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Deep Learning for Diabetic Retinopathy

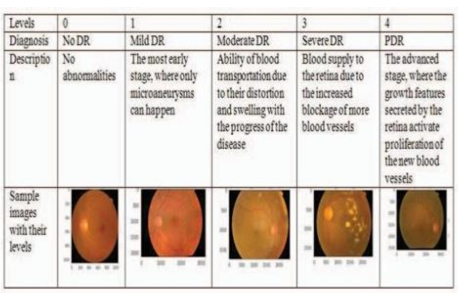
Bhushan Pansare[1*], Ninad Deorukhakar[2], Tanmay Hajare[3], Piyush Nalawade[4], Pushpmala Nawghare[5]
[1,2,3,4,5]Department of Computer Science, Zeal College of Engineering, Pune, India

***Abstract*: Diabetic Retinopathy (DR) is a human eye disease that affects diabetics and damages their retina, potentially leading to blindness in the long term. DR has been manually tested by ophthalmologists until now, and is a time- consuming process. As a result, this job (project) will focus on analyzing various DR levels using Deep Learning (DL), which is a derivative of Artificial Intelligence (AI). We used an enormous dataset of around 3662 train images to train a model called DenseNet to automatically detect the DR point, which is then categorized into high resolution fundus images. The dataset we're using is free to use on Kaggle. There are five different DR stages: 0, 1, 2, 3, and 4. the input parameters in this paper are the patient's fundus eye pictures. The features of fundus images of the eye will be extracted by a qualified model (DenseNet Architecture), and then the activation function will provide the output. The precision of this architecture for DR detection was 0.9611 (quadratic weighted kappa score of 0.8981). Finally, we compare the two CNN architectures, the VGG16 architecture and the DenseNet121 architecture.**

***Keywords*: Deep learning, diabetic retinopathy (DR), densenet 121 architecture, vgg16 architecture, dataset, fundus camera.**

1. Introduction

DR is the most disabling type of diabetes, in which the eye is severely damaged and vision impairments result. It damages the veins that run through the retinal tissue, causing them to leak fluid and distort vision. Along with disorders that cause vision disability, such as waterfalls and glaucoma, DR is one of the most common. DR is divided into five stages: 0, 1, 2, 3, and 4. The below table gives the overall details about DR stages:



Levels	0	1	2	3	4
Diagnosis	No DR	Mild DR	Moderate DR	Severe DR	PDR
Descriptio n	No abnormalities	The most early stage, where only microaneurysms can happen	Ability of blood transportation due to their distortion and swelling with the progress of the disease	Blood supply to the retina due to the increased blockage of more blood vessels	The advanced stage, where the growth features secreted by the retina activate proliferation of the new blood vessels
Sample images with their levels					

Fig. 1. DR Stages

Each stage has its own signs and characteristics, and doctors can no longer distinguish between the DR stages based on normal photographs. Furthermore, current diagnostic procedures are ineffective because they take a long time, causing therapy to go in the wrong direction. To find out whether you have retinopathy. Doctors used a fundus camera to diagnose retinopathy, which takes pictures of veins and nerves behind the retina. Since there are no symptoms of DR in the early stages of this condition, identifying it as such can be difficult. We used various CNN (Convolutional Neural Network) algorithms for early detection so that doctors could begin care at the appropriate time. In this paper the dataset which we are using for the project is collected from “Aravind Eye Hospital” and it is available on kaggle that is “(Asia Pacific Tele- Ophthalmology Society)”. We compare the two CNN architecture that is VGG16 architecture and DenseNet121 architecture, and showing the results of these two architectures. The dataset for this paper was obtained from “Aravind Eye Hospital” and is available on kaggle under the name “(Asia Pacific Tele Ophthalmology Society)”. We reveal the effects of two CNN architectures, VGG16 and DenseNet121. Recent projects and research have found that AI models, especially "Deep Learning" in AI, provide the most accurate results in detecting hidden layers in different AI tasks, particularly in the field of medical image analysis [1]-[3]. Deep learning models are used to identify diseases and help medical decision-making, as well as to boost continuous concern (extra care) [4]. The remainder of the paper is structured as follows: The literature reviews of the DR image classification are included in Section II. The dataset details is detailed in Section III. The Methodology of DL Architectures is covered in Section IV .The key outcome of this project is described in Section V.

