

## Detection of Diabetic Retinopathy

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### Abstract:

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Biomedical engineering faces a significant challenge in assessing the physiological changes occurring in the human body non-invasively, particularly when detecting abnormalities in the eye due to the complexities involved. Traditional disease identification techniques in retinal images rely on manual intervention, which can be error-prone and have a low success rate. Long-term diabetics are susceptible to the multistage progressive condition known as diabetic retinopathy, which has aberrant retinal imaging characteristics such as microaneurysms, haemorrhages, and exudates. It uses the dataset which consists of total 13970 images which includes the images of all stages collected from kaggle APTOS competition. Deep learning, a key method in health informatics, is used in this work to identify diabetic retinopathy and its stages. Residual Network and Densely connected convolutional network deep learning approaches are employed, and transfer learning is used to achieve good accuracy in identifying the stages of diabetic retinopathy. The accuracy obtained by using the ResNet101 is 92.37% and with the DenseNet121 is 98.37%.

**Keywords:** Deep Learning, DenseNet121, Diabetic Retinopathy Detection, Ophthalmology, ResNet101, Retinal fundus images, Transfer Learning.

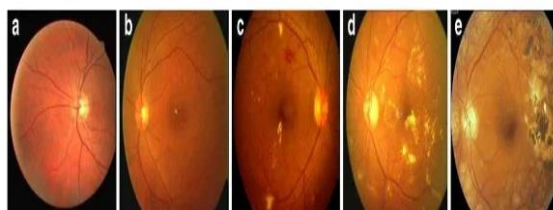
### Introduction

Ophthalmology is a medical field that focuses on the scientific examination, diagnosis, and treatment of various eye diseases. In the past, ophthalmologists had to manually examine eye problems, which was time-consuming. Many consequences, such as diabetic retinopathy, neuropathy, nephropathy, cardiomyopathy, gastroparesis, skin issues, and more, can be brought on by diabetes. Blindness in senior persons is frequently brought on by issues with the eyes. Additionally, as the global population ages, the number of patients with visual impairments is expected to increase. Therefore, there is significant interest in applying artificial intelligence to improve vision care while reducing healthcare costs, especially when telemedicine is involved. Compared to the number of medical facilities available, the proportion of people with eye diseases is high. One of the most typical causes of vision loss is diabetic retinopathy. Diabetic retinopathy is a consequence of diabetes that

can harm the eyes. It is a disorder that develops when the blood vessels in the retina, which is in charge of seeing light and relaying signals to the brain, are harmed by high blood sugar levels. Over time, the harmed blood vessels may bleed or leak fluid, impairing vision and even resulting in blindness. Diabetic retinopathy is the main cause of blindness in working-age individuals in developed nations. Non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR) are the two main subtypes of this condition. The earlier and less serious form of NPDR occurs when blood vessels in the retina start to leak or swell. In PDR, the retina develops new blood vessels, which can cause bleeding, scarring, and retinal detachment.

High blood sugar, high blood pressure, high cholesterol, and long-term diabetes are risk factors for diabetic retinopathy. Diabetic retinopathy is a concern for people with Type 1 or Type 2 diabetes, and the risk rises with age and disease duration. Vision loss can be prevented by detecting and treating diabetic retinopathy early. Frequent eye exams, maintaining healthy blood pressure, cholesterol, and blood sugar levels, as well as early diagnosis and treatment of the illness can all help lower the risk of diabetic retinopathy-related vision loss. Some of the signs and symptoms of diabetic retinopathy include hazy, fluctuating, impaired colour vision, and poor night vision and even it can cause complete blindness. The Diabetic Retinopathy is classified into five stages. They are

- No DR
- Mild DR
- Moderate DR
- Severe DR
- Proliferative DR



(a) normal (b) mild DR (c) moderate DR  
(d) severe DR (e)proliferative DR

Figure 1: Stages of DR

Many characteristics of diabetic retinopathy, such as microaneurysms, haemorrhages, and exudates, can be seen on retinal imaging.

These features can be identified by ophthalmologists and other trained healthcare professionals during a dilated eye exam. Also, as was previously indicated, deep learning algorithms can be trained to automatically detect these patterns in retinal pictures, which

can help with the detection and treatment of diabetic retinopathy..The visual changes in the DR eye is shown in figure 2.

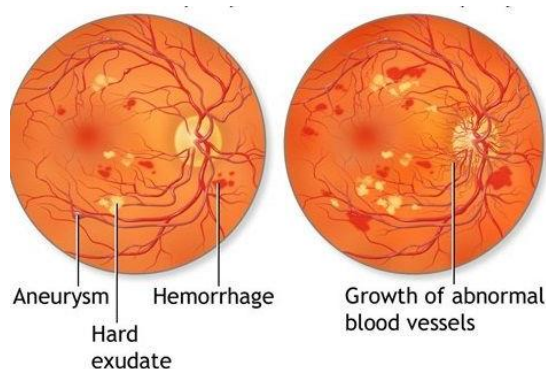


Figure 2: Visual Changes in the DR eye

## 2. Literature Survey

All notable works are mentioned in this section. [1]This study explores the use of deep learning model ResNet34 for detection of diabetic retinopathy.The authors have achieved an accuracy of over 83% on dataset of 11,734 and 1537 UWF fundus photographs of DR patients. [2]-This study explores the use of machine learning for detecting the diabetic retinopathy.The ML models that they used are SVM, KNN, Random Forest classifier. The accuracy obtained for SVM, KNN, Random Forest are 68%, 76%, 90% on dataset of 2000 images. Voting of three classifiers(82%) are chosen as final prediction.[3]-This proposed model is using the machine learning approach Support Vector Machine for classification. The accuracy obtained by authors on dataset of 1200 retinal images is 83%.[4]This study explores the deep learning CNN model using the transfer learning techniques. EfficientNet models are used on dataset APTOS of 3662 images. The accuracies obtained for respective models are 97.82%, 98.91%, 96%,97.64%,98.95%.[5]-This study explores the deep learning CNN model for detecting the diabetic retinopathy.InceptionV3 approach is used in this work. The dataset is collected from Shanghai Zhongshan Hospital and Shanghai First People's Hospital of 19,233 images. The accuracy obtained by using this model is 93.49%. [6][7]-This proposed work uses the deep learning models. The models used for detecting the disease are Dense121 and VGG16 on dataset of 3662 images of APTOS kaggle competition. The accuracies obtained for VGG16 is 73% and DenseNet121 is 96%. Here DenseNet121 got higher accuracy than VGG16.[8]This proposed work uses the ResNet of 18 layers (ResNet18) for detection. The dataset is collected from the EyePacs Kaggle dataset. The accuracy obtained for this model is 69.4%.[9]This study proposes a deep learning-based approach for automated detection of diabetic retinopathy using a dataset of retinal fundus images. The model uses a convolutional neural network (CNN) architecture. [10-13] This study proposes a deep learning framework for diabetic retinopathy detection using retinal fundus images. The model uses a pre-trained CNN model (Inception-v3) and a customized dense layer for classification.[14-17]This paper reviews recent deep learning-based

approaches for the detection of diabetic retinopathy. The study covers different methods, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transfer learning.

### **3. Problem Identification**

One of the main problems in diabetic retinopathy detection is the large number of patients with diabetes and the limited availability of ophthalmologists and other healthcare professionals trained to detect and diagnose diabetic retinopathy. This can result in delays in diagnosis and treatment, which can lead to vision loss and other complications. Another difficulty is the subjectivity of conventional techniques for detecting diabetic retinopathy, which rely on experienced professionals visually examining retinal pictures. This can result in inter-observer variability and inconsistencies in diagnosis, which can further delay treatment and increase the risk of complications.

Furthermore, the severity of diabetic retinopathy can fluctuate, making it challenging to distinguish between early-stage illness and normal retinal pictures, especially in the absence of overt symptoms. This can make early detection and intervention more challenging, which can impact patient outcomes and quality of life.

The screening and diagnosis of diabetic retinopathy also face logistical and budgetary challenges, particularly in environments with low resources. These include the cost and availability of screening tests and equipment, the need for trained healthcare professionals, and the need for effective referral and follow-up systems to ensure that patients receive timely and appropriate care.

### **4. Proposed Methodology**

The commonly used techniques for diabetic retinopathy (DR) detection are learning-based convolutional neural network (CNN) structures and transfer learning. This study proposes a method that categorizes retina images based on the level of disease severity. It does so by creating an enhanced CNN model utilizing transfer learning techniques. The image is first subjected to image processing and then prepared for feature extraction. In the feature extraction stage, the image is transformed into a feature vector that is suitable for use in the final classification stage. In this stage, the feature vector is assigned to one of the five classes.

Input: A retinal fundus image.

Output: The DR level of the individual detected.

System: The system will classify the image into one of the DR levels.

#### 4.1 Data Collection

The dataset is taken from kaggle which is provided by author Sachinkumar pune,India. Generally there is competition which contains diabetic retinopathy images collected from all over the world. The dataset provided by the author is updated in 2019. The image of the retina of the human eye is captured using fundus photography.13970 images with five levels of severity are present in the dataset. These five stages are No\_DR, mild, moderate, severe, Proliferative. The dataset is resized into 32\*32 pixels. Finally the resized image was reshaped into 32\*32\*3 pixels square area as actual training image. The dataset is divided between training and testing data with an 80% to 20% ratio in this case.

Class Name	Number of images	Percentage of images
No DR	6000	42.94%
Mild	2400	17.17%
Moderate	4000	28.63%
Severe	870	6.22%
Proliferative	700	5.01%

Table1: Number and distribution of images per class

#### 4.2 Feature Extraction

Feature extraction is a crucial step in diabetic retinopathy (DR) detection, where relevant information is extracted from retinal images to aid in the classification of normal and abnormal retinas.

**Microaneurysms:** These tiny blood vessel enlargements in the retina are an early indicator of diabetic retinopathy. The majority of the time, microaneurysms are tiny, rounded, and coloured red or yellow. They are often identified using computer vision techniques that analyze the shape, size, and color of the lesions.

**Hemorrhages:** These are areas of bleeding in the retina, and their presence is an indicator of more severe DR Hemorrhages can appear as small dots or larger blotches on the retina.

**Exudates:** Lipid deposits of this type can build up in the retina. Exudates can appear as yellow or white spots on the retina, and they are often identified using computer vision techniques that analyze the color and texture of the lesions.

#### 4.3 Classification

The ResNet101 and DenseNet121 models are used for classification of Diabetic Retinopathy disease. In this the extracted feature maps are used to classify the levels of severity, which can aid in early detection and treatment of disease.

**5. Implementation**

A system was developed using two models such as ResNet101 and DenseNet121 architecture.

**5.1 Resnet101 Architecture**

In ResNet101 the number 101 means 101 layers that have weight. This architecture introduces the idea of Residual Blocks to address the vanishing gradient issue. It makes use of a method known as skip connections. Remaining blocks are stacked to create Resnets. By skipping some layers in between, skip connection joins the activations of one layer to those of other levels, creating a residual block. A classification block was utilized to classify the output of the images. To reduce the destruction of Deep Neural Networks ResNet uses residual learning units. RGB images of diabetic retinopathy are passed to the model after resizing and reshaping. For that ResNet 101 model was loaded which was PreTrained on ImageNet dataset.

Input layer: The input to the network is an RGB image of the retina with dimensions of 32\*32 pixels.

Convolutional layers: The input image using learned filters to detect features in the image are followed by batch normalization and ReLU activation

Residual blocks: This block contains convolutional layers for feature mappings.

Pooling layers: In this layer down sampling of feature maps occurs which reduces the spatial dimensions.

Fully Connected layers: A group of fully linked layers with ReLU activation receive the output of the pooling layers after being flattened.

Output Layers: The output layer of the Resnet101 produces the final detection for the input image, indicating the stage of disease

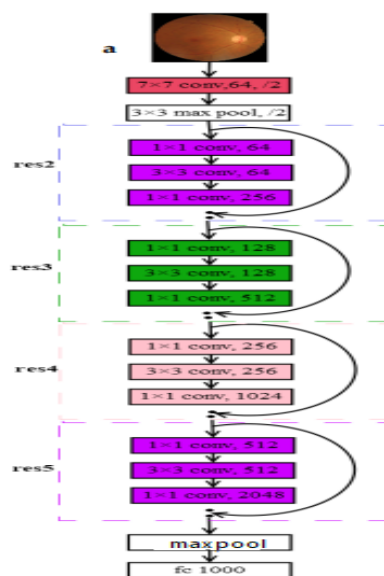


Figure3: Architecture of ResNet101



## 5.2 DenseNet121 Architecture

DenseNet121 is another deep neural network architecture that has been shown to achieve high performance on image classification tasks. Each layer in the network's dense blocks is connected to every other layer in a feed-forward manner. This enables the network to learn more complex features with fewer parameters than traditional convolutional neural networks. In DR detection, DenseNet121 can also be trained on retinal images to classify them into different DR severity levels. The input to the network is an RGB image of the retina, and the output is a probability distribution over the different DR severity levels. The network is trained using a large dataset of labeled retinal images, and the weights of the network are optimized using back propagation.

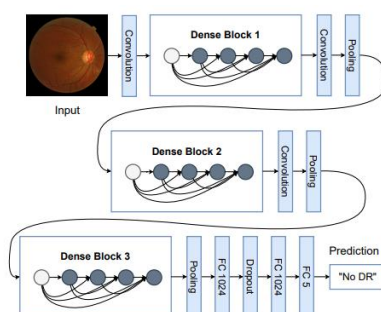


Figure 4: Architecture of DenseNet121

**Input layer:** The input to the network is an RGB image of the retina with dimensions of 32\*32 pixels.

**Convolutional layers:** In this the layers are used for feature mappings and are followed by batch normalization and ReLU activation

**Dense Blocks:** In dense blocks each layer receives the feature-maps from previous layer and the convolutional layers in this concatenate the feature maps.

**Transition Layers:** This layer contains both convolutional and pooling layers. It performs down samplings.

**Fully Connected layers:** The output of pooling layers is flattened and passed through a set of fully-connected layers with ReLU activation.

**Output Layers:** The output layer of the DenseNet121 produces the final detection for the input image, indicating the stage of disease.

## 6. Results & Conclusions

From the two models the Densenet121 has better performance than Resnet101. Hence, it is concluded that DenseNet121 is best suitable for diabetic retinopathy detection. Models are compared by using performance such as Precision, Recall, F1-Score along with Accuracy

Model	ResNet101	DenseNet121
Accuracy	92.37	98.99
Precision	94.08	98.86
Recall	91.75	99.01
F1-Score	92.73	98.93

Table 2: Comparison of Models

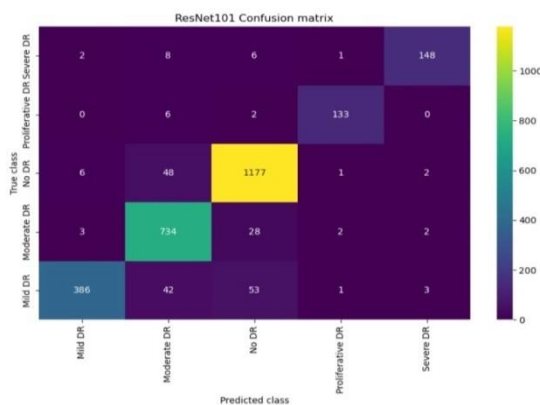


Figure 5: Confusion matrix of ResNet101

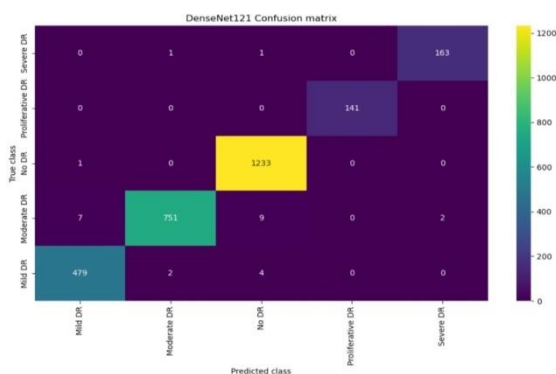


Figure6: Confusion Matrix of DenseNet121

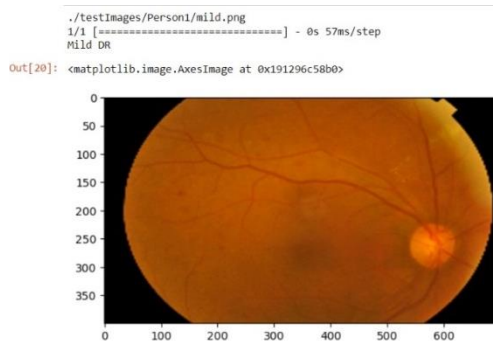


Figure 7: Detection of image



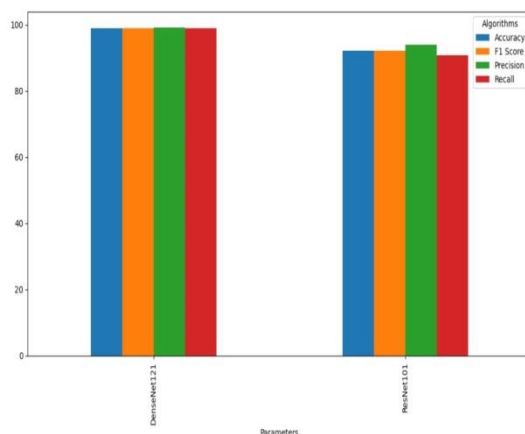


Figure 7: Comparison Graph

## 7. Limitations & Future Scope

Following are the limitations:

- As the dataset that used for this project doesn't particularly identify the which eye image is being detected i.e, either the right eye or the left eye because the dataset is combination of both eyes of a numerous patients.

For further extension of project, can use a well defined dataset with images mentioning that which eye that image is. And also can focus on better performance for Resnet by adding more layers.

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