the eyes, including those in the retina, over time. The retina is the layer of tissue that covers the back part of the eye. It senses light and transmits information to the brain via the optic nerve. Sugar can cause the retina's small blood vessels to leak or bleed if it obstructs them. The eye may then develop new blood vessels that are weaker and more likely to leak or hemorrhage.

**DIABETIC RETINOPATHY CAUSES**

Diabetes causes elevated blood sugar, which leads to diabetic retinopathy. Too much sugar in your blood can damage your retina, which detects light and transmits information to your brain through some kind of nerve at the back of your eye, over time (optic nerve). Diabetes wreaks havoc on the body's blood vessels. Sugar obstructs the nerves and blood vessels that lead to your retina, forcing them to ooze fluid or bleed, causing damage to your eyes. Your eyes generate new blood vessels that don't operate adequately to compensate for the blocked blood vessels. These young blood vessels are prone to leaking or bleeding.

**COMPLICATIONS**

Diabetic retinopathy is characterized by abnormal blood vessel development in the retina. Serious vision difficulties can arise as a result of complications:

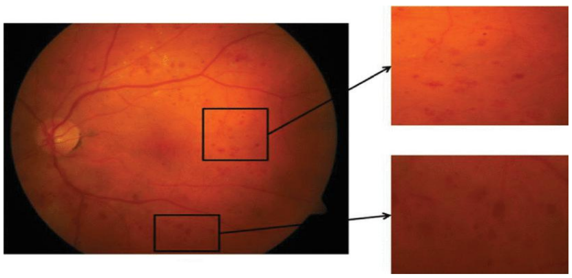

**Figure 1:** Enlarged Retinal Images indicating bigger red hemorrhage in the eyes of the patient.

**Vitreous hemorrhage** is a condition in figure (1) that affects the eyes. It's possible that the new blood vessels will leak into the transparent, jelly-like fluid that fills your eye's center. Only just few dark patches may appear if the volume of bleed is minor (floaters). Blood can fill the vitreous cavity and entirely obstruct your vision in more severe cases. In most cases, a vitreous hemorrhage does not result in permanent visual loss. Within a few weeks or months, the blood in the eye usually clears. The vision might restore to its previous sharpness if your retina is not damaged.

**Detachment of the retina**: Diabetic retinopathy causes aberrant blood vessels to form, causing scar tissue to grow and drag the retina away from the back of the eye. This can result in floating dots in your vision, bright flashes, or serious vision loss.

**Glaucoma:** is a disease that affects the eyes. New vessels may form in the front of your eye, obstructing the usual flow of the fluid out of the eye and causing pressure to build up in the eye (glaucoma). The nerve that transmits images from your eye to your brain can be damaged by this pressure (optic nerve).

Thus, our proposed model aims to build a user-friendly interface where patients can capture eye images and know if they have diabetic retinopathy and get the treatment done accordingly using sequential learning.

## 2. LITERATURE SURVEYS

In (1), they try and summarize the various models and techniques used along with methodologies used by them and analyze the accuracies and results. It will give us exactness of which algorithm will be appropriate and more accurate for prediction.

In (2), This paper used Convolutional neural networks are more widely used as a deep learning method in detection of Diabetic retinopathy, the recent state-of-the-art methods of Diabetic retinopathy color fundus images detection and classification using deep learning techniques have been reviewed and analyzed.

In (3) In the paper, a novel algorithm based on deep convolutional neural network (DCNN). Unlike the traditional DCNN approach, we replace the commonly used max- pooling layers with fractional max-pooling. Two of these DCNNs with a different number of layers are trained to derive more discriminative features for classification.

In (4), The idea behind this paper is to propose an automated knowledge model to identify the key antecedents of DR. Proposed Model have been trained with three types, back propagation NN, Deep Neural Network (DNN) and Convolutional Neural Network (CNN) after testing models with CPU trained Neural network gives lowest accuracy because of one hidden layers whereas the deep learning models are out performing NN.

In (5), A proposed deep learning approach such as Deep Convolutional Neural Network(DCNN) gives high accuracy in classification of these diseases through spatial analysis. A DCNN is more complex architecture inferred more from human visual prospects. Amongst other supervised algorithms involved, proposed solution is to find a better and 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 publicly.

In (6), To develop this proposed system, a detection of red and bright lesions in digital fundus photographs is needed. Micro-aneurysms are the first clinical sign of DR and it appear small red dots on retinal fundus images. To detect retinal micro-aneurysms, retinal fundus images are taken from Messidor, DB-rect dataset. After pre-processing, morphological operations are performed to find micro-aneurysms and then features are get extracted such as GLCM and Structural features for classification.