2. Literature Review

It provides an overview of emerging methods that used "Deep Learning" for DR automated early detection in one subject. A. The development and testing of a deep learning algorithm for automated detection of DR. Deep learning was used to develop an algorithm for detecting DR automatically. Since it is a statistical approach and learning from a wide collection of instances that illustrate the desired behavior, deep learning has the ability to program an algorithm itself. Medical imaging employs these methods. The Messidor-2 had 1748 images from 874 patients, while the EyePACS-1 had 963 images from 4997 patients. The algorithm had a region under the receiver operating curve of 0.991 (EyePACS1) and 0.990 (Messidor-2) for accuracy detection [5]. The automated identification of DR is important, since it is the leading cause of permanent vision loss in the world's working-age and young-age populations. Even for experienced physicians, classifying DR photographs is difficult. As a result, DCNN (Deep

*Corresponding author: bpansare3@gmail.com

Convolutional Neural Network) was used to classify DR with a 94.5 percent accuracy [6]. Currently, a novel DCNN is being developed that performs the initial time recognition by identifying all microaneurysms (MAs), the first sign of DR, as well as correctly assigning names to retinal fundus images divided into five groups. The architecture was put to the test on the Kaggle dataset, yielding a QWK score of 0.851 and an AUC score of 0.844. The model had a sensitivity of 98 percent and a precision of 94 percent in early stage identification, demonstrating the technique's efficacy [7].

A master-checked data set integrity increases the recognition of discrete highlights and finds that pre- processing with restricted AHE contrast. Transfer learning on ImageNet models improves classification accuracies by 74.5 percent, 68.8%, and 57.2 percent (2-ary, 3-ary, and 4-ary) models, respectively [8]. With proper treatment at the early stages of DR, this form of disease can be avoided. For the diagnosis of DR disease, a new function extraction method called Modified Exception Architecture has been seen in the picture. When opposed to the original exception architecture, the modified deep feature extractor increases DR classification with an accuracy of 83.09 percent versus 79.59 percent [9].

The aim is to use a general approach to automate the discovery of DR and access the severity with high performance. Investigate the use of various CNN architectures on images from the dataset after they've been exposed to appropriate image processing techniques. Unfortunately, determining the DR level is notoriously difficult and involves professional human interpretation of fundus images. Currently, an automated deep learning-based system for DR stage detection using individual photography of the human fundus is being developed. On the Dataset, the tool can be used for early stage identification since it has a sensitivity and accuracy of 0.78 unfortunately, the particular diagnosis of the DR stage is known to be risky and needs a skilled knowledge of fundus images. Right now an automated, deep learning approach for the detection of the DR stage by individual human fundus image.

3. Dataset

The image data for this study was derived from a dataset. The dataset we used is a free dataset, which means that everyone can use it. It was obtained from “Aravind Eye Hospital” and was readily accessible on Kaggle for Blindness Detection. This dataset was the most comprehensive publicly accessible for pre-training our CNN architecture or model. We used a dataset that included a vast number of high- resolution retina photographs taken under a range of imaging conditions. The photographs in the dataset were taken with a fundus camera that produces a color fundus picture of DR. A fundus camera is a low power an inverted (fundus) camera is a low-power microscope linked to a camera to shoot the inside surface of the eye [13]. The picture from the fundus was utilized to capture the DR situation as a consistent identifying image.

