IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.39 ⁜ Vol. 11, Issue 5, May 2022

DOI: 10.17148/IJARCCE.2022.115109

Prediction of Diabetic Retinopathy using Neural Networks

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Abstract: Diabetic retinopathy is a consequence of Diabetes Mellitus that affects the Retina (back of the eye) due to excessive blood sugar levels. If left undiagnosed and untreated, it might result in blindness. The retina is the light-sensitive layer of cells that turns light into electrical signals at the back of the eye. The signals are transmitted to the brain, which transforms them into the images you see. The retina requires a constant supply of blood, which is delivered via a network of small blood capillaries. Advanced cases of diabetic retinopathy may necessitate a surgical treatment to remove and replace the vitreous, a gel-like fluid in the back of the eye. A retinal detachment may also necessitate surgery. This is a separation of the rear of the eye's light-receiving lining. Diabetic retinopathy (DR) diagnosis by colour fundus images necessitates skilled doctors recognizing the presence and significance of several minor characteristics, which, combined with a complicated grading system, makes this a challenging and time-consuming task. In this study, we present a CNN approach for diagnosing DR and reliably grading its severity from digital fundus images. [1-4] We create a network with CNN architecture and data augmentations that can recognize the complex elements involved in the classification task, such as micro-aneurysms, exudates, and haemorrhages on the retina, and deliver diagnosis automatically and without the need for human input. We train our network on the acquired images, which are applied with Gaussian filters. On 3500 validation photos, our suggested CNN achieves a sensitivity of more than 95% and an accuracy of 98% on the image set. The proposed method is extremely accurate at objectively diagnosing and grading diabetic retinopathy, removing the requirement for a retina specialist and increasing access to retinal care. This technique allows for early detection and objective tracking of disease progression, which may aid in the optimization of medical therapy to reduce visual loss. [5]

Keywords: Diabetes Mellitus, Deep Learning, Convolutional Neural Networks (CNN), Diabetic Retinopathy, Image Classification, retina, Gaussian filters, Mild DR, Moderate DR, Severe DR, Proliferate DR and NO DR.

I. INTRODUCTION

Fluid can collect in the lens inside the eye that controls focusing when persons with diabetes have high blood sugar for lengthy periods of time. This alters the curvature of the lens, causing vision to shift. Once blood sugar levels are under control, the lens will normally revert to its former shape and eyesight will improve. Diabetic retinopathy will be delayed and progressed in patients who can better control their blood sugar levels. According to the AOA's 2018 American Eye Q Survey, nearly half of Americans are unaware that diabetic eye illnesses have visual symptoms (which are often absent in the early stages of diabetic retinopathy). Diabetic retinopathy can cause considerable vision loss if it is not detected and treated early. Diabetic retinopathy is treated differently depending on the severity of the condition. Laser surgery may be required for people with diabetic retinopathy to seal leaking blood vessels or to prevent other blood vessels from leaking. To reduce inflammation or prevent the production of new blood vessels, your optometrist may need to inject drugs into your eye. Advanced cases of diabetic retinopathy may necessitate a surgical treatment to remove and replace the vitreous, a gel-like fluid in the back of the eye. A retinal detachment may also necessitate surgery. This is a separation of the rear of the eye's light-receiving lining. Symptoms of diabetic retinopathy include:

i. Seeing spots or floaters
ii. Blurred vision
iii. Having a dark or empty spot in the center of your vision
iv. Difficulty seeing well at night

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II. LITERATURE SURVEY

[1] **Application of higher order spectra for the identification of diabetes retinopathy stages.** Feature extraction based classification and DL has been used to classify DR. In Acharya et al. higher order spectra technique was used to extract features from 300 fundus images and fed to a support vector machine classifier; it classified the images into 5 classes with sensitivity of 82% and specificity of 88%. Different algorithms were developed to extract DR lesions such as blood vessels, exudates, and microaneurysms. Exudates have been extracted for DR grading. Support vector machine was used to classify the DIABETDB1 dataset into positive and negative classes using area and number of microaneurysms as features.

[2] **Rethinking the inception architecture for computer vision**. Feature extraction based classification methods need expert knowledge in order to detect the required features, and they also involve a time consuming process of feature selection, identification and extraction. Furthermore, DL based systems such as CNNs have been seen to outperform feature extraction based methods. DL training for DR classification have been performed in two major categories: learning from scratch and transfer learning.