In (7), Two groups were identified, namely nonproliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). In this paper, to diagnose diabetic retinopathy, two models like Probabilistic Neural network (PNN) and Support vector machine (SVM) are described and their performances are compared. Experimental results show that PNN has an accuracy of 89.60% and SVM has an accuracy of 97.608 %. This infers that the SVM model outperforms the other model.

In (8), The aim of this paper is to develop and validate systems for detection of hard exudates and classify the input image as normal or diseased one. The authors have proposed and implemented novel method based on color and texture features. Performance analysis of SVM and KNN classifiers is presented. Images classified by these classifiers are validated by expert ophthalmologists.

In (9), authors proposed the automated algorithm that applies mathematical modeling which enables light intensity levels emphasis, easier exudates detection, efficient and correct classification of retina images. The proposed algorithm is robust to various appearance changes of retinal fundus images which are usually processed in clinical environments.

In (10), They demonstrate this functionality through pre-segmentation of input images with a fast and robust but loose segmentation step, to obtain a set of candidate objects. These objects then undergo a spatial transformation into a reduced space, retaining but a compact high-level representation of their appearance.

## 3. BACKGROUND AND RELATED WORK

In this section, we shall briefly discuss some of the related works that provide a background for our approach: (1) CNN and (2) Machine Learning Algorithms.

**CNN:**

CNN or convolutional neural networks has become a renowned algorithm of deep learning. Most CNN models require images as the inputs and then recognize/classify/predict their features. Convolutional Neural Network processes these images and identifies them on the basis of certain features. Convolutional Neural Network has gained so much popularity in artificial neural networks. The reason for this circumstance is that it is used mostly in every field like in this project, for diabetic retinopathy detection.

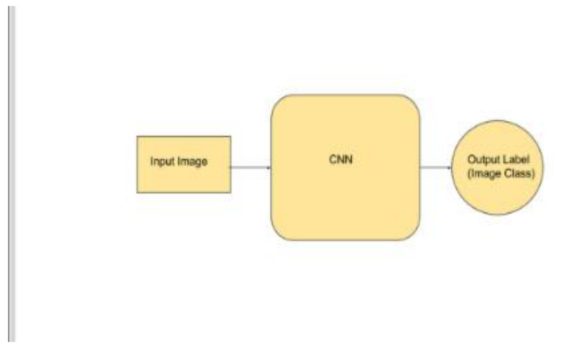


**Figure 2** – Basic Structure of CNN

**Steps in a CNN Model:**

1. Convolution Operation
2. Re LU Layer
3. Pooling
4. Flattening
5. Full Connection

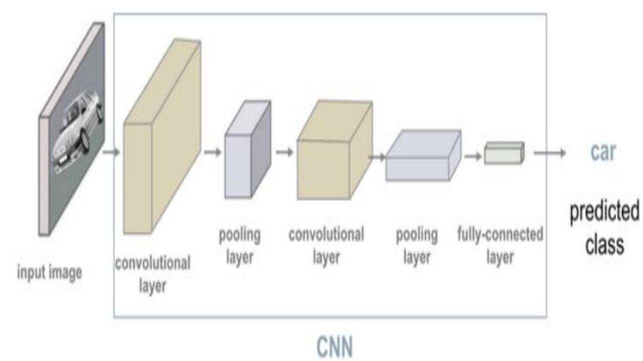


**Figure 3: Layers of CNN Model**

**Convolutional Layer**

There are multiple convolutional layers in CNN that extract low to high-level features based on whatever you wish to extract. To give a simplified notion,

ISSN : 2057-5688

initial convolutional layers provide lower-level features (like lines and edges) whereas farther convolutional layers give higher-level features. The result of further layers depends on the inputs from lower-level features. This is similar to how vision works in humans.

**Pooling Layer**

The main purpose of CNN is classification in most cases. However, high-dimensional image data is tough to be death with. This is why dimensionality reduction is done and this is done in the pooling layer. Pooling mainly reduces the spatial dimension of image-based mathematical operations. First, this layer works as a noise suppressant. Then, it makes the data invariant for image classification. Finally, it captures several structure-based features of those images without curtailing the finer details.

**Fully-connected Layer**

This layer can be imagined as a denser series of convolutional and pooling layers. Mainly, it takes the compressed output of previous layers and fits a basic NN perceptron in order to classify.

