



# DIABETIC RETINOPATHY USING CONVOLUTIONAL NEURAL NETWORK

Sandula Devipriyanka<sup>#1</sup> Karri Sravanthi <sup>\$2</sup>Malla Jagan <sup>\$3</sup> Boddepalli Mohan Kumar <sup>\$4</sup>  
Potnuru Lithin <sup>\$5</sup>

<sup>#1,\$2,\$3,\$4,\$5</sup> B.Tech UG Students, Dept.Of CSE, AITAM, Tekkali, AP, India.

<sup>#1</sup>[deviprivankasandula@gmail.com](mailto:deviprivankasandula@gmail.com) <sup>\$2</sup>[karrisravanthi91@gmail.com](mailto:karrisravanthi91@gmail.com) <sup>\$3</sup>[mallajagan2001@gmail.com](mailto:mallajagan2001@gmail.com)

<sup>\$4</sup>[kannamnaidub478@gmail.com](mailto:kannamnaidub478@gmail.com) <sup>\$5</sup>[lithinpotnuru394@gmail.com](mailto:lithinpotnuru394@gmail.com)

## ABSTRACT

Diabetic retinopathy is the most common cause of blindness of the eye depend on diabetes. However, due to slow progression, the disease shows few signs in early stages, hence making disease detection a difficult task. For this reason, early detection of diabetic retinopathy is of critical importance. Therefore, a fully automated system is required to support the detection and screening process at early stages. The manual diagnosis process of DR retina fundus images by ophthalmologists is time, effort, and cost-consuming and prone to misdiagnosis unlike computer-aided diagnosis systems. Recently, deep learning has become one of the most common techniques that has achieved better performance in many areas, especially in medical image analysis and classification. In this project, we propose a CNN approach to diagnosing DR from digital fundus images and accurately classifying its severity. We develop a network with CNN architecture and data augmentation which can identify the intricate features involved in the classification task such as micro-aneurysms, exudate and haemorrhage on the retina and consequently provide a diagnosis automatically and without user input.

## INTRODUCTION

### Motivation

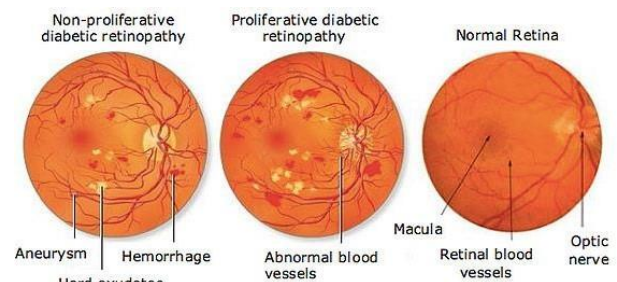
In recent times, India and other parts of the world have been faced with an increase in age and society related diseases like diabetes. According to recent survey, 4% of the country

population has been diagnosed of diabetes disease alone and it have been recognize and accepted as one of the main cause of blindness in the country if not properly treated and managed. Early detection and diagnosis have been identified as one of the way to achieve a reduction in the percentage of visual impairment caused by diabetes with more emphasis on routine medical check which the use of special facilities for detection and monitoring of the said disease. The effect of this on the medical personnel need not be over emphasized, it has lead to increase work load on the personnel and the facilities, increase in diabetes screening activities just to mention a few. A lot of approaches have been suggested and identified as means of reducing the stress caused by this constant check up and screening related activities among which is the use medical digital image signal processing for diagnosis of diabetes related disease like diabetic retinopathy using images of the retina. Diabetes is a disorder of metabolism. The energy required by the body is obtained from glucose which is produced as a result of food digestion. Digested food enters the body stream with the aid of a hormone called insulin which is produced by the pancreas, an organ that lies near the stomach.

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During eating, the pancreas automatically produces the correct amount of insulin needed for allowing glucose absorption from the blood into the cells. In individuals with diabetes, the pancreas either produces too little or no insulin or the cells do not react properly to the insulin that is produced. The build up of glucose in the blood, overflows into the urine and then passes out of the body. Therefore, the body loses its main source of fuel even though the blood contains large amounts of glucose. Basically there are three types of diabetes, Type 1 Diabetes, is caused as a result of auto immune problem. The immune system of the body destroys the insulin producing beta cells in the pancreas leading to no or less production of the required insulin by the pancreas. Type 2 Diabetes is a result of malfunctioning of the beta cell itself. This malfunction includes non production of insulin or a situation known as insulin resistance. In insulin resistance, the muscles, fat and other cells do not respond to the insulin produced. Type 3 is known as gestational diabetes and only occurs during pregnancy. During this stage, the body resist the effect of insulin produced. The effect of diabetes on the eye is called Diabetic Retinopathy (DR). It is known to damage the small blood vessel of the retina and this might lead to loss of vision. The disease is classified into three stages viz: Non-Proliferate Diabetic Retinopathy (NPDR), Proliferate Diabetic Retinopathy (PDR) .In PDR phase, the arteries in the retina become weakened and leak, forming small, dot like Haemorrhages. These leaking vessels often lead to swelling or edema in the retina and decreased vision. In the NPDR phase, circulation problems cause areas of the retina to become oxygen-deprived or ischemic. New fragile, vessels develop as the circulatory system attempts to maintain adequate oxygen levels within the retina. This phenomenon is called neovascularisation. Blood may leak into the