These DRs have been classified by professionals in five classes depicting DR stages:

- No DR (class 0)
- Mild DR (class 1)
- Moderate DR (class 2)
- Sever DR (class 4)
- PDR (Proliferative DR) (class 5)

There are some directories in this dataset, including train.csv, test.csv, train images, test images, and sample submission.csv. The CSV (Comma Separated Values) file contains all of the image material in an excel sheet. The fundus eye picture name, intensity rating (class), and test are all stored in Train.csv. Since the eye image name will be tested after the CNN architecture has been trained, the csv only contains the name of the eye image. The image below is a reference image of a fundus camera, and it is a sample from the dataset:

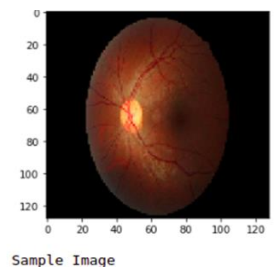


Fig. 2. Sample image

The above figure shows all the nerves which is behind the eye. In our dataset all the image have 128X128 pixels and 3 channels that is RGB channel and divided into five classes. Dataset includes 3307 train images and 1094 test images (in below figure).

```
Reshaping ValX at....2021-05-31 13:16:41.354720
<class 'pandas.core.series.Series'>
(1094,)
(1094, 128, 128, 3)
Reshaped trainX at....2021-05-31 13:16:41.942150
```

Fig. 3. Number of test dataset

```
Reshaping trainX at...2021-05-31 13:16:33.702294
<class 'pandas.core.series.Series'>
(3307,)
(3307, 128, 128, 3)
Reshaped trainX at...2021-05-31 13:16:34.580918
```

Fig. 4. Number of train dataset

1) ImageNet

The ImageNet dataset was used to pre-train our CNN architecture. In our case, the ImageNet dataset increases the consistency of the DenseNet121 architecture by improving the accuracy of CNNs models. The ImageNet dataset is a vast collection of images used to create computer vision, AI (Artificial Intelligence), ML (Machine Learning), and DL (Deep Learning) algorithms and models (Deep learning). When there is an annual competition, the challenges, models, and algorithms all use subsets, which are images that we choose to train from the ImageNet dataset. According to the dataset's stats on ImageNet, there are 14 million separate images in the dataset, including images of animals, medical images, plant data, and so on. The dataset was created with the aim of serving as a guide to aid in the research and creation of better approaches for computer vision, AI, machine learning, and deep learning.

4. Methodology

As we all know, a major cause of blindness is an issue with DR identification. The first concern in overcoming this issue is early identification. So, for early detection, we're using the "Dense Net 121Architecture" deep learning framework.

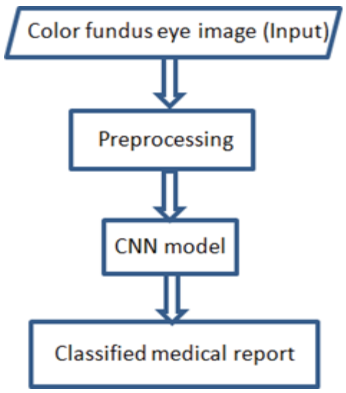


Fig. 5. Deep learning framework

The architecture of deep learning for DR is depicted in fig. 5.

1) Preprocessing

During preprocessing, there are a few steps that must be followed:

a) Use an illustration as a starting point.
b) Use a preprocessing strategy to draw attention to key elements.
c) Photo cropping and resizing
d) Correct data cleaning and black icon removal.
e) Image rotation and mirroring to align the dataset if it is unbalanced.
f) Numpy array conversion.
g) Now you can use it to practice or test.

2) CNN model

After preprocessing, the next step is to train our CNN model or architecture. In deep learning approaches, there are several CNN models or architectures available to train the network.

3) Medical report

Now that we've trained our model, we'll receive the final report, which is the output of the input picture. It means that if we use an unknown image as a test, it will provide a report for that unknown image.