In the existing systems for diabetic retinopathy, the bi-channel or multi-channel CNN networks have been used.

The grey and green components are two significant elements that may be retrieved from an image in this system. This system mixes both images and uses the entropy of the outcome to determine which image is infected. The bi channel CNN performs the merging and classification process.

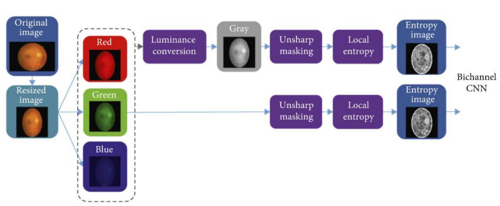


**Figure 4:** CNN for Diabetic Retinopathy Classification

**Machine Learning Algorithms:**

As prospective ensemble members, the following classifiers were employed in the existing research papers:

1. KNN
2. SVM

**KNN:**

The test data is classified by the KNN classifier based on the majority votes of the k-nearest neighboring datasets. The nearby object's class will be known, and this will serve as the algorithm's training. The information will be sorted into the most common class among its k-nearest neighbors. The value of K is determined by the number of nearby datasets considered, and the decision is made based on the overall dataset's nature.

**SVM**

SVM stands for supervised learning model and is used for classification. Images must be classified into two categories in this system: healthy and diseased. SVM draws a hyperplane between both the datasets to show which class they belong to. The training of the machine to grasp the features of the data and map it to the correct class is the most important element of the SVM classifier. The hyperplane should have the most separation here between data from both classes for optimal performance.

## 4. PROPOSED SYSTEM

Sequence models are machine learning algorithms that input or output data sequences. Sequential data includes text streams, audio snippets, video clips, time-series data, and other forms of sequential data. In sequence models, recurrent neural networks (RNNs) are the most well approach.

Sequence Models were created to analyze sequential data such as textual sentences, time series, and other finite sequence data. Convolutional Neural Networks are more adapted to handle spatial data, whereas these models are better placed to handle sequential data.

In our proposed model, sequential model has been used to detect diabetic retinopathy in patients alongside CNN. The sequential model used for diabetic retinopathy on the data set of 1000 images used in this algorithm and achieves train and label the images based on the range.

**Methodologies Framework**

ISSN : 2057-5688

1. **Input layer:** Data collection and Batch normalization
2. **Hidden layer:** Pooling, Soft Max, Dropout
3. **Output layer:** Dense

**Input Layer**

**Dataset Collection**

Data collection is the process of collecting various dataset, from the kind source, like Kaggle. Dataset is eye fundus images. 1000 of fundus images in different ranges have been selected for our project.

**Batch Normalization**

Normalization is a data pre-processing technique for converting numerical data to a common scale without changing the shape of the data.

When we feed data into a machine learning or deep learning system, we usually modify the numbers to a balanced scale. Normalization is done in part to ensure that our model can generalize correctly.

Returning to Batch normalization, it is the process of adding more layers to a deep neural network to make it faster and more reliable. The standardizing and normalizing procedures are performed by the new layer on the input of a previous layer.

The input is first adjusted, and then rescaling and offsetting are applied.

**The Input Is Normalized**

The process of altering data to have a mean of zero and a standard deviation of one is known as normalization. We have our batch input from layer h in this phase, and we must first average was calculated of this latent activation.

$$\mu = \frac{1}{m} \sum h_i$$

Here, m is the number of neurons at layer h. Now, we calculate the standard deviation of these latent or hidden activations.

$$\sigma = \left[ \frac{1}{m} \sum (h_i - \mu)^2 \right]^{1/2}$$

Finally, to normalize the hidden values, we subtract we subtract the average from each of the input values and then divide them by the sum of SD and smoothing term Ɛ.

$$h_{i(norm)} = \frac{(h_i - \mu)}{\sigma + \varepsilon}$$

**Offsetting rescaling**

The final process consists of rescaling and offsetting the input. (gamma) and (alpha) are two BN algorithm components that come into play here (beta). These parameters are used to rescale γ and shift β the vector containing the results of preceding operations.

$$h_i = \gamma h_{i(norm)} + \beta$$

These two parameters are learnable, and the neural network ensures that the best values of and are chosen throughout training. This will allow each batch to be accurately normalized.

**Hidden Layer:**

1. **Pooling:**

Pooling is the process of extract reducing the dimension of the images and strides. Max Pooling is an operation that is used to downscale the image if it is not used and replace it with Convolution to extract the most important features.