[3] **Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs**. A convolutional neural network (CNN) was trained to classify a dataset of 128,175 fundus images into 2 classes, where the first class contains images with severity levels 0 and 1, and the second class contains levels 2, 3 and 4. In an operating cut point picked for high sensitivity, had a sensitivity of 97.5% and specificity of 93.4% on the EyePACS-1 dataset which consists of 9963 images; it scored a sensitivity of 96.1% and a specificity of 93.9% on the Messidor-2 dataset; and in an evaluation cut point selected for high specificity, the sensitivity and specificity were 90.3% and 98.1% on the EyePACS-1, while 87% and 98.5% was scored on the Messidor-2, consecutively.

[4] **Convolutional neural networks for diabetic retinopathy**. Using a training dataset of over 70,000 fundus images, Pratt et al. trained a CNN using stochastic gradient descent algorithm to classify DR into 5 classes, and it achieved 95% specificity, 75% accuracy and 30% sensitivity. A DL model was trained from scratch on the MESSIDOR-2 dataset for the automatic detection of DR in, and 96.8% sensitivity and 87% specificity were scored.

[5] **Deep-learning-based automatic computer-aided diagnosis system for diabetic retinopathy.** Mansour put to use the Kaggle dataset to train a deep convolutional neural network using transfer learning for feature extraction when building a computer aided diagnosis for DR. In Dutta et al. 2000 fundus images were selected from the Kaggle dataset to train a shallow feed forward neural network, deep neural network and VggNet16 model. On a test dataset of 300 images, the shallow neural network scored an accuracy of 41%, and the deep neural network scored 86.3% whiles the VggNet-16 scored 78.3% accuracy.

[6] **Comparative Study of Fine-Tuning of Pre-Trained Convolutional Neural Networks for Diabetic Retinopathy Screening.** In order to avoid the time and resource consumed during DL, Mohammadian et al. fine-tuned the Inception-V3 and Exception pre-trained models to classify the Kaggle dataset into two classes. After using data augmentation to balance the dataset, reached at an accuracy score of 87.12% on the Inception-V3, and 74.49% on the Exception model.

[7] **Diagnosis of Diabetic Retinopathy Using Deep Neural.** Networks A training dataset of size 4476 was collected and labeled into 4 classes depending on abnormalities and required treatment; they resized input images into 600x600 and cut every image into four 300x300 images, and fed these images into separate pre-trained Inception-V3 models, which they called the Inception@4. After it was seen that accuracy result of the Inception@4 surpassed the VggNet and ResNet models, it was deployed on a web-based DR classification system.

III. EXISTING CNN MODELS

i. Inception V3: Szegedy et al proposed the Inception architecture in 2014. The original architecture was called GoogleLeNet. All the subsequent versions were called Inception Vn (n is the version number). Batch Normalization was added in Inception V2 as an improvement over Inception V1. In InceptionV3 model factorization methods were introduced as an improvement over V2.[6-9]

ii. ResNet50: In 2015 He et al proposed ResNet - The Residual Networks architecture. It has 50 convolutional layers with skip connections that help in improving the learning accuracy of the model. Also, it uses global averaging pooling instead of fully connected layers thereby reducing the model size.[10]

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iii. MobileNet: In 2017 another CNN architecture called MobileNet was proposed by Howard et al. In this separable convolution have been arranged depth-wise and they apply the convolution operation on each color channel separately instead of taking them as a whole. The cost of computation gets reduced in this architecture.[11]

iv. Xception: François Chollet developed Xception in 2017. This model can be considered as an improvised version of Inception as modules of Inception have been replaced with depth wise separable convolutions. This latest and accurate model scores upon speed and accuracy.

IV. PROBLEM STATEMENT

Using the Keras_h5 model of CNN, we predict the stage of diabetic retinopathy using fundus photograph images. The project's major goal is to diagnose diabetic retinopathy early enough to prevent blindness. Using Deep transfer learning and classification techniques, we detect the Complication of the disease by classifying the images of the patient's retina into five labels numbered from 0 to 4, where each label named Normal, Mild DR, Moderate DR, Severe DR, and Proliferate DR represents the disease complication. For the given input fundus image, one of these five steps is detected as an output label. Realtime images or new images of newer subjects has to be predicted for Normal, Mild DR, Moderate DR, Severe DR, and Proliferate DR. Also, the model obtained out of CNN needs to be re-validated for better accuracy through feedback method. This research work is divided into four parts

First. Image Acquisition, categorization and applying Gaussian filters.
Second. Image Pre-processing, Image to array formation and image matrix handling.
Third. Applying CNN and creating and validating retina.model for Prediction.
Fourth. Testing on real time images and verification.

V. IMAGE SET

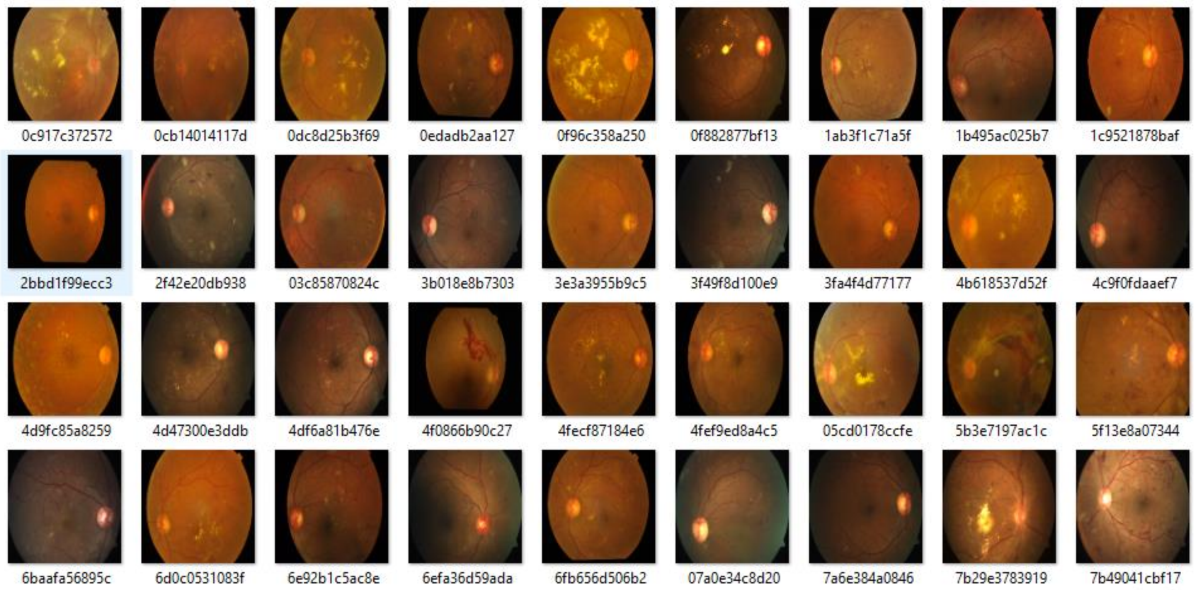
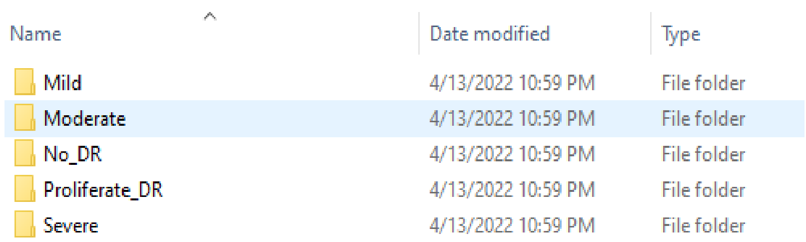


Figure 1 shows the image of acquire image set.



Name	Date modified	Type
Mild	4/13/2022 10:59 PM	File folder
Moderate	4/13/2022 10:59 PM	File folder
No_DR	4/13/2022 10:59 PM	File folder
Proliferate_DR	4/13/2022 10:59 PM	File folder
Severe	4/13/2022 10:59 PM	File folder

Figure 2 shows the categorization of the image set into above categories.

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Figure 1 shows the image of acquire image set. The images are classified into folders:

i. No_DR
ii. Mild
iii. Moderate
iv. Proliferate_DR
v. Severe_DR

Figure 2 shows the categorization of the image set into above categories. Figure 3 shows the countplot of the imageset. Figure 3 indicates the total number of images belonging to each of the above five categories. For easier classification the above classified image set can be reduced to only 2 image folders:

i. No_DR
ii. DR

Where, DR includes

i. Mild
ii. Moderate
iii. Proliferate_DR
iv. Severe_DR

Figure 4 shows the Gaussian filtered image set. When lowering the size of an image, Gaussian filters are widely utilised. When downsampling images, it is a usual practise to add a low-pass filter before resampling. This is to verify that the downsampled images do not contain any erroneous high-frequency information (aliasing).

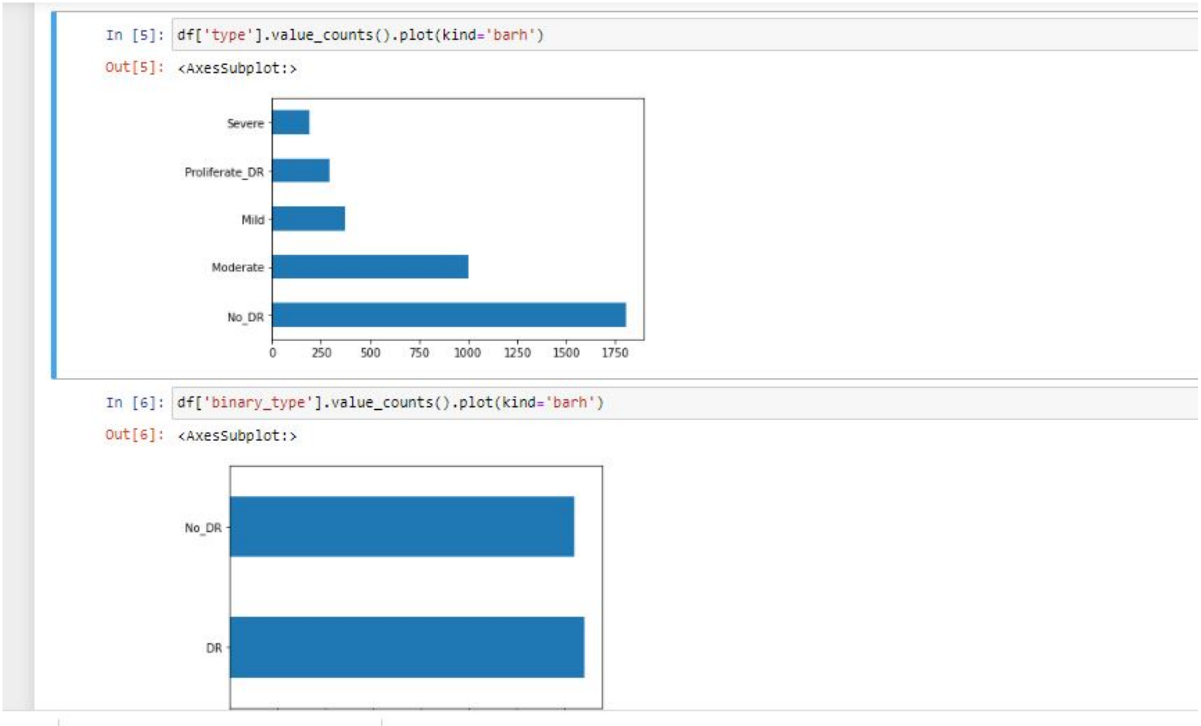

Figure 3 shows the count plot of the image set.

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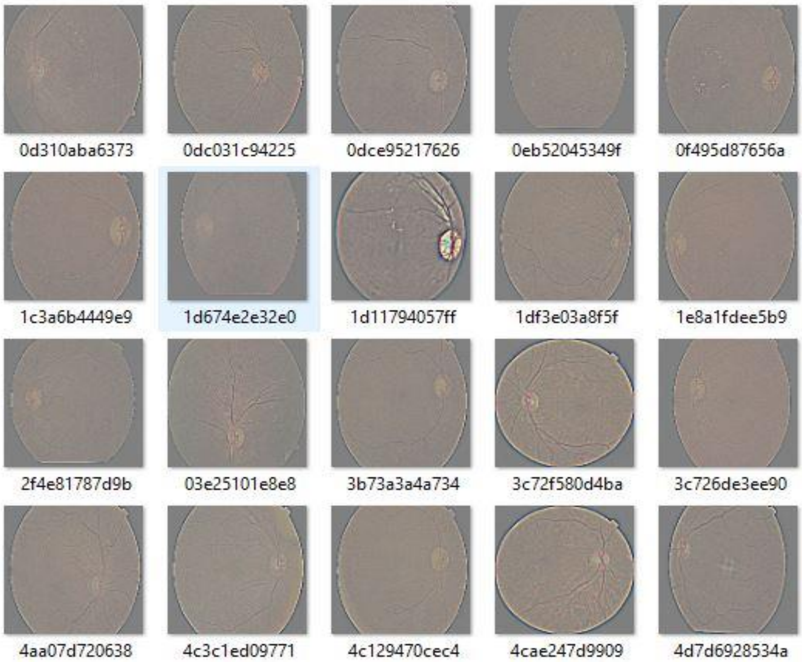

Figure 4 shows the Gaussian filtered image set.

VI. SOFTWARE AND HARDWARE REQUIREMENTS

Software configuration
Operating system: Windows 7 or newer, 64-bit macOS 10.13+, or Linux, including Ubuntu, RedHat, CentOS 6+, and others.
System architecture: Windows- 64-bit x86, 32-bit x86; MacOS- 64-bit x86; Linux- 64-bit x86, 64-bit Power8/Power9.
Environment: Python 2.7 or above version 4.1.2
Hardware configuration
Processor: Intel core i5 or above Ram: 8GB (OR) above
Storage: Minimum 5 GB disk space to download and install.

VII. SOFTWARE INSTALLATION

Python 2.7 and above needs to be installed during creation of tensorflow environment. Using Anaconda Navigator command prompt (or Anaconda Prompt) various packages needs to be installed. Few of the essential packages are

i. Keras
ii. openCV
iii. pillow
iv. tensorflow
v. os
vi. matplot

Keras is a lightweight Python deep learning package that runs on top of Theano or TensorFlow. It was created to make implementing deep learning models for research and development as simple and quick as possible. Tensorflow is a deep learning framework which gives you the power to build different kinds of Neural Networks including Convolution Neural Networks which are used mainly in image processing problems. OpenCV is a library with huge number of tools and functions for a very wide range of Image Processing problems. The de facto image processing package for the Python language is Python Imaging Library (extension of PIL). It comes with a set of lightweight image processing tools that help you edit, create, and save photos. In 2011, the Python Imaging Library was deprecated, but a project called pillow forked the original PIL project and provided Python3.x compatibility. For future use, Pillow has been announced as a substitute for PIL. BMP, PNG, JPEG, and TIFF are just a few of the image file types supported by Pillow. By developing new file decoders, the library encourages users to provide support for newer formats. Figure 5 shows the installation of keras on tensorflow environment.[12]

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```
Anaconda Prompt
(C:\Users\ab9bh\Anaconda3) C:\Users\ab9bh>activate tensorflow

(tensorflow) C:\Users\ab9bh>conda install keras
Fetching package metadata .............
Solving package specifications: .

Package plan for installation in environment C:\Users\ab9bh\Anaconda3\envs\tensorflow:

The following NEW packages will be INSTALLED:

    keras:          2.1.3-py36_0
    libprotobuf:    3.4.1-h3dba5dd_0
    protobuf:       3.4.1-py36h07fa351_0
    tensorflow:     1.1.0-np112py36_0

The following packages will be UPDATED:

    anaconda:       5.0.1-py36h8316230_2  --> custom-py36h363777c_0
    vs2015_runtime: 14.0.25123-hd4c4e62_2 --> 14.0.25420-0

The following packages will be DOWNGRADED:

    numba:          0.35.0-np113py36_10   --> 0.35.0-np112py36_0
    numpy:          1.13.3-py36ha320f96_0 --> 1.12.1-py36hf30b8aa_1

Proceed ([y]/n)? y

vs2015_runtime 100% |################################| Time: 0:00:00   8.27 MB/s
anaconda-custo 100% |################################| Time: 0:00:00 576.98 kB/s
libprotobuf-3. 100% |################################| Time: 0:00:00  10.04 MB/s
numpy-1.12.1-p 100% |################################| Time: 0:00:00  10.20 MB/s
numba-0.35.0-n 100% |################################| Time: 0:00:00   9.72 MB/s
protobuf-3.4.1 100% |################################| Time: 0:00:00   7.84 MB/s
tensorflow-1.1 100% |################################| Time: 0:00:03   5.12 MB/s
keras-2.1.3-py 100% |################################| Time: 0:00:00   3.46 MB/s

(tensorflow) C:\Users\ab9bh>
```

Figure 5 shows the installation of keras on tensorflow environment.

VIII. CONCLUSIONS AND FUTURE WORK

A training dataset of size 3500 was collected and labelled into 4 classes depending on abnormalities and required treatment. We collect all the fundus images from APTOS (Asia pacific Tele-Ophthalmology Society) dataset. In this dataset the fundus images are labelled as 0,1,2,3 and 4 for Normal, Mild DR, Moderate DR, Severe DR, and Proliferate DR respectively. This dataset provides 4700 fundus images in total. Among these 3500 (stored in Train.csv with image ID and its diagnosis label) and were used for model training and remaining 1200 (stored in Test.csv with image ID and its diagnosis label) are used for model testing. The following steps will be carried out in our upcoming research papers: Image Pre-processing, Image to array formation, image matrix handling, Applying CNN and creating and validating retina.model for Prediction. Testing on real time images and verification.

IX. ACKNOWLEDGEMENT

We wish to express our sincere thanks and gratitude to our project guide Dr. G M Swamy and Dr. Kalmeshwar Ullegaddi, Department of Mechanical Engineering, JSSATE, Bangalore, India for their simulating discussions, in analyzing problems associated with our research work and for guiding us throughout the project. Project meeting were highly informative. We express our sincere thanks for the encouragement, untiring guidance and the confidence they had shown in us.

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IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

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BIOGRAPHY

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