4) Flowchart of our project

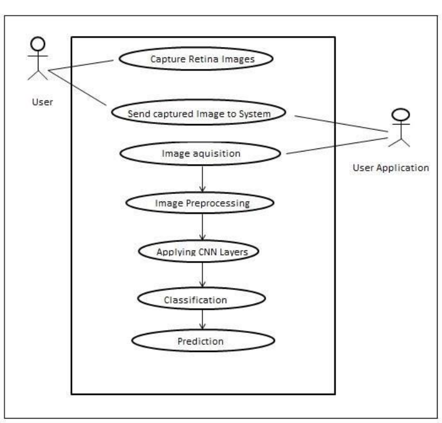


Fig. 6. Flow chart

The complete flowchart of our project, which uses ImageNet for improved precision with DenseNet architecture, can be found in Figure 6. We don't use ImageNet for VGG16 architecture, and we'll see the gap between VGG16 and DenseNet 121 architecture. The flowchart is self-explanatory, as it involves preprocessing, displaying dataset detail, displaying the shape of the image, using quadratic weighted kappa and ImageNet, and finally running the epochs and obtaining the output, as shown in the above figure.

5) DenseNet 121 Architecture

The below figure shows the block diagram of DenseNet 121 architecture. DCNN's depth or substrate is being increased by DenseNets. DenseNets take advantage of the network's capacity by repurposing the functionality. There is no need to study function maps for DenseNet121 Architecture, and it only takes a few or minor maps.

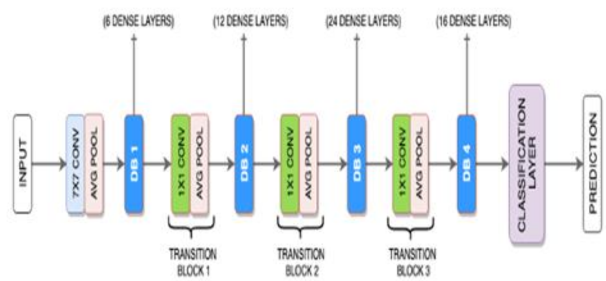


Fig. 7. Dense Net 121 architecture

The DenseNet architecture is a more advanced variant of ResNet. This design concatenates the performance of the layer's features with the incoming features rather than summarizing or adding them. DenseNet121 is divided into Dense Blocks, with the dimensions of the features being unchanged or unchanging within a block but the number of filters changing between blocks; these layers are known as transformation layers. The measurements of each volume, as seen in the above diagram, reflect the sizes of the 2D, that is, its depth and distance, while the numbers on the top include the features dimension. The growth rate of the model is 32. The growth rate multiplied by the number of dense layers within a dense block increases the thickness of that dense block. Per layer builds on the previous one of these 32 growth rates, which is a new aspect. In the case of each volume the dimensions of the 2D are the depth and breadth of the volume as indicated in the above picture, while the numbers above reflect the characteristic dimensions. The growth rate of the model is here 32. The volume of each dense-block blocks rises with the rate of expansion by the number of dense-block layers. Each layer adds a new characteristic to the previous pace of growth of this 32. All this increases the layers after 6 layers from 64 to 256. Moreover a 1 x 1 convolution block with 128 filters is performed. 2 X 2 pools with step 2, which divides the volume and the size.

6) VGG16 architecture

The below figure shows the VGG16 architecture. We do not use the ImageNet in this architecture.

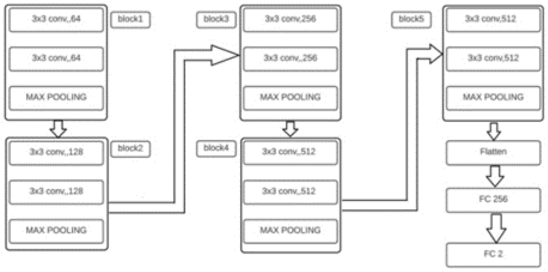


Fig. 8. VGG16 architecture

The input of the conv1 layer is the same size (128 X 128), regardless of where we see it, and it is an RGB file. The picture is passed into a series of convolutional layers (multiple layers), where the filters are applied. After convolution, the spatial resolution of the convolutional layer input is maintained, so the padding is one pixel for 3 X 3 conv layers. Five max-pooling layers obey some of the conv layers and do spatial pooling. Max-pooling had a window of over 2 X 2 pixels and stride 2. A stack of convolution layers (which has a different depth in different architectures) follows a stack of fully connected (FC) layers, which is almost the last layer.

7) Quadratic Weighted Kappa

When ordering codes, the quadratic weighted kappa is extremely useful. The observed score matrix, the predicted score matrix dependent on chance agreement, and the weight matrix are all used. The QWK is calculated in a few phases, which are as follows:

- Phase 1: Between the expected and real values, build a multiclass uncertainty matrix (confusion matrix) 0.
- Phase 2: Each factor is weighted in this step. Predictions that are farther from the actuals are penalized more severely than predictions that are closest to the actuals (create the weighted matrix that measures the weight between the actual and expected values).
- Phase 3: Measure value counts() for each rating in preds and actuals, and create two vectors, one for preds and one for actuals, to show how many values of each rating occur in each vector.
- Phase 4: Calculate E, which is the exterior product of the two vectors measured in step 3 (calculate E, which is the outer product of two value count vectors).
- Phase 5: Equalize the sums of both matrices. E and 0 matrix can be normalized.
- Phase 6: Calculate the weighted kappa numerator and denominator and return the weighted kappa matrix as 1-(num/ den).

5. Results and Analysis

We received the experiment results after we completed the tests, which demonstrated the consistency of our project. We compared the accuracies of two architectures with the same dataset.

VGG16 is used without ImageNet and QWK, and DenseNet is used with ImageNet as seen in the table above. As a result, without ImageNet, VGG16 has lower accuracy, while Dense Net has higher accuracy than VGG16. Now we'll look at the VGG16 and Dense Net precision and a graphs, respectively.

Table 1
Results and analysis

Architecture	Dataset	Loss	Accuracy
VGG16	Kaggle	0.84	0.631
DenseNet121	Kaggle	1.89	0.785

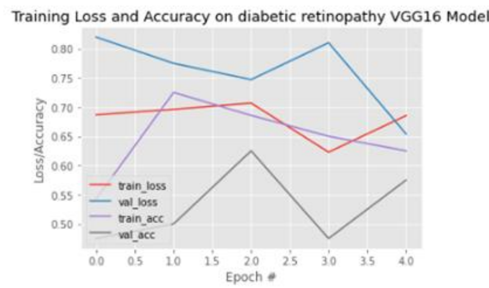


Fig. 9. VGG16 Graph

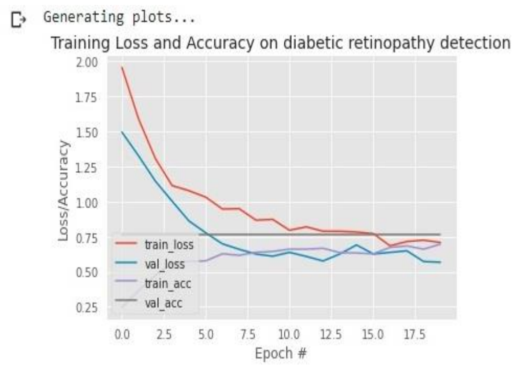


Fig. 10. Dense net Graph

```
Performance Report:
Accuracy score is : 0.785
Precision score is : 0.616225
Recall score is : 0.785
F1 Score is : 0.6904481792717087
Cohen Kappa Score: 0.0
               Classification Report:
              precision    recall  f1-score   support

           0       0.79      1.00      0.88       157
           1       0.00      0.00      0.00        43

    accuracy                           0.79       200
   macro avg       0.39      0.50      0.44       200
weighted avg       0.62      0.79      0.69       200
```

Fig. 11. Dens net Performance Score

The accuracies and losses of VGG16 and DenseNet121 architectures, respectively, as seen in the following figures fig.9 (a), fig.9 (b) and fig.10 (a), where VGG16 architectures do not use ImageNet and Dense Net architectures.

6. Conclusion

As we all know, DR (Diabetic Retinopathy) is a major problem for diabetic patients, and manually detecting DR takes a long time. Then we created an architecture for automated detection of DR, and we compared two architectures to see which one is better in which situation. VGG16 and DenseNet121 are the two architectures, with accuracies of 0.631 and 0.785, respectively.

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