2. **Soft Max**

In neural network algorithms to determine a multinomial probability distribution, the softmax function is utilised as the activation function in the output layer. Softmax has been used as an input signal for multi-class classification problems requiring class membership on more than two labels.

3. **Dropout**

In a neural network, dropout is implemented per layer. Most types of layers, including dense fully

INTERNATIONAL JOURNAL OF TECHO-ENGINEERING

ISSN : 2057-5688

connected, pooling layer, and recurrent layers like the long short-term memory network layer, can be used with it. Dropout can be used on any or all of the network's hidden layers, as well as the accessible or input layer. On the output layer, it isn't used.

In our proposed model, Dropout is used to prevent for trained data lose, this layer utilized wherein a few neurons are dropped from the neural network during training.

**Ouput Layer**

**1. Dense**

A Dense layer feeds all outputs from the previous layer to all its neurons, each neuron providing one output to the next layer. It's the most basic layer in neural networks.

The regular deeply linked neural network layer is the dense layer. It is the most popular and often utilized layer. The following operation is performed on the input by the dense layer, and the output is returned.

**where, output = activation(dot(input, kernel) + bias)**

The input data is represented by input.

The weight data is represented by the kernel.

Numpy dot product of all inputs and their weights is represented as a dot.

bias is a skewed value used in machine learning to improve the model's performance.

The activation function is represented by activation.

## 5. RESULTS

The person has to upload an image of the eye using the detection system as shown in Figure 5.

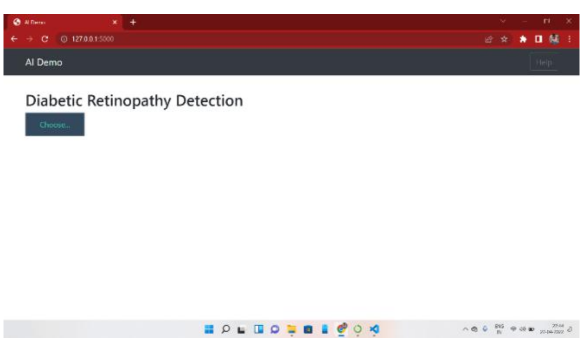


**Figure 5:** Choose an image and upload in the framework.

Once the photo has been uploaded, the next step is to click on Predict to see the results as show in Figure 5.

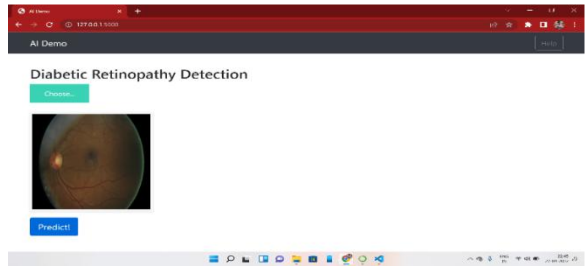


**Figure 6:** Click on predict to get the desired results.

The system will then generate the desired output as shown in the figures below:

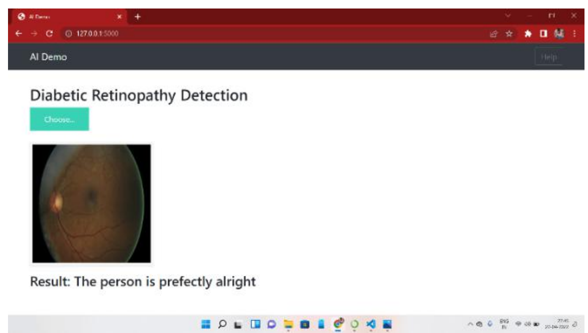


**Figure 7:** The photo uploaded by the person shows that the person is perfectly alright.

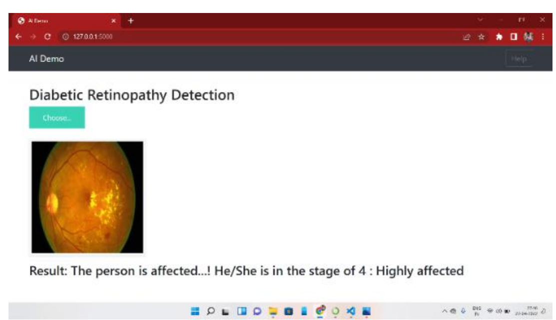


**Figure 8:** The photo chosen shows that the person is highly affected and has stage 4 diabetic retinopathy.

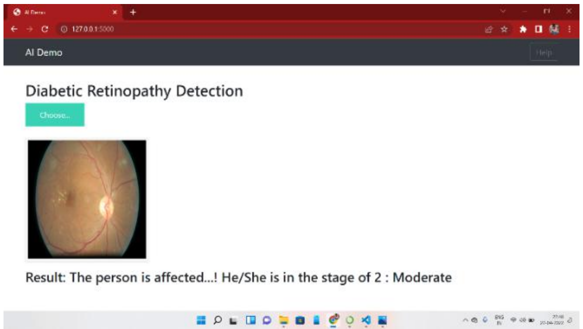


**Figure 9**: It shows a person with moderate and Stage 2 diabetic retinopathy as predicted by our proposed model.

## 6. CONCLUSION

Automated screening methods drastically shorten the time it takes to determine diagnoses, saving ophthalmologists time and money while also allowing patients to receive treatment sooner. Automated DR detection systems are critical for identifying DR at an early stage. The DR phases are determined by the type of retinal lesions that occur. The most recent automated methods for diabetic retinopathy detection and classification that used deep learning techniques were examined in this paper. The publicly released fundus DR datasets have been provided, and deep-learning methodologies have been briefly explained. The helpful strategies for detecting and classifying DR using DL were also explored in this paper.

## REFERENCES

[1] Aryan Kokane, Gourhari Sharma, Akash Raina, Shubham Narole, Prof. Pramila M. Chawan, "Detection of Diabetic Retinopathy using Machine Learning" in International Research Journal of Engineering and Technology(IRJET),2020.

[2] Wejdan L.Alyoubi, Wafaa M.Shalash, Maysoon F.Abulkhair, "Diabetic retinopathy detection through deep learning techniques: A review" in Informatics in Medicine Unlocked, 2020.

[3] Yung-Hui Li , Nai-Ning Yeh, Shih-Jen Chen and Yu-Chien Chung, "Computer-Assisted Diagnosis for Diabetic Retinopathy Based on Fundus Images Using Deep Convolutional Neural Network" in Mobile information systems, 2019.

[4] Suvajit Dutta, Bonthala CS Manideep, Syed Muzamil Basha, Ronnie D. Caytiles and N. Ch. S. N. Iyengar, "Classification of Diabetic Retinopathy Images by Using Deep Learning Models" in International Journal of Grid and Distributed Computing, 2018.

[5] T Chandrakumar, R Kathirvel, "Classifying Diabetic Retinopathy using Deep Learning Architecture" in International Journal of Engineering Research & Technology (IJERT), 2016.

[6] J.Lachure, A.V.Deorankar, S.Lachure, S.Gupta, R.Jadhav, ―Diabetic Retinopathy using Morphological operations and Machine Learning‖, IEEE International Advance Computing Conference(IACC), (2015).

[7] R.Priya, P.Aruna, ―SVM and Neural Network based Diagnosis of Diabetic Retinpathy‖, International Journal of computer Application

[8] S.Giraddi, J Pujari, S.Seeri, ―Identifying Abnormalities in the Retinal Images using SVM Classifiers‖, International Journal of Computer Applications(0975-8887), Volume 111 – No.6,(2015).

[9] Vesna Zeljkovi et al, ―Classification Algorithm of Retina Images of Diabetic patients Based on Exudates Detection‖, 978-1-4673-2362-8/12, IEEE(2012)

[10] G.Lim, M.L.Lee, W.hsu, ―Transformed Representations for Convolutional Neural Networks in Diabetic Retinopathy Screening‖, Modern Artificial Intelligence for Health Analytic Papers from the AAAI(2014).

[11] P Kulkarni, J Zepeda, F Jurie, P Perez, L Chevallier, ―Hybrid Multi-layer Deep CNN/Aggregator feature for Image Classification‖, Computer Vision and pattern recognition, ICASSP conference, (2015).

[12] E M Shahin, T E Taha, W Al-Nuaimy, S.El Raaie, O F Zahran, F E Abd El-Samie, ―Automated Detection of Diabetic Retinopathy in Blurred Digital Fundus Images‖, IEEE International Computer Engineering Conference , pages-20- 25,(2012).

[13] Xiang chen et al, ―A novel method for automatic hard exudates detection in color retinal images‖, Proceedings of the 2012 International Conference on Machine Learning and Cybernetics, Xian (2012). ations(00975-8887), volume 41-No.1,(March 2012).

[14] N.Srivastava, G.Hinton, A.Krizhevsky, I Sutskever, R Salakhutdinov, Dropout: A simple way to prevent Neural networks from overfitting‖, Journal of Machine learning research(2014) 1929-1958