retina and vitreous, causing spots or floaters, along with decreased vision. In the SDR phase of the disease, there is continued abnormal vessel growth and scar tissue, which may cause serious problems such as retinal detachment and glaucoma and gradual loss of vision.



*Fig: fundus images*

The manual diagnosis process of DR retina fundus images by ophthalmologists is time effort and cost- consuming and prone to misdiagnosis also. Therefore we use deep learning technology which has achieved better performances in many areas , especially in image analysis and classification. In this project we propose CNN model to diagnosis DR from digital fundus images and which can identify the detailed features like (micro-aneurysms, exudate and haemorrhage) and classify the severity of the disease like normal, mild, moderate, severe, proliferative.

**Objective:**

The main objective of this project is to build the CNN model using deep learning to diagnosing Diabetic Retinopathy at the early stages so that patients can avoid the risk of blindness. To accurately classify the severity of the disease i.e. normal, mild, moderate, severe, proliferative. To calculate the performance metrics of the train model.

**Approach to Problem:**

Approach to Problem: In order to accomplish the objectives of the project, the approach is to

develop a system that can identify the stages of the diabetic retinopathy. The system is developed using the deep learning concept.

- Collect a large and diverse dataset of retinal images of both diabetic and non-diabetic patients. This dataset should have a good representation of different levels of diabetic retinopathy, including early stages and severe cases.
- Pre-processing the collected data This includes resizing the images to a standard size, applying colour normalization, and augmenting the dataset.
- In the deep learning there is no need to define the features that are to be consider by the model during the training
- Instead the model during the training at each layer it identifies what are the features to be consider in order to classify. In this way the model is trained using the deep learning. Then the part of the data set collected is used to evaluate the model that has trained. Then the model is evaluated to find to what extent the model is able to predict the results accurately, through this the precision of the model can be found.
- Then the trained model is used to predict the new data by giving the test image as input to the model, then the model identifies the severity of diabetic retinopathy
  - Calculate and measure the performance of the model like precision , recall, f1-score and confusion matrix.
- Finally ,the trained model is saved for further use.

## METHODOLOGY

### Convolutional Neural Networks (CNN)

Convolutional neural networks refer to a sub-category of neural networks. A Convolutional neural network (CNN) is a neural network that has one or more convolutional layers and are used mainly for image processing, classification, segmentation and also for other auto correlated data. A convolution is essentially sliding a filter over the input. There are four types of layers for a convolutional neural network.

1. Convolutional Layer
2. Pooling Layer
3. ReLu Activation Layer
4. Fully Connected Layer

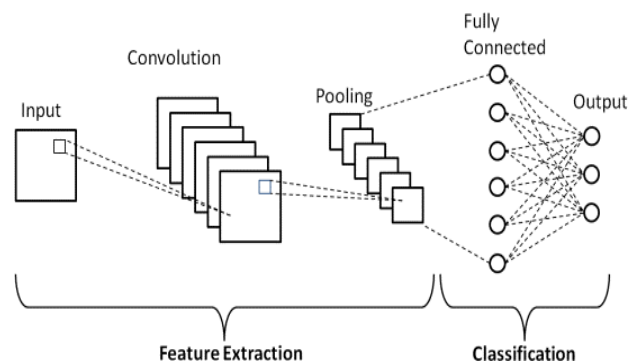


Fig: Basic CNN Architecture

### Convolutional Layer

Its purpose is to detect the presence of a set of features in the images received as input. This is done by convolution filtering: the principle is to “drag” a window representing the feature on the image, and to calculate the convolution product between the feature and each portion of the scanned image.

### Pooling Layer

The pooling operation consists in reducing the size of the images while preserving their important characteristics.



### ReLU activation function

ReLU (Rectified Linear Units) refers to the real non-linear function defined by  $ReLU(x)=\max(0,x)$ . The ReLU correction layer replaces all negative values received as inputs by zeros. It acts as an activation function.

### Fully Connected Layer

The last fully-connected layer classifies the image as an input to the network: it returns a vector of size N, where N is the number of classes in our image classification problem.

### DENSENET-121 MODEL

In a **DenseNet** architecture, each layer is connected to every other layer, hence the name **Densely Connected Convolutional Network**. For L layers there are  $L(L+1)/2$  direct connections. For each layer, the feature maps of all the preceding layers are used as inputs, and its own feature maps are used as input for each subsequent layers.

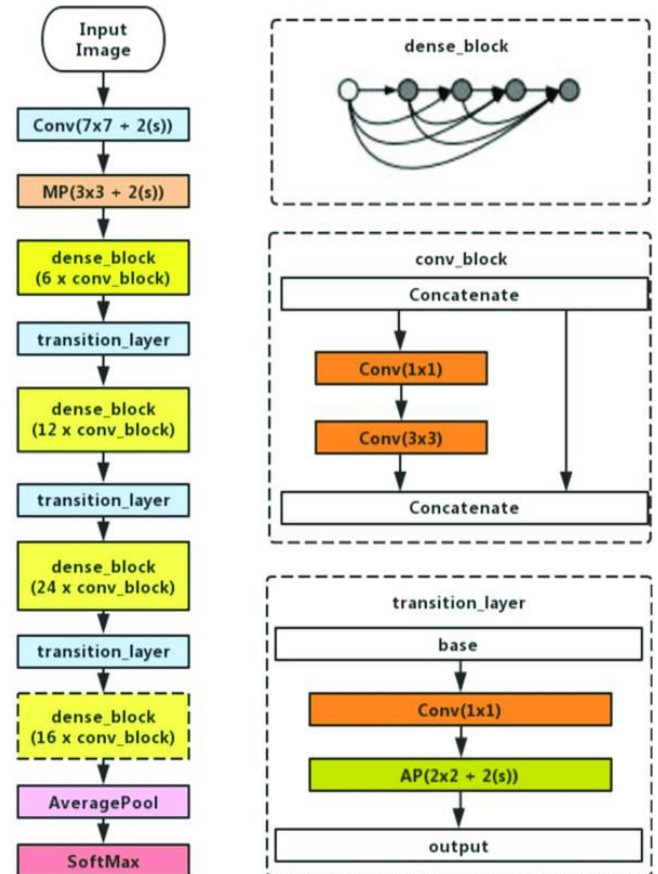
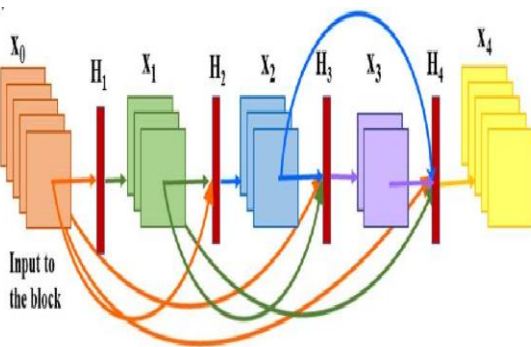
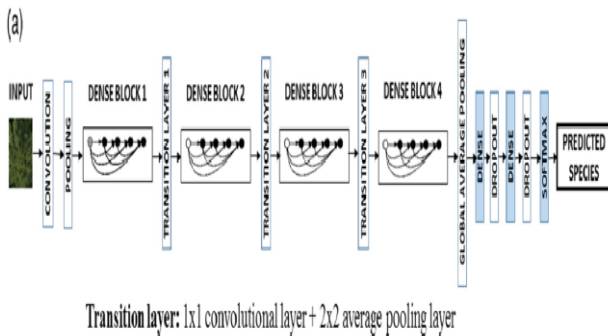


Fig: Densenet -121 model

### Dense Block:

Every layer in a dense block is directly connected to all its layers. Each layer receives the feature-maps from previous layers. Means The input of a layer inside DenseNet is the concatenation of feature maps from previous layers. We cannot concatenate the feature maps, if the size of feature maps is different. So, to be able to perform the concatenation operation, we need to make sure that the size of the feature maps that we are concatenating is the same. But we can't just keep the feature maps the same size throughout the network - an essential part of convolutional networks is down-sampling layers that change the size of featuremaps.

### Convolutional Layer:

Each convolution layer is consist of three consecutive operations: batch normalization (BN) followed by a rectified linear unit (ReLU) and a  $3 \times 3$  convolution (Conv). Also dropout can be added which depends on your architecture requirement.

### Transition Layer:

$1 \times 1$  Conv followed by  $2 \times 2$  average pooling are used as the transition layers between two contiguous dense blocks. Feature map sizes are the same within the dense block so that they can be concatenated together easily.

Layers	Output Size	DenseNet-121
Convolution	$112 \times 112$	
Pooling	$56 \times 56$	
Dense Block (1)	$56 \times 56$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$
Transition Layer (1)	$56 \times 56$ $28 \times 28$	
Dense Block (2)	$28 \times 28$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$
Transition Layer (2)	$28 \times 28$ $14 \times 14$	
Dense Block (3)	$14 \times 14$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$
Transition Layer (3)	$14 \times 14$ $7 \times 7$	
Dense Block (4)	$7 \times 7$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 16$
Classification Layer	$1 \times 1$	$7 \times 7$ global average pool 5D fully connected layer

Fig: DenseNet architecture

### Advantages of DenseNet:

1. Strengthen feature propagation : features learned by layer 1 are directly accessible by layer 4 .
2. Encourage feature reuse : Layer 4 doesn't have to relearn a feature learnt by layer 1 because it can access that information directly via concatenation.

3. Reduce number of parameters: a. The filter size (number of convolutions each layer has to do to pass to the next one) is reduced in DenseNet compared to architectures without skip because to communicate the same amount of information, we now have to allow each layer to "talk" more to the very next layer than we otherwise would have. When information "skips" intermediate layers, that filter depth is no longer required so we don't have to keep track of as many convolutional parameters.

## RESULTS

### Model accuracy

The trained model achieved a training accuracy of 91.50% and a validation accuracy of 92.94% after running 25 epochs.

### Performance Measures

To evaluate the performance or quality of the model, different metrics are used, and these metrics are known as performance metrics or evaluation metrics. These performance metrics help us understand how well our model has performed for the given data.

To evaluate the performance of a classification model, different metrics are used, and some of them are as follows:

- Accuracy
- Confusion Matrix
- Precision
- Recall
- F-Score
- AUC(Area Under the Curve)-ROC

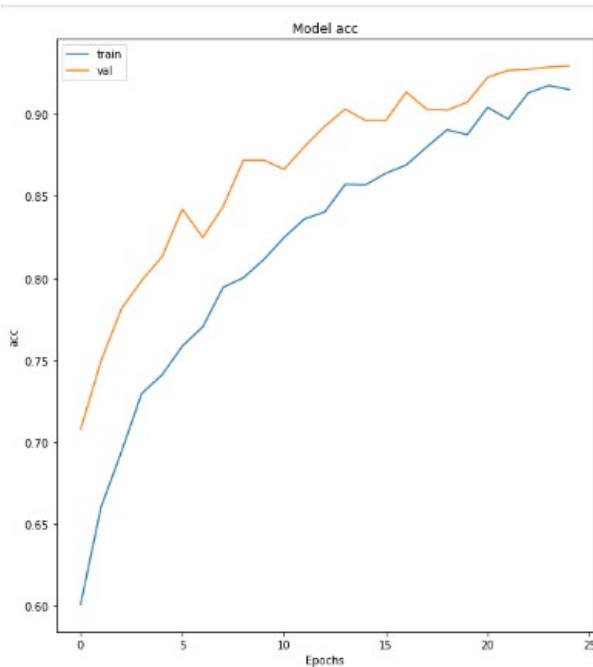


Fig: Train and validation data accuracy

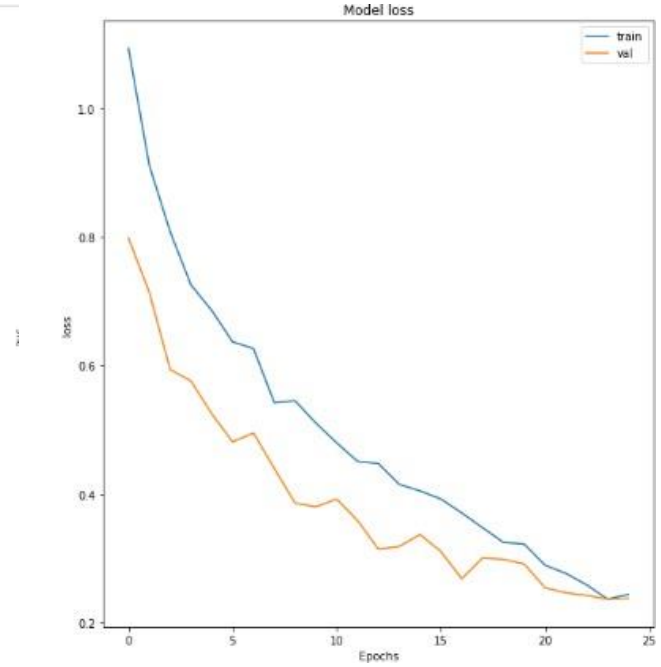


Fig: Train and validation data loss

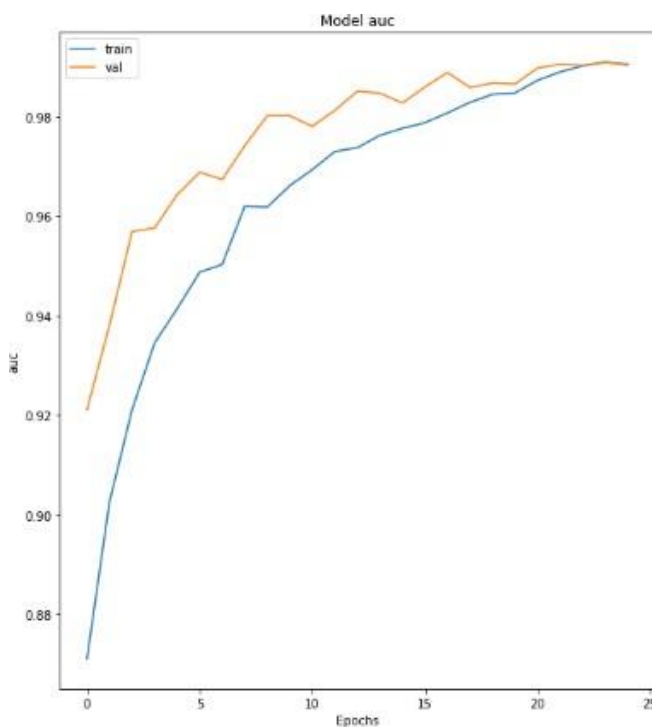


Fig: Train and validation data auc

### Test data results

#### Balanced accuracy:

Balanced accuracy is a metric we can use to assess the performance of a classification model. It is calculated as:  $\text{Balanced accuracy} = (\text{Sensitivity} + \text{Specificity}) / 2$

where: Sensitivity: The "true positive rate" - the percentage of positive cases the model is able to detect.

Specificity: The "true negative rate" - the percentage of negative cases the model is able to detect. This metric is particularly useful when the two classes are imbalanced that is, one class appears much more than the other.

#### Matthews correlation coefficient

Matthews correlation coefficient (MCC) is a metric we can use to assess the performance of a classification model.

#### Test data accuracy

The test data accuracy results is 91.36% balanced accuracy score: 91.42% matthew's



Correlation Coefficient: 89.25%

### Confusion Matrix

Below shown is the confusion matrix for the test data.

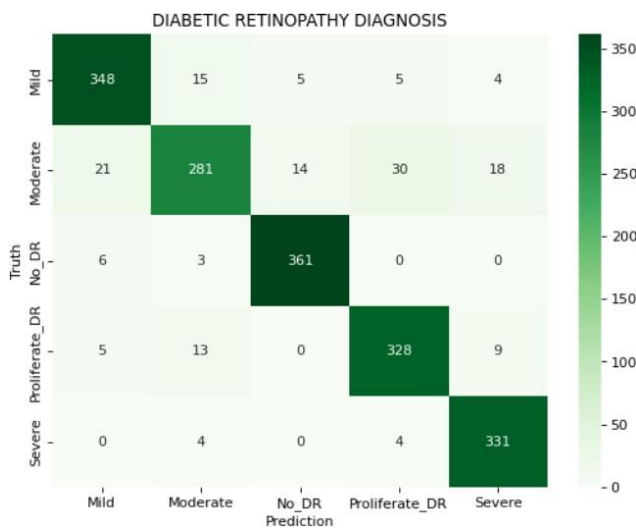


Fig:

confusion matrix

### Classification Report

	Precision	Recall	f1-score	Support
Mild	0.92	0.92	0.92	377
Moderate	0.89	0.77	0.83	364
No_DR	0.95	0.98	0.96	370
Proliferate_D R	0.89	0.92	0.91	355
Severe	0.91	0.98	0.94	339
Micro avg	0.91	0.91	0.91	1805
Macro avg	0.91	0.91	0.91	1805
Weighted avg	0.91	0.91	0.91	1805
Samples avg	0.91	0.91	0.91	1805

### CONCLUSION

we have developed a densenet-121 model which is used to detect the diabetic retinopathy in patient and its classify the severity of the disease .the stages its classify mild, moderate, normal proliferative, non-

proliferative. we have achieved the accuracy of the training model is 91.50% and validation accuracy is 92.94 % and performance metrics like sensitivity, f1 score, precision, recall have been calculated